A model to understand and scaffold novices in estimation problem solving using a technology-enhanced learning environment

A thesis submitted in partial fulfillment of
the requirements for the degree of

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by

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Dedicated to

Advait

your infinite imagination and curiosity have been an inspiration throughout this work

Declaration

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

Engineers routinely make estimates of physical quantities such as power before they begin designing or making (Dym et al., 2005). In order to estimate a quantity, say power, a solver needs to make a simplified model, i.e., an equation relating power to parameters that significantly impact its value in the given real-world system (Mahajan, 2014). This is challenging for students because they must apply conceptual knowledge to a real-world system, identify the parameters that will dominate power requirements, make assumptions and make judgments regarding numerical values (Linder, 1999). Thus estimation is an ill-structured problem, very different from the well-structured problems which remain the emphasis of engineering curricula (Jonassen et al., 2006). Research has found a marked difference between the estimation performance of expert engineers and graduating engineering students (Linder, 1999). However, there is a dearth of research exploring the processes underlying the good estimation performance of experts. Thus, there is a need to understand these processes and explicitly train engineering students in estimation problem solving. While some researchers (Linder, 1999; Mahajan, 2014; Shakerin, 2006) have offered guidelines for learning estimation, these guidelines have not been empirically validated for their effectiveness for learning estimation. Thus the motivation of this thesis is twofold; firstly, to develop an understanding of good estimation processes and identify the cognitive mechanisms underlying good estimation and secondly, use this understanding to design supports for novices to do engineering estimation.

We followed a design-based research methodology (Reeves, 2006) with two iterations. Our first research goal was to understand estimation problem solving, i.e., what it means to do good estimation and what are the cognitive mechanisms underlying good estimation. To identify these, we performed a cognitive ethnography (R. Williams, 2006) of expert engineers (Study 1) as they solve estimation problems and identified their estimation process. We also identified the cognitive mechanisms which facilitated experts in doing estimation. We found that model-building via mental simulation is the key estimation process of experts. Next, we performed

a cognitive ethnography of novice undergraduates (Study 2), who solved estimation problems without any support in order to understand their estimation process, to identify differences from the expert process and their challenges in doing estimation. We found that novices follow a process of model-searching rather than model-building, focus on equation manipulation rather than mental simulation and have difficulty with model contextualization. The expert study also showed that identifying the causal relationships of the parameter to be estimated with other parameters is an important aspect of estimation. Hence we performed a lab study (Study 3) with novice undergraduates who solved estimation problems with a simple causal mapping tool. Interaction (Jordan & Henderson, 1995) and thematic (Braun & Clarke, 1996) analyses enabled us to identify where and what scaffolds are needed to support novices estimation problem solving. The expert and novice studies together helped us identify the scaffolds needed to support novice estimation problem solving.

In order to support novice estimation problem solving, we used the insights from studies 1, 2 and 3 to design Modelling-based Estimation Learning Environment (MEttLE), an open-ended technology-enhanced learning environment (TELE). Broadly, the pedagogy is designed based on the intertwining of cognitive and metacognitive tasks in such a manner as to support learning of estimation while solving an estimation problem. Specifically, MEttLE is based on triggering learners to build models for solving estimation problems, by providing them explicit model-building sub-goals and affordances such as simulations, a causal mapping tool and an equation builder. In addition, learners are provided guidance regarding expert estimation practices to make comparisons and judgments, choose values and evaluate their estimates. Finally, there are intermittent metacognitive prompts and scaffolds for evaluation, planning, monitoring and reflection.

The design was evaluated in a lab study (Study 4) wherein we applied interaction analysis to study how novices used the features in the TELE to solve an estimation problem. Based on this evaluation, we revised our design and then evaluated the revised TELE in a field study (Study 5). Here again we applied interaction analysis to study how the revised features supported novices in solving the estimation problem. Thus, in constantly refining our design to better support novices to solve estimation problems, we refined our understanding of what it means to do good estimation, how experts are able to do it well and how we can support novices in estimation problem solving.

The major contributions of this thesis include a detailed characterization of the expert and

novice estimation process and its underlying cognitive mechanisms; a set of scaffolds necessary in any learning environment that supports novice estimation problem solving and a model for solving estimation problems that leads to good estimates.

Keywords: Engineering Estimation, model-based reasoning, design-based research, technology-enhanced learning environment

Contents

List of Figures

List of Tables

Abbreviations and Nomenclature

DBR	Design-Based Research
MBR	Model-based reasoning
ISP	Ill-structured Problem
TELE	Technology-enhanced learning environment
MEttLE	Modelling-based Estimation Learning Environment
BotE	Back-of-the-envelope
OoM	Order-of-Magnitude
SENECA	Simulate to Expand, Narrow using Engineering concepts and problem Context, evaluate and reflect

Chapter 1

Introduction

1.1 Background and Motivation

One of the main requirements from a professional engineer is the ability to solve "broadly-defined engineering technology problems" (*ABET Criteria for Student Outcomes*, 2018; *Washington Accord: Graduate Attributes and Professional competencies*, 2009). These "engineering technology problems" are ill-structured and complex (Jonassen et al., 2006), in that they have unclear starting points, multiple and often conflicting solutions and solution paths. Further these are often solved by applying concepts from different areas of engineering. Therefore one of the main goals of engineering education is training students to solve engineering technology problems which they will encounter in their practice, such as,

> You are participating in an electric car race in which you are required to design an electric car of weight 10kg that can traverse a track length of 30m. The current record is 7 seconds. Estimate how much power you need to break that record without causing the motor to burn out. Can you use the motor of a vacuum cleaner to build this car?

Professional engineers must routinely solve problems such as this which involve estimating an unknown quantity (power) and using it to make a judgment (regarding feasibility of using a vacuum cleaner motor). Such estimates are also necessary in many other situations in engineering practice, such as, setting up, finding parameters for and evaluating detailed analyses; when the exact calculation is too difficult or not necessary; when tools like a calculator or computer are not available; when exact information, data and the actual governing equations are not available; to eliminate candidate design solutions; to check on the reasonableness of results; to obtain upper and lower bounds; to plan projects and experiments; in the selection of materials or components (Adolphy et al., 2009; Dunn-rankin, 2001; Dym et al., 2005; Linder & Flowers, 2001; Mahajan, 2014; Nachtmann & Lehrman, 2002; Paritosh, 2007; Raviv et al., 2016; Shakerin, 2006). Further, such estimation allows engineers to make decisions that allow them to proceed in the design process when faced with lack of information, resources or strategies (Adolphy et al., 2009; Nachtmann & Lehrman, 2002). Thus estimation is a practice for efficient engineering and an example of an engineering technology problem that graduating engineers must be able to solve.

Research, however, has shown that even graduating engineering students cannot make estimates of simple physical quantities such as force and energy (Linder, 1999; Trotskovsky & Sabag, 2016). Linder (1999) studied the estimation performance of engineering practitioners and senior undergraduate engineering students and found a marked difference between the performance of the two groups on the quality of estimates for drag force and energy. This may be because engineering programs emphasize conceptual knowledge and well-structured, analysis-based problems as Ferguson (1977) describes *"The real "problem" of engineering education is the implicit acceptance of the notion that high-status analytic courses are superior to those that encourage the student to develop an intuitive "feel" for the incalculable complexity of engineering practice in the real world."* This has also been reiterated by Mahajan (2014) who says *"To decide what is reasonable, you have to talk to your gut. The idea of talking to your gut may feel strange, especially as science and engineering are traditionally considered the most cerebral of subjects."* Estimation, on the other hand, requires an intuition for the values of quantities, which students do not have. However, practitioners have good intuition for these quantities, which is a result of their workplace engineering practice.

If as reported above, engineering estimation requires intuition and "gut-based reasoning", then how is estimation done and learned? This is a question also raised in (Guzdial, 2016), *"Every expert engineer does back-of-the-envelope estimation before starting a project. It's completely natural for them. How does that develop? Can we teach that process to students?(...) I find this problem interesting because estimation might be one of those hard-to-transfer higher-order thinking skills OR it could be a rule-of-thumb procedure that could be taught."* Thus, the good processes underlying estimation are not well-understood. This is the motivation of this thesis:

To develop an understanding of good estimation processes, identify the cognitive mechanisms underlying good estimation and use this understanding to design supports for novices to do engineering estimation.

1.2 Research Goal

There are several definitions for estimation in literature (Adolphy et al., 2009; Dunn-rankin, 2001; Linder, 1999; Mahajan, 2014; Paritosh, 2007; Shakerin, 2006). Synthesizing these definitions, we use the following definition of estimation in this thesis, "the process of determining approximate values for a physical quantity without access to complete information and knowledge." The learning activities of the current engineering curricula are primarily well-structured in nature while estimation is ill-structured (Jonassen et al., 2006). Literature describes these differences between the characteristics of the learning activities of engineering curricula and estimation (Dunn-rankin, 2001; Linder & Flowers, 2001; Nachtmann & Lehrman, 2002; Shakerin, 2006). Researchers have argued that the current engineering curricula do not prepare students for estimation activities because the ability to solve well-structured problems does not transfer to the ill-structured problems such as estimation (Jonassen et al., 2006). Estimation problems are especially hard to solve because they involve "mastering the complexity" of a physical system by identifying physical quantities that can be safely neglected (Adolphy et al., 2009; Dunn-rankin, 2001; Dym et al., 2005; Linder, 1999; Mahajan, 2014; Shakerin, 2006).

Recently, the teaching-learning of engineering design has received a lot of emphasis in engineering education (Dym et al., 2005). However, other ill-structured problems in engineering, such as estimation, are rarely explicitly taught (Lunt & Helps, 2001). Our literature survey confirmed that estimation is not a part of engineering curricula, except cost and time estimation in Civil and Software Engineering, and research related to the teaching-learning of estimation is sparse and fragmented. Further, the process of doing good estimation is not understood and only guidelines of how to do estimation are available (Dunn-rankin, 2001; Linder, 1999; Lunt & Helps, 2001; Mahajan, 2014; Nachtmann et al., 2003; Shakerin, 2006). We did not find literature on cognitive mechanisms underlying the process of estimation. Without such an understanding, it is not possible to design environments that effectively support the doing and learning of engineering estimation. Hence the broad research problem guiding this thesis is:

Developing a detailed understanding of estimation problem solving, and designing a technology-

enhanced learning environment to support novice estimation problem solving.

1.3 Solution Overview

Our solution approach is shown in Figure 1.1. We followed a design-based research methodology Barab & Squire (2004) and conducted two iterations. Our first research goal was to understand estimation problem solving, i.e., what it means to do good estimation and what are the cognitive mechanisms underlying good estimation. To identify these, we performed a cognitive ethnography (R. Williams, 2006) of expert engineers (Study 1) as they solve estimation problems and identified their estimation process. We also identified the cognitive mechanisms which facilitated experts in doing estimation. We found that model-building via mental simulation is the key estimation process of experts. Next, we performed a cognitive ethnography of novice undergraduates (Study 2), who solved estimation problems without any support in order to understand their estimation process, to identify differences from the expert process and their challenges in doing estimation. We found that novices follow a process of model-searching rather than model-building, focus on equation manipulation rather than mental simulation and have difficulty with model contextualization. The expert study also showed that identifying the causal relationships of the parameter to be estimated with other parameters is an important aspect of estimation. Hence we performed a lab study (Study 3) with novice undergraduates who solved estimation problems with a simple causal mapping tool. Interaction (Jordan & Henderson, 1995) and thematic (Braun & Clarke, 1996) analyses enabled us to identify where and what scaffolds are needed to support novices estimation problem solving. The expert and novice studies together helped us identify the scaffolds needed in the TELE to support novice estimation problem solving.

In order to support novice estimation problem solving (research goal 2), we designed a technology-enhanced learning environment (TELE) called Modelling-based Estimation Learning Environment (MEttLE). We used the insights from studies 1, 2 and 3 to design MEttLE1.0 and then applied interaction analysis to study how novices used the features in the TELE to solve an estimation problem (Study 4). Based on this evaluation, we revised our design to MEttLE2.0 and used interaction analysis to identify how the revised features supported novices in solving the estimation problem (Study 5). Thus, in constantly refining our design to better support novices to solve estimation problems, we refined our understanding of what it means to do good

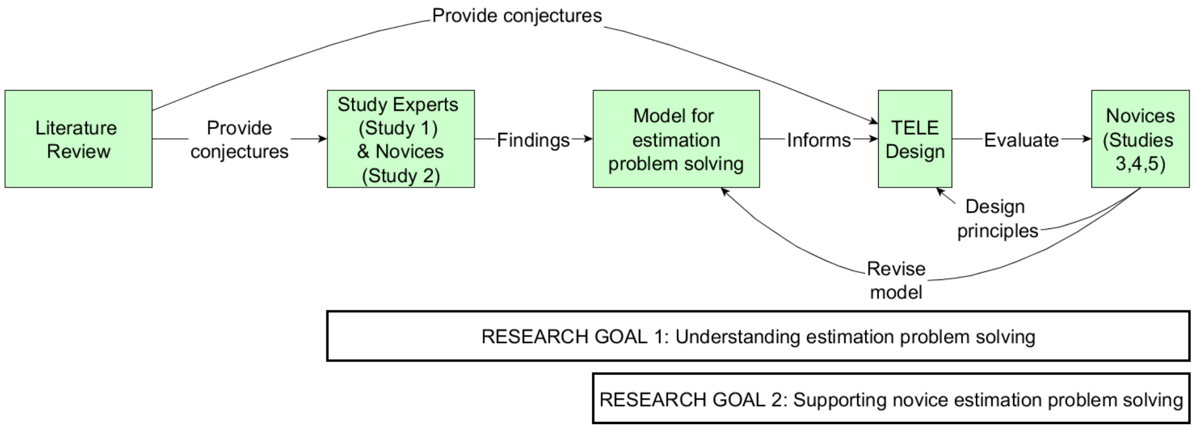


Figure 1.1: Overview of the solution approach of this thesis

estimation and how experts are able to do it well.

1.3.1 Theoretical Basis

Broadly, our approach is based on recent literature in cognitive science which suggests that engineering design and problem solving is distributed, situated and embodied rather than a search process (Aurigemma et al., 2013; Brereton, 2004; Hollan et al., 2000; Kirsh, 2009; Suchman, 2000). This means that solvers interact with their environment while solving problems, and use representations, resources and scaffolds in the environment to obtain a solution. Hence, our methods to investigate the estimation processes of experts and novices are chosen to analyse this interaction between the solver and his/her environment, understand which resources and scaffolds in the environment facilitate estimation, and how they do so. Further, we designed an environment embedded with resources and scaffolds that we conjectured would facilitate estimation (some of which we identified above), and studied how novices used these to solve an estimation problem.

1.3.2 MEttLE Pedagogy

Literature suggests that ill-structured problem solving requires both cognitive and metacognitive processes (Hong, 1998; Howard et al., 2001; Mayer, 1998). The nature of metacognitive processes required and the manner in which the cognitive and metacognitive processes are intertwined depends on the specific ill-structured problem. We identified these aspects for estimation problems from our expert and novice studies (1, 2 and 3) and used them in our pedagogy. The pedagogy is designed to support both cognitive and metacognitive processes, with the cognitive and metacognitive tasks intertwined in such a manner as to support novices in *progressively abstracting* the estimation problem solving process, as they are working on the problem.

Broadly, MEttLE is based on triggering novices to do modelling by providing them explicit model-building sub-goals (Mulder et al., 2011; Sun & Looi, 2013) and focus questions. They are provided model-building affordances and a problem simulator (Buckley, 2000; Jonassen, 2004) for creating models, along with scaffolds for model evaluation and model contextualization (Ge & Land, 2004; Quintana et al., 2004). In addition, novices are provided guidance regarding expert practices (Quintana et al., 2004) to choose values and evaluate their estimates by comparison. There are also intermittent metacognitive prompts (Ge & Land, 2004) for planning, monitoring and reflection. Thus, MEttLE has many affordances for novices to solve an estimation problem and an example of this is shown in Figure 1.2.

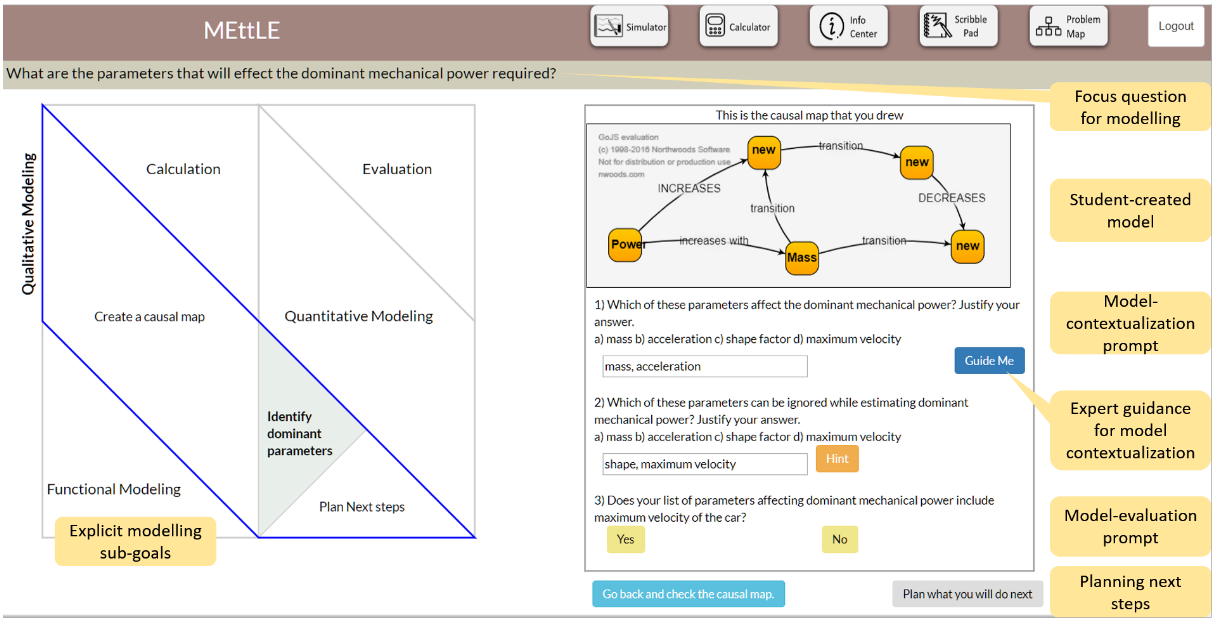


Figure 1.2: Screenshot of a modelling activity in MEttLE

MEttLE is an open-ended learning environment in that there is no prescribed sequence of tasks to solve an estimation problem and so novices have agency in deciding how they want to solve the problem. A possible estimation workflow for novices in MEttLE is shown in Figure 1.3. Novices are free to use the resources and scaffolds to solve the estimation problem in any manner. MEttLE thus serves as a means to support the estimation processes of model-building, mental simulation, model contextualization and evaluation, and a way to study how these processes come together to solve an estimation problem.

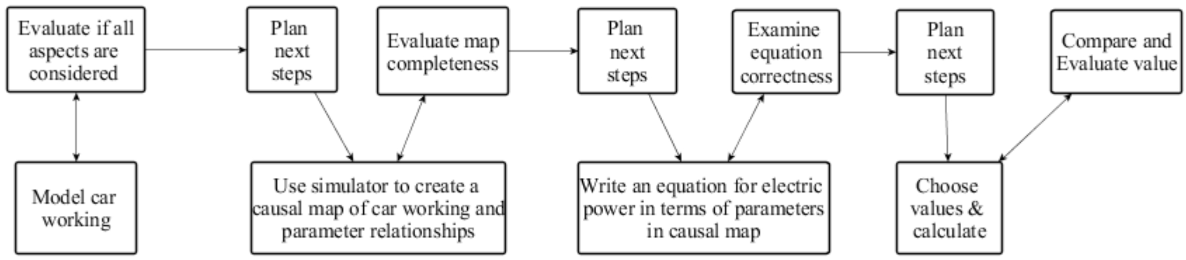


Figure 1.3: Possible estimation workflow for novices

1.4 Methodology

As described in the previous sections, the research goals of this thesis are to understand the estimation process and design a TELE to support novices estimation problem solving. The objective of the design itself is two-fold: to iteratively refine a set of design principles for supporting estimation problem solving and characterize the novice process of estimation problem solving in the designed environment. These dual goals align well with the methodology of design-based research (DBR).

DBR is a flexible and pragmatic research methodology that allows incorporation of all the stakeholders and the real-world context into the design and evaluation of interventions (Barab & Squire, 2004; Cobb et al., 2003). Each iteration of DBR has three phases namely Analysis/Exploration, Design/Construction and Evaluation/Reflection (Reeves, 2006). In this thesis, we conducted two iterations of DBR as shown in Figure 1.4. The first iteration had the goal of understanding estimation processes and identifying novice challenges in estimation, while the second iteration had the goal of designing a TELE for supporting novice estimation problem solving. Our research questions (RQs) emerged from these two research goals and our literature review of estimation, ill-structured problem solving and model-based reasoning. Next we give an overview of the research questions we investigated in this thesis.

1.4.1 Research Questions

DBR 1: Understanding estimation processes and identifying novice challenges

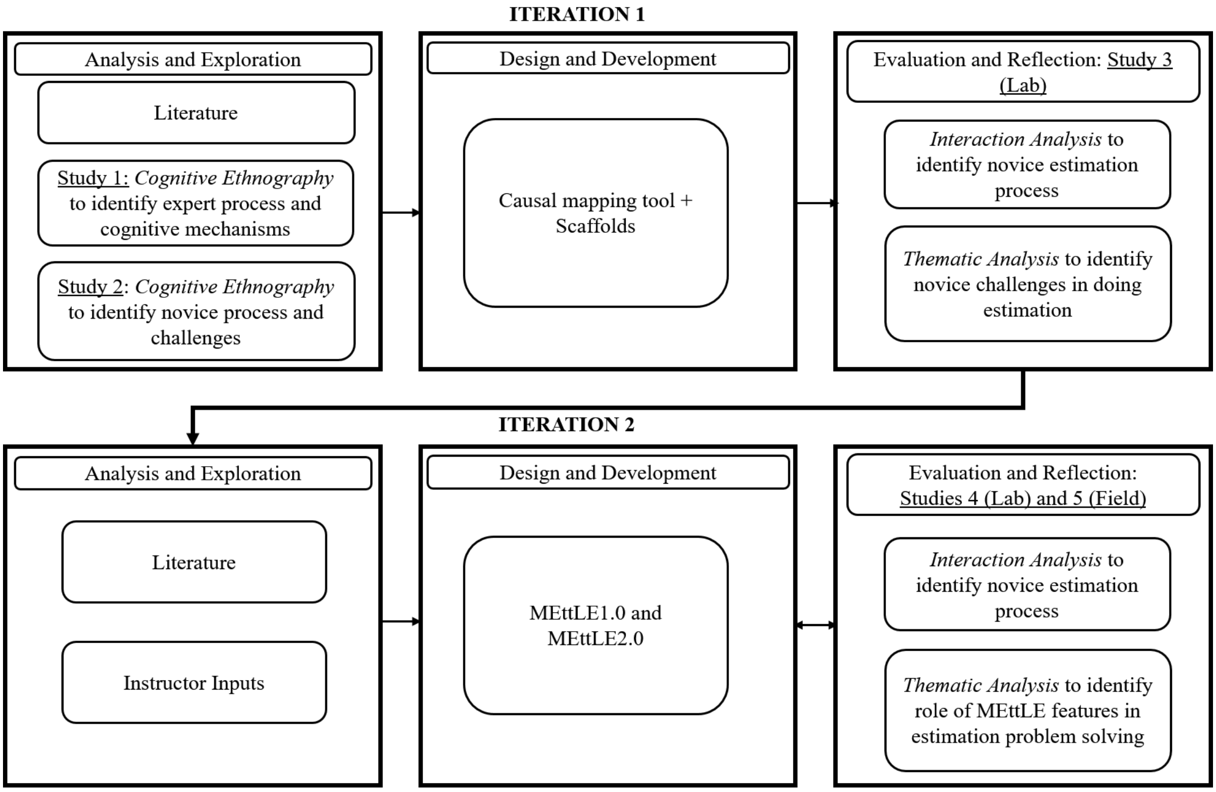


Figure 1.4: Design-based research as applied in this thesis

1. **Study 1:** Broad RQ - How do experts solve estimation problems?

   RQ1a What is the expert estimation process?

   RQ1b What are the cognitive mechanisms that play a role in obtaining order-of-magnitude estimates?

   We did a cognitive ethnography (R. Williams, 2006) of two experts who each solved three estimation problems. The data was analysed using microgenetic analysis (Hutchins & Nomura, 2011).

2. **Study 2:** Broad RQ - How do novices solve estimation problems?

   RQ2a How is the novice process of solving estimation problems different from the expert process?

   RQ2b What are the challenges that novices face while solving estimation problems?

   We did a cognitive ethnography of ten second year engineering students who each solved one estimation problem. The data was analysed using microgenetic analysis.

3. **Study 3:** Broad RQ - How do novices solve estimation problems using a scaffolded causal mapping intervention?

   RQ3a How does the scaffolded causal mapping intervention support novices in solving estimation problems?

   RQ3b What challenges do novices face while solving estimation problems using a scaffolded causal mapping intervention?

   We did a lab study with six first and second year engineering students, who each solved three estimation problems. We performed interaction analysis (Jordan & Henderson, 1995) to answer RQ3a and thematic analysis (Braun & Clarke, 1996) to answer RQ3b.

DBR 2: Supporting novice estimation problem solving

1. **Study 4** Broad RQ - How do novices do estimation in MEttLE1.0?

   RQ4a What is the novice process of solving an estimation problem in MEttLE1.0?

   RQ4b How do novices use the features in MEttLE1.0 to solve the estimation problem?

   We did a lab study with ten second year engineering students, who each solved one estimation problem. We performed interaction analysis to answer RQ4a and thematic analysis to answer RQ4b.

2. **Study 5:** Broad RQ - How do novices do estimation in MEttLE2.0?

   RQ5a What is the novice process of solving an estimation problem in MEttLE2.0?

   RQ5b How do novices use the features in MEttLE2.0 to solve the estimation problem?

   We did a field study with twelve second year engineering students, who each solved one estimation problem. We performed interaction analysis to answer RQ5a and thematic analysis to answer RQ5b.

A summary of the studies done in this thesis are shown in Figure 1.5.

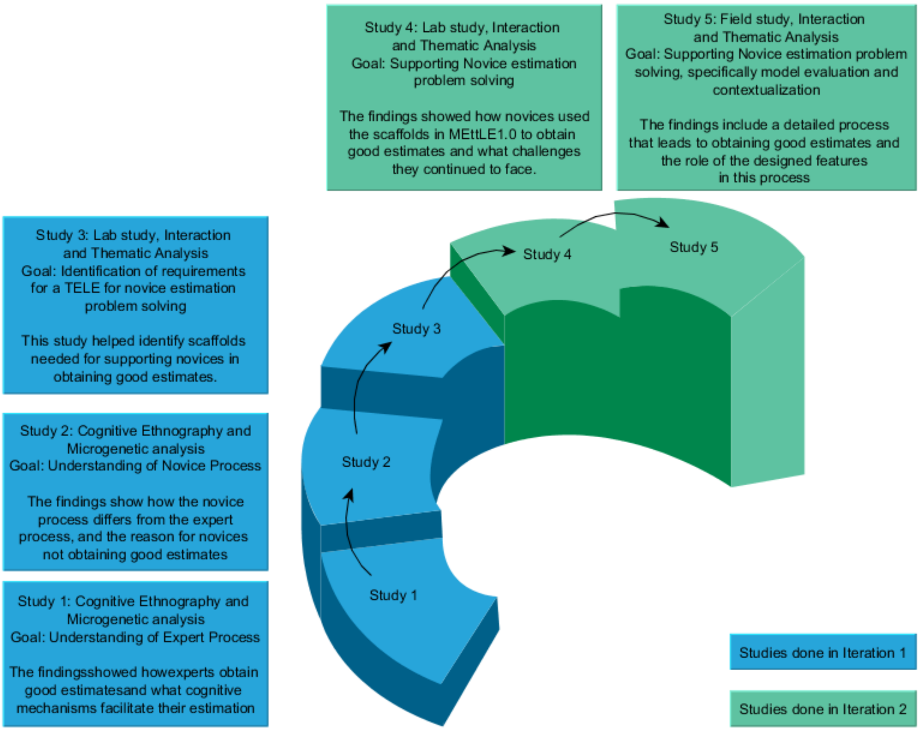


Figure 1.5: An overview of the studies done in this thesis

1.5 Delimitations

We scope the research done in this thesis along the dimensions of estimation problem, learners, context and technology.

1.5.1 Estimation Problem

The quantities which are estimated and the purposes for which estimation is done is shown in Figure 1.6. For the research goal of understanding the estimation process, we scope ourselves to three estimation purposes, namely, select a material or component, establish feasibility of a design and approximate analysis of objects, systems or phenomena and two sets of quantities of power/energy and length/area/volume/weight since these are related quantities. These are the nodes indicated in yellow and green in Figure 1.6. For the research goal of supporting estimation, we scope ourselves to the estimation purpose of select a material or component and the quantity of power/energy (related quantities). These are the nodes marked in green in Figure 1.6. We do not consider probabilistic parameter estimation which is undertaken in communications engineering, aerospace engineering and software engineering.

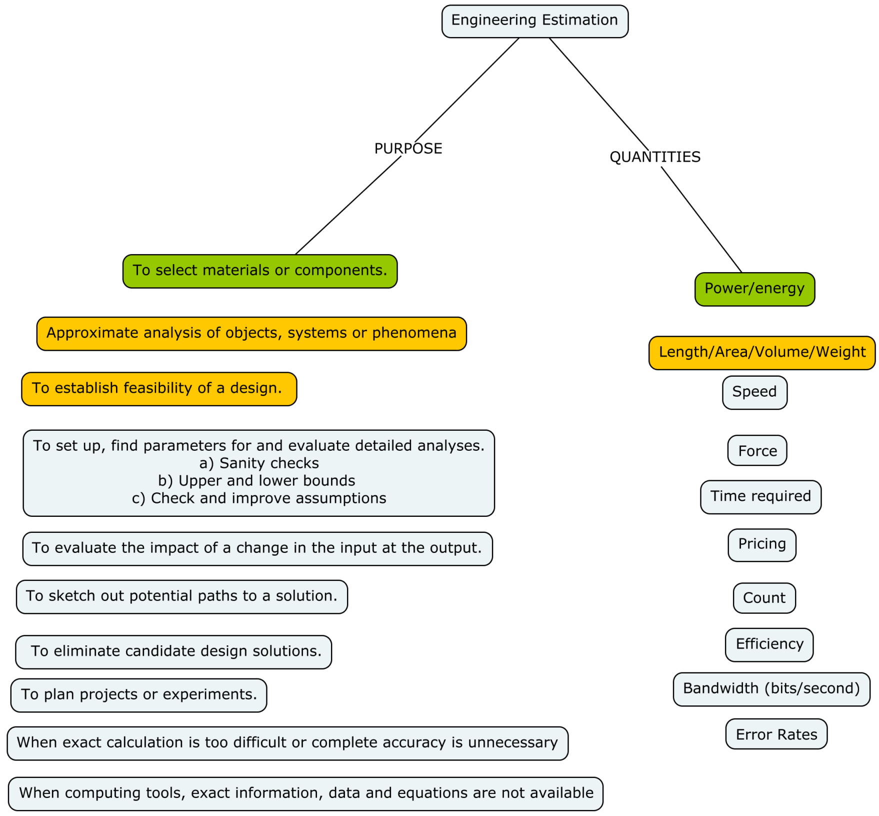


Figure 1.6: Estimation purposes and quantities

1.5.2 Novice Characteristics

The novice is chosen to be first or second year undergraduate mechanical or electrical engineering students, from any institute or university in India. Further the domain knowledge required by novices is scoped to the domains of first and second year mechanical and electrical engineering. Based on the curricula of the institues and universities we recruited participants from, we assumed that novices had the background knowledge of courses in Mechanics and Electrical Machines. We scope ourselves to students whose medium of instruction is English and are proficient in the use of technology.

1.5.3 Context

MEttLE is designed for self-learning by a novice, so an instructor is not needed. It is intended as supplementary learning material to the engineering curriculum. It can be assigned by an instructor as homework in a regular course or as a pre-lab activity in a design or project lab. In this thesis, we are considering novices individually as they work on MEttLE; collaborative problem solving in MEttLE is out of the scope of this thesis.

1.5.4 Technology

MEttLE is developed entirely in HTML5 and Javascript with a backend of NodeJS and MongoDB. It is currently designed only for desktop and laptop screens. In this thesis, we are not considering any augmented or physical (making) technologies in MEttLE.

1.6 Contributions

1.6.1 Theoretical Understanding of Estimation

In this section, we highlight the contributions of this thesis to theory, which have implications for researchers in the learning sciences, cognitive science, educational technology and engineering education.

1. We obtained a detailed characterization of the expert estimation process and its underlying cognitive mechanisms.

2. We obtained a detailed characterization of the novice estimation processes without and within a designed estimation learning environment. We also identified the role of various scaffolds in novice estimation problem solving.

3. Based on expert and novice processes, we proposed a model for solving estimation problems that leads to good estimates.

1.6.2 Pedagogy

In this section, we highlight the contributions of this thesis to pedagogy and learning design, which has implications for instructional designers, engineering educators and researchers in learning sciences.

1. We created the pedagogical design of a learning environment that supports novice estimation problem solving.

2. We identified a set of scaffolds necessary in any learning environment that supports novice estimation problem solving.

3. We proposed *progressive abstraction* as the basis for the pedagogical design of learning environments for teaching-learning of different types of problem solving.

1.6.3 Learning environment development

We designed a TELE called MEttLE, which is an instantiation of the pedagogical design for supporting novice estimation problem solving. It can be re-developed for multiple problems and used by novices to learn estimation by repeating the problem solving activity with different problems.

1.7 Structure of the Thesis

The organization of the rest of the thesis is as follows and also shown in Figure 1.7.

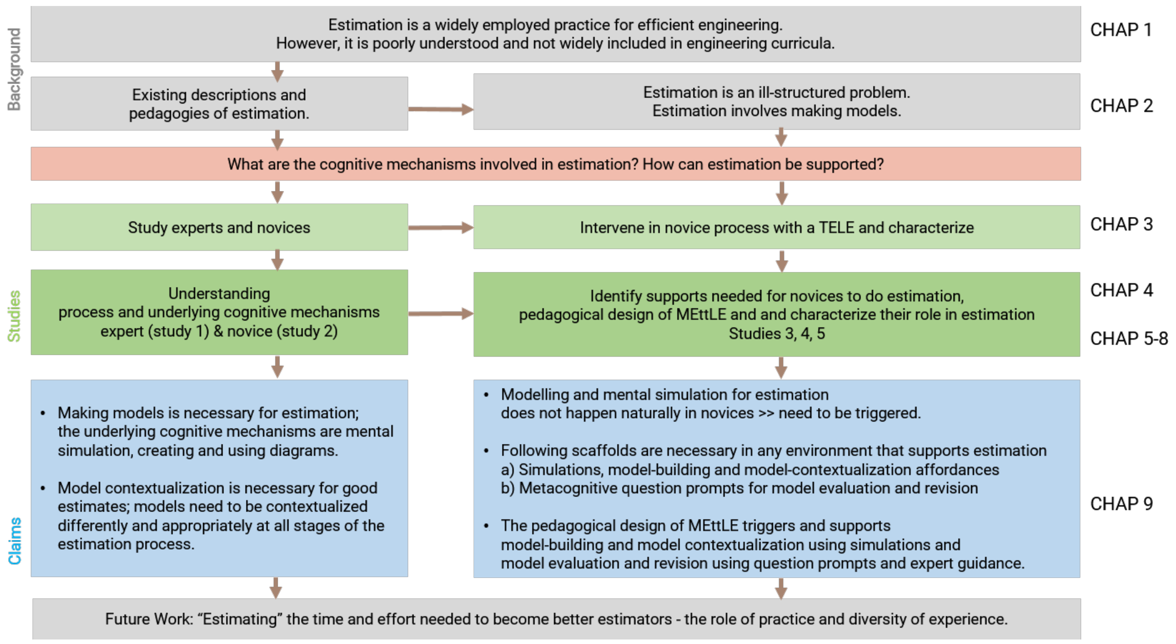


Figure 1.7: Structure of the thesis

- Chapter 2 describes the related work in estimation. Then, as the literature in estimation is sparse, we step back into two parents areas of estimation, namely, ill-structured problem solving and model-based reasoning, along with the cognitive mechanisms underlying these two. Our theoretical basis and conjectures emerge from this literature survey.
- In Chapter 3 we describe our overall methodology. It begins by describing our chosen methodology to answer our broad RQ and moves onto the studies that we did to answer our specific research questions.

- Chapters 4 and 5 describe the first iteration of DBR. Chapter 4 describes the problem analysis phase wherein we undertook two studies and Chapter 5 describes the design and evaluation phase wherein we undertook one study.
- Chapters 6,7 and 8 describe the second iteration of DBR. Chapter 6 describes the problem analysis phase of iteration 2, chapter 7 the design and evaluation (one study) of MEttLE1.0 and chapter 8 discusses the design and evaluation of MEttLE2.0 (one study).
- Chapters 9 and 10 summarize the results and reflections of all our studies and discuss the claims, limitations and generalizability of this research. Finally in chapter 10 we discuss our contributions and future work.

Chapter 2

Literature Review

In this chapter, we review literature related to the process of estimation and supporting estimation problem solving. From the literature review, we synthesize the gaps in exisiting work where we position this work. Then in order to develop conjectures regarding the process and underlying cognitive mechanisms of estimation, we also review literature from the parent disciplines of estimation, namely, ill-structured problem solving and model-based reasoning. Synthesis of this literature gives us a set of conjectures that we investigate in this thesis. The organization of this chapter in shown in Figure 2.1 and elaborated below.

We began with our dual research goals of understanding and supporting novice estimation problem solving and reviewed literature related to each of these goals in Sections 2.1 and 2.2. Next we synthesized this literature, identified the gaps in literature and the parent disciplines of estimation in Section 2.3. Then we stepped back and reviewed literature from the parent disciplines ill-structured problem solving (Section 2.4) and model-based reasoning (Section 2.5), focussing on three aspects within each discipline namely (1) the process of solving or doing (Sections 2.4.1 and 2.5.1, in order to understand what might be process of solving estimation problems (2) expert-novice differences (Sections 2.4.2 and 2.5.2), to understand which aspects of the estimation process novices might do differently and find challenging, and (3) ways of scaffolding learning (Sections 2.4.3 and 2.5.3), which gives us insights into how to scaffold novices' estimation problem solving.

Literature related to ill-structured problem solving and model-based reasoning showed that these activities are distributed, situated and embodied. So we also reviewed literature related to the cognitive mechanisms underlying ill-structured problem solving and model-based reasoning (Section 2.6) with the goal of understanding what might be the cognitive mechanisms underlying

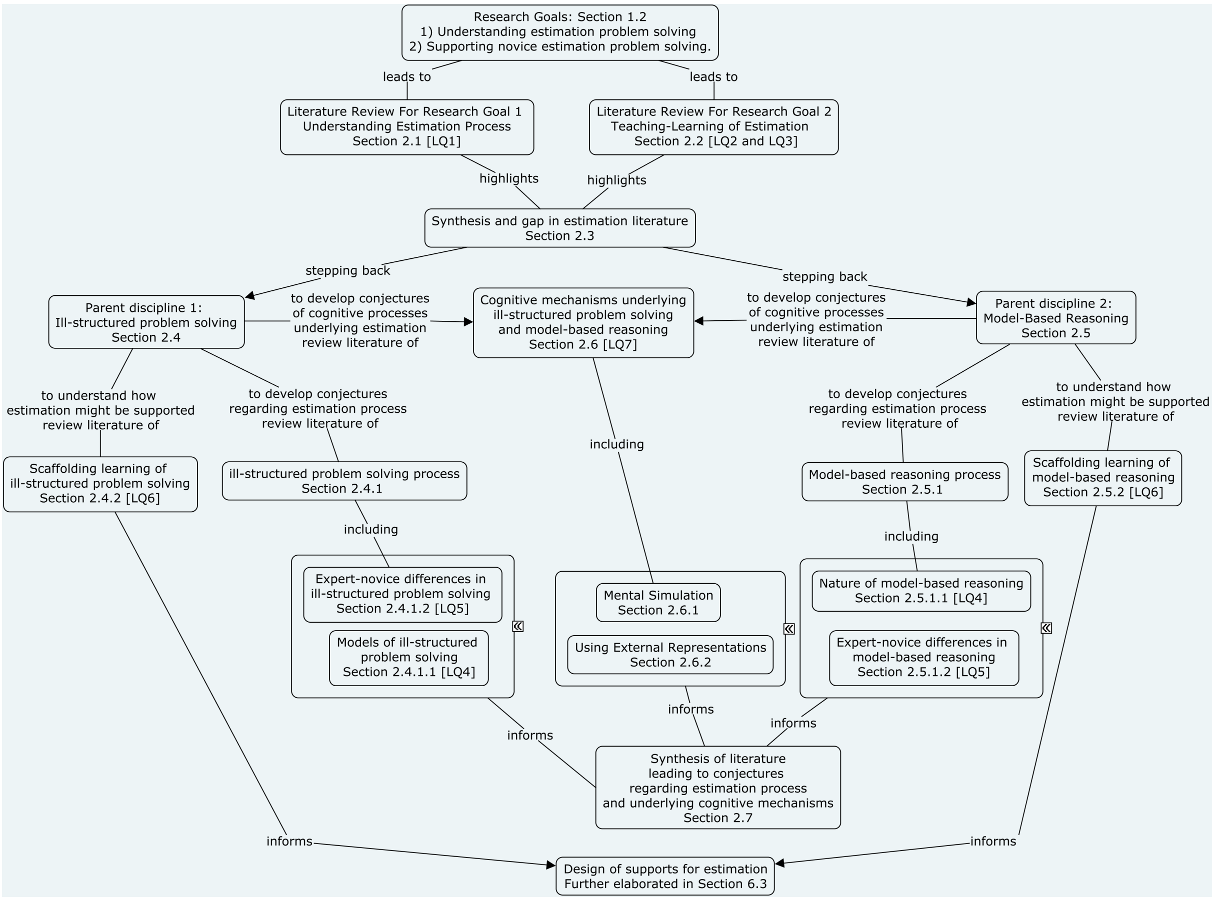


Figure 2.1: Organization of Literature Review

good estimation. Ultimately, we want to scaffold novices to do these cognitive mechanisms while solving estimation problems. Finally, in Section 2.7 we synthesize our literature review and present a set of conjectures that we will study in this thesis.

The first step in the literature search was to survey literature related to the estimation process and teaching-learning of estimation problem solving. The guiding questions for this literature search were,

LQ1 What is the process of estimation problem solving? (Section 2.1)

LQ2 What are the differences between experts and novices in estimation problem solving? (Section 2.2.1)

LQ3 What are the ways of supporting learning of estimation problem solving? (Section 2.2.2)

To identify relevant papers we searched internet academic databases such as Google Scholar and Scopus, in addition to the proceedings of specific conferences and journals which are relevant for this work, such as the American Society of Engineering Education Annual Conference.

The key words used were *engineering estimation*, *back-of-the-envelope reasoning*, *engineering approximation*, *guesstimation* and *feasibility analysis*. In addition, we also reviewed seminal papers in the fields of quantitative estimation, measurement estimation and computational estimation. The literature coverage was "exhaustive with selective citation" (Cooper, 1988).

The goal of the literature review was to obtain an integrated view of the research in the field, along the three dimensions represented by LQ1, 2 and 3. We categorized the papers according to whether they presented findings about LQ1, 2 or 3. Next, we summarize the findings reported, separately along each dimension and present it here. LQ1 is answered in Section 2.1, while LQ2 and LQ3 are answered in Section 2.2. Then in Section 2.3, we synthesize and identify the gaps in literature.

2.1 The process of engineering estimation

Engineering estimation has been variously defined as *"an analysis to determine all quantities to some level of specificity"* (Linder, 1999) and *"making decisions or selecting from a multitude of options based on incomplete or unavailable details or data"* (Shakerin, 2006) among others. We believe that each of these definitions is incomplete for our purposes; while the first one does not mention the incompleteness of data, the second one emphasizes decision-making over determining values. Engineering estimation is done in situations that are characterized by low information and lack of clarity regarding the context, objects, systems and methods. It can be understood as a way of getting insight into engineering problems by "mastering the complexity" (Mahajan, 2014) using tools to organize and discard complexity. Often an estimate is not only acceptable, but more useful than a detailed analysis because it provides useful information about a problem or a design in situations where accurate values are unnecessary, impractical or impossible because of a lack of time, information and/or resources (Dunn-rankin, 2001; Linder, 1999; Paritosh & Forbus, 2003; Shakerin, 2006). Hence for the purpose of this thesis, we define engineering estimation as "the process of determining approximate values for a physical quantity without access to complete information and knowledge."

Several engineering practitioners and teachers (Adolphy et al., 2009; Dunn-rankin, 2001; Lunt & Helps, 2001; Mahajan, 2014; Nachtmann et al., 2003; Shakerin, 2006) have offered broad guidelines on the process of doing estimation. In his book Mahajan (2014) presents a set of tools to make estimates and build insight. These tools can be understood as heuristics that can be applied to a certain set of problems. These include tools to organize complexity and some to discard complexity. The latter can happen without loss of information and with loss of information. Each of these tools can be applied in isolation, but often in combination, to make estimation problems tractable. Further, since estimation involves determining approximate values for quantities, it requires having a *quantity sense*, i.e. a combination of quantitative knowledge and quantitative reasoning abilities (Paritosh, 2007). From the techniques used by Mahajan (2014) to make direct estimates of quantities, we identified that this sense requires measurement estimation, incorporating general knowledge to identify realistic values, comparing against known values, estimating ratios rather than absolute values and using intuition (or as Mahajan likes to call it "talking to your gut").

Similarly, Adolphy et al. (2009) suggest that estimation involves experience and comparison with known objects. He further provides ways of improving estimates such as 1) dividing the estimation task into smaller manageable tasks, 2) involving multiple people in the process so that their knowledge and experience can be combined, 3) combining estimation and exact calculation, 4) comparison with data of similar problems and 5) experience with the topic and the estimation method.

Paritosh (2007) presents a model for back-of-the-envelope (BotE) reasoning (shown in Figure 2.2) that includes 1) direct estimation using knowledge about quantities and values and 2) creating estimation models using simplifying heuristics. In this model of BotE reasoning, the quantity sense is necessary for estimation and is developed by increasing experience in the domain which leads to acquiring more quantitative facts and relations between them. Estimation models relate the parameter in question to other parameters which can further be directly estimated or modeled. The simplifying heuristics using which this is done include object-based heuristics (such as using the similarity between objects), quantity-based heuristics (such as using the underlying domain laws) and system-based heuristics (which include system laws). The heuristics often yield sub-problems that are easier to solve and can be combined to create get an estimate of the quantity in question.

Linder (1999) presents a set of effective actions that emerged from solvers estimation problem solutions including, identifying a problem system, identifying a quantity with a system, providing a value for a quantity, count a set of things, compare two objects for a quantity, identify a relationship between quantities, change the system scope ("has a" action), identify a similar system ("is a" action), external representation, guessing, brainstorming, providing a

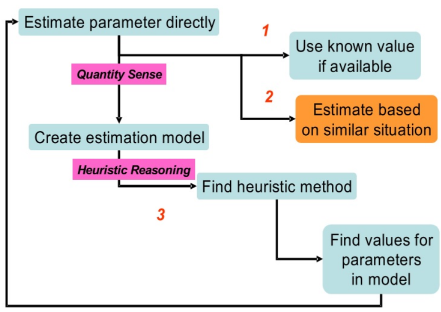


Figure 2.2: Model for BotE reasoning (Paritosh, 2007)

range of values, considering the consequence of an action, using units and dimensional analysis. In addition, Linder suggests that knowledge, mental abilities and beliefs, characteristics of situation, visualization skills, anchoring effects and preferences or biases mediate the estimation process.

Dunn-rankin (2001) suggests that engineering analyses requires modelling the physical system that one is trying to analyze and then validating the model through a test or by relaxing the assumptions, because the nature of the estimate will depend on the nature of the model used. Foundation facts, depending on the engineering specialty, play an important part in the estimation process and so engineers should carry these with them. There are several simple formulae, basic facts, rules of thumb, key relations and equations that are valuable in estimation. These must be easily accessible to the solver.

Nachtmann et al. (2003) recommend the following steps for estimation namely problem definition, criticality determination, data collection, model selection, estimate generation, estimate Assessment, estimate revision and final estimation. Finally, Shakerin (2006) summarizes the processing of performing estimation in science and engineering as follows: "Successful engineering estimation is performed based on knowledge of dimensions and units, basic laws of physics and modeling, the ability to relate and compare, and common sense. Like many other attributes, an engineers' ability to estimate is enhanced and strengthened by experience and gaining professional judgment."

2.1.1 Synthesis of literature related to estimation processes

We synthesize this literature into following guidelines for doing estimation:

1. Estimation problems are solved by creating a model of the problem system.

2. Basic engineering concepts and simplifying assumptions, approximations and heuristics are used to make the models.

3. The models must be evaluated to ensure that the estimates obtained are reasonable.

4. Knowledge of commonly encountered values and the ability to reason about these (compare, relate, etc) is required to make good estimates. This knowledge and ability improves with experience. Engineers build a repertoire of knowledge about quantities and their values (quantitative facts) as they solve more real-world problems. This repertoire helps engineers reason about values, compare them, extrapolate and generalize from one situation to the next, and is built by practice and experience with similar problems and values (Dunn-rankin, 2001). Thus *intuition* about numerical values plays an important role in estimation (Mahajan, 2014).

In order to better understand the modelling aspect of estimation, we introduce two new terms related to estimation problem solving here.

- **Problem Context:** A quantity has to be estimated within the context of an object or system, whether already existing in the real world or to be designed. We refer to the *problem context* as this object or system, the constraints on it and the requirements from it, both implicit and explicit.

- **Model Contextualization:** A model that incorporates all aspects of the problem context is said to be *complete*. A model in which certain aspects of the problem context are ignored by making reasonable assumptions or approximations in order to focus on the dominating aspects is said to be *simplified*. A model which is in terms of parameters whose values are known, either from the problem context or because they are standard values, is called *useful*. Thus estimation requires construction of simplified and useful models. A *contextualized* model for estimation is one which is simplified and useful. It is important to note that depending on the constraints and requirements of the problem context, the same object or system may have different contextualized models for estimation.

The above mentioned guidelines, however, are heuristic in nature and lack empirical validation. The model proposed in Paritosh (2007) has been validated by building a solving system, but it characterizes the modelling process only at the heuristic level and does not describe the cognitive mechanisms required to do these heuristics. While these heuristics work for the set of problems considered in that work, they are not applicable for our problems of estimation which include more complicated systems. The other research-based characterization of engineering estimation from Linder (1999) does not include a description of when and how such effective actions are applied, and what are the cognitive mechanisms that facilitate the doing of these actions.

The key takeaway from literature related to the process of estimation is that all available characterizations agree that estimation begins with modelling. However they fall short of describing the modelling process in detail and the cognitive mechanisms underlying this modelling process. Thus there is a need for a detailed characterization of the estimation process and its underlying cognitive mechanisms.

2.2 Teaching-Learning of Estimation

2.2.1 Expert Novice Differences in Estimation

In this section, we review results from studies of experienced and novice engineers in order to understand whether there is a difference in their estimation performance. The first study comes from Linder (1999) who compared the performances of experienced practicing engineers with senior engineering students on two engineering estimation tasks. The students in the study were seniors in mechanical engineering at MIT and five top engineering universities. The practitioners studied were all attendees of a plenary talk at an American Society of Engineering Education conference whose median experience was between 26 and 30 years. Practitioners involved in academics were chosen because they have knowledge and backgrounds similar to senior students.

The findings showed that students have difficulty making estimates because they do not have a sound understanding of fundamental engineering concepts, much lesser in fact than was expected. Students did not relate the estimates they made to their physical significance. Also, they do not have reference values for the quantities they are estimating and have difficulties working with units. The authors suggest that students knowledge of units, or lack of it, may be an indicator of their shallow conceptual understanding of engineering concepts and hence a useful predictor of their ability to make estimates. If students have great difficulty associating the correct units with quantities, they will also have difficulty making estimates, since estimates involve several quantities.

This study was replicated by Shakerin (2006) with senior students who solved two estimation problems in class. The data of their estimates corroborated the findings of Linder (1999) that students are not adequately prepared for even simple estimation problems, and have difficulties with dimensions and units. A similar study was conducted by Trotskovsky & Sabag (2016) who analysed interviews with experienced engineering instructors and students' written exams, lab and project reports in order to identify electrical and electronics engineering students typical estimation errors. The findings showed that students have difficulties in estimation of real physical values and evaluation of designed systems. They do not evaluate if their obtained values are in the reasonable range and if their design meets the requirements. Further, as found in the above two studies, this study also found that students used incoorect units.

Synthesis

These studies highlight that their exist differences between expert and novice engineers estimation performances and reiterate the need to explicitly teach students estimation. However what in experts' behavior contributes to these differences is not clear from these studies. While the above authors propose that lack of deep conceptual understanding and understanding of units contributes to the poor estimates, this conjecture has not been empirically investigated.

2.2.2 Guidelines for teaching-learning of estimation

Several authors have recognized the importance of estimation for engineers and made attempts to explicitly teach estimation (Bourn & Baxter, 2013; Eastlake & Blackwell, 2000; Linder & Flowers, 2001; Lunt & Helps, 2001; Mahajan, 2014; Malcolm, 2013; Nachtmann & Lehrman, 2002; Shakerin, 2005; Varma, 2009). Some of this work also includes computer software that automates aspects of the estimation, especially cost estimation in construction (Varma, 2009) and aircraft design (Eastlake & Blackwell, 2000). Below we summarize a few of the proposed strategies.

1. Linder (1999) recommends teaching the conceptual knowledge of estimation and estimation problem solving skills, increasing the number of estimation activities done by students and including learning activities that have characteristics like those of estimation activities such as engineering analysis, sketching, building, explaining and diagnosing.

2. Mahajan (2014) teachers a course on “The Art of Approximation in Science and Engineering” in which he teaches tools (heuristics) for estimation such as divide and conquer, illustrating its application in a few domains and providing practice in applying the tools to new problems.

3. Dunn-rankin (2001) recommends providing several back-of-the-envelope calculation activities for students to work on individually or in a group, including some rhetorical questions that can add to the discussion and tie the numerical values to everyday physical objects and activities.

4. Shakerin (2006) recommends estimation activities should be included in courses at all levels, especially the lower division courses where the foundations of engineering are established like units, dimensions and basic engineering concepts.

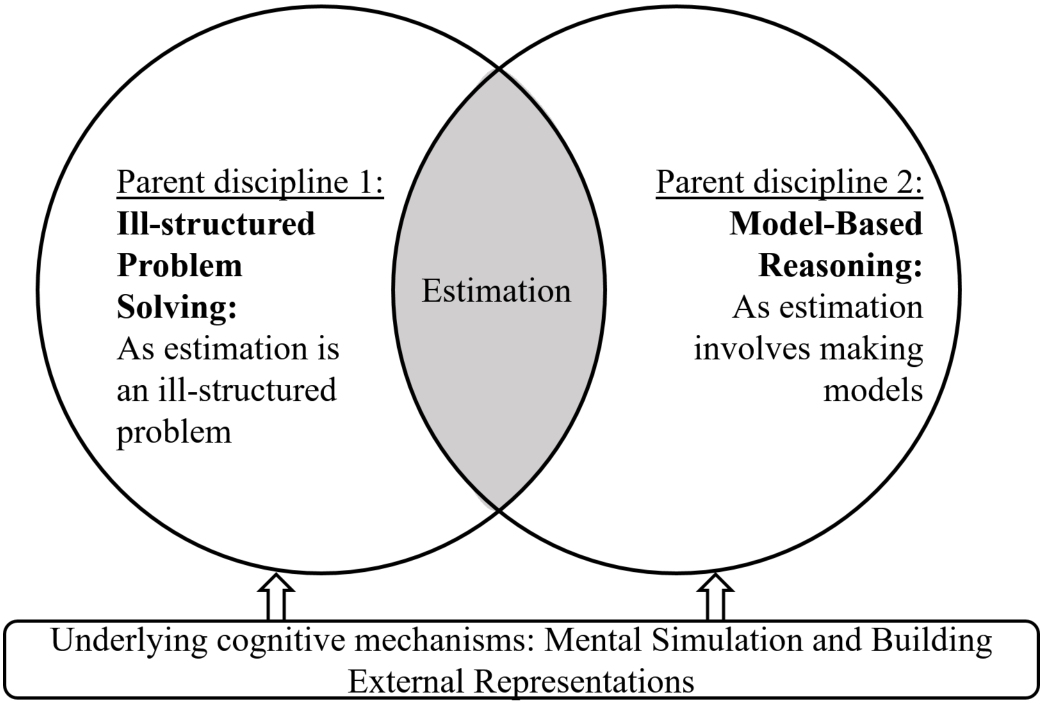
5. Bourn & Baxter (2013) found from observations that using problem-based learning with open-ended real-world problems and group work improved students measurement estimation.

6. As part of a pilot study Nachtmann et al. (2003) developed a software called “Estimation Exercise Tool” which consists of estimation exercises for students to solve. The authors correlated students’ estimation performance with students’ use of the six steps of estimation that they proposed. These results are part of a larger project on characterizing students’ estimation process.

Synthesis

We found several suggestions from literature for activities that instructors and practitioners conjecture will support the learning of estimation. These recommendations focus on the role of heuristics and practice in learning estimation, without discussing the role of the scaffolds a learner needs during this practice. Importantly though, these reports are mostly unsubstantiated by empirical evidence and are recommendations by engineering instructors and practitioners. While some authors have evaluated their strategies, the evaluation is mostly based on surveys of students perceptions of their learning and confidence, and untriangulated with other objective measures. Thus, there is a need for developing empirically evaluated teaching-learning strategies for estimation.

Figure 2.3: Theoretical Basis of this thesis



2.3 Identifying parent disciplines of estimation

Our literature survey shows that the literature in estimation processes and teaching-learning strategies is sparse. Futher most of the work comes from instructors and practitioners and are in the form of guidelines and recommendations. We found that estimation has not been systematically studied in engineering education. However, we found that there are differences between expert and novice performance of estimation which establishes the need for explicit teaching-learning strategies in estimation. The design of teaching-learning strategies must begin with understanding the estimation process and its underlying cognitive mechanisms, so that we can design instruction specfically for these processes. In this thesis, we propose to understand estimation processes by studying experts and comparing their process with novices in order to identify the good processes of estimation and the underlying cognitive mechanisms.

In order to begin our investigation into the estimation process, we need to develop a set of conjectures regarding the process of estimation and its underlying cognitive mechanisms, as this will guide our research question and the research methods we choose in this thesis. So we stepped back into the wider domains of which estimation is a part and look into these areas for insights regarding estimation processes and how to support it (Figure 2.3). We already know that estimation is an ill-structured problem, so one of the parent domains is ill-structured problem solving. Based on section 2.1, estimation begins by creating simplified models of the given system. The process of creating and reasoning with models is referred to as model-based reasoning in science (Nersessian, 1999). So, in order to understand and support estimation we need to understand and support ill-structured problem solving and model-based reasoning processes.

Given the recent developments in cognitive science and increasing evidence in support of a distributed, situated and embodied cognition (Glenberg et al., 2013; Hollan et al., 2000; Lave, 1991), we examine related work through this lens. We also survey literature related to the cognitive mechanisms underlying ill-structured problem solving and model-based reasoning. This will give us potential cognitive mechanisms underlying estimation that we need to support. Finally we present our synthesis of this literature and the set of conjectures that emerge from this literature review. Our guiding questions for this literature review were,

LQ4 What is the process of ill-structured problem solving and model-based reasoning? (Sections 2.4.1 and 2.5.1)

LQ5 What are the differences between experts and novices in ill-structured problem solving and model-based reasoning? (Sections 2.4.2 and 2.5.2)

LQ6 What are the ways of supporting ill-structured problem solving and model-based reasoning? (Sections 2.4.3 and 2.5.3)

LQ7 What are the cognitive mechanisms underlying ill-structured problem solving and model-based reasoning? (Section 2.6)

2.4 Parent discipline 1: Ill-structured problem solving

The criteria for ill-structured problems have been defined in several places, for example, (Jonassen et al., 2006; Shin et al., 2003). According to these criteria estimation is an ill-structured problem because not all the problem elements are presented, the goals are unclear, there are implicit constraints, there are multiple solutions, multiple solution paths and multiple evaluation criteria, and there is an uncertainty about which concepts, rules or principles to apply. In order to understand and support estimation processes, we reviewed literature related to how ill-structured, specifically engineering problems are solved, differences between expert and

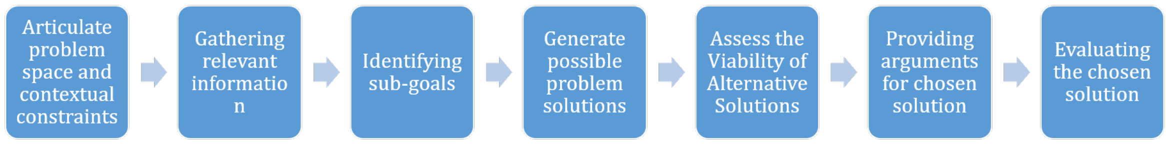


Figure 2.4: A model for ill-structured problem solving (Jonassen, 2011)

novice processes and how we can support problem-solving. Finally we synthesize our findings from these three streams and develop initial conjectures.

2.4.1 Models of Ill-structured Problem Solving

There are many models for ill-structured problem solving processes available in literature (Jonassen, 2011; Sinnott, 1989; Voss & Post, 1988) which describe a sequence of solving processes, namely, problem representation, solution search and monitoring & evaluation processes. These models are based on the information-processing view of cognition and were synthesized into a seven step problem-solving strategy (Figure 2.4) for ill-structured problems in (Jonassen, 2011). To summarize, the steps involved in solving ill-structured problems are defining the problem, gathering relevant information, identifying the sub-goals, developing solutions, assessing alternate solutions, providing arguments for chosen solutions and evaluating the chosen solution.

For engineering problem-solving, similar solving models have been proposed and we compare these models with the ill-structured problem-solving model in Table 2.1.

A situated theory of problem-solving (Kirsh, 2009) however, argues that the framing, registration (problem space construction) and solution search processes are intertwined and the problem may be reformulated as the solver interacts with the environment during problem solving. These theories suggest that context and experience affects problem solving by influencing the manner in which the problem solver (1) performs framing and registration (or problem space construction); (2) interacts with the environment, uses external representations to support problem solving, adds structure to the environment and performs epistemic actions; (3) uses the resources in the environment and generates scaffolds/affordances in the environment to support problem solving; (4) uses knowledge, ie, whether the solver uses knowledge about the context,

Engineering problem solving steps (Wankat & Oreovicz, 2015)	Engineering design problem solving steps (Sobek & Jain, 2004)	Ill structured problem solving steps (Jonassen, 2011)
Define	Problem Definition	Articulate Problem Space and Contextual Constraints
Explore		Gathering relevant information
Plan	Idea generation	Identifying sub-goals
Do it	Engineering Analysis	Developing solutions; Assessing alternate Solutions; Providing arguments for chosen solution
Check	Design refinement	Evaluating the chosen solution

Table 2.1: Comparison of models of engineering problem solving

the environment and has a host of methods, heuristics, etc to solve problems or whether the solver uses formal knowledge.

Further there is recent literature in engineering education argues that ill-structured problem solving in engineering, such as design, is situated, distributed and embodied (Aurigemma et al., 2013; Brereton, 2004; Date & Chandrasekharan, 2018; Johri & Olds, 2011; Suchman, 2000). Research suggests that engineering as a practice uses multiple representations and materials, is highly interactive and collaborative, and engineers have a strong community of practice. Further, the interactions of engineers with the representations and materials in their environment leads to innovation.

Synthesis

Literature shows us that is appropriate to adopt a situated, distributed and embodied view of estimation in this work. We conjecture that the interaction between the estimator and his/her environment during the iterative problem space construction and solution search processes lead to the solution.

2.4.2 Expert-Novice Differences in Ill-Structured Problem Solving

In the previous section, we ended with the conjecture that estimation proceeds by the interaction between the solver and his/her environment. The question that follows is, what might be the nature of the interaction that leads to a solution? Further, what might be the role of the environmental resources and knowledge in this solution process? To answer these questions we examine literature from an area of research related to the differences between experts and novices in their problem solving processes. There has been extensive research studying the differences between experts and novices in terms of domain knowledge and problem solving skills (Jonassen, 2000; Maloney, 2011; Schoenfeld, 1992; Shekoyan, 2009a; Singh, 2002, 2008; Sweller, 1988). The goal is to understand how experts' knowledge, knowledge organization and problem solving skills differs from that of novices so that instruction can be tailored to the goal of getting novices to behave like experts. Research has shown that experts have well-organized domain knowledge structures on the basis of key domain principles, draw diagrams extensively, visualize the problem, make simplifying assumptions, spend more time redescribing the problem, are able to draw inferences from incomplete data, look for patterns, do limiting case analysis, monitor their progress and have better epistemic cognition.

Studies of the differences between the perceptions of expert and novice engineering problem solvers (Adams et al., 2008; Elger et al., 2003) showed that students emphasize analytical and Math skills, and practice. However, solving ill-structured engineering problems, such as estimation, require more than the analytical and Math skills that engineering students value (Adams et al., 2008). The same studied demonstrated that experts (including both academics and professionals) place a higher emphasis on multiple representatons (visual, verbal and mathematical), asking questions, synthesizing information and scoping problems, metacognition (reflection on method) and epistemic cognition (recognising what they know and don't know).

Further, as articulated by the MIT Committee on Engineering Design (Taylor et al., 1961), *"It seems unlikely that numerical analysis will ever answer more than a small proportion of these questions. The remainder of the questions must be decided on the basis of ad hoc experiment, experience (the art of applying knowledge gained by former experiments on the same or similar problems), logical reasoning and personal preference. The subconscious reasoning process, based on experience, which we call intuition, can play a large part."*. As Ferguson writes of engineering practice (Ferguson, 1994), *"Necessary as the analytical tools of science and mathematics most certainly are, more important is the development in student and neophyte* *engineers of sound judgment and an intuitive sense of fitness and adequacy."*

Synthesis

These expert-novice differences lead us to conjecture that external representations such as resources in the environment, deep understanding of engineering concepts, metacognition, epistemic cognition and intuition will play a role in the estimation process. However, we need to understand the manner in which these aspects are used in estimation.

2.4.3 Scaffolding learning of ill-Structured Problem Solving

Literature has many strategies for supporting the learning of ill-structured problem solving (Bixler, 2007; Ge & Land, 2004; Jonassen, 2011; Shekoyan, 2009b; Shin et al., 2003), with scaffolds for each step of problem solving depending on the cognitive requirements of the step. Several researchers have empirically evaluated the role of various scaffolds on the learning of ill-structured problem solving. For example, the use of concept mapping in a TELE for the learning of problem solving has been investigated extensively (Hwang et al., 2014; Stoyanov & Kommers, 2006; Wu & Wang, 2012) and found to be effective for learning. Similarly, the roles of different types of question prompts (Ge & Land, 2004) employed as scaffolds at each step of the instructional design for ill-structured solving has been studied and found to improve learning significantly. Research has also shown that hierarchical knowledge structures such as sub-goals support problem solving performance (Catrambone, 1998) and help students learn to solve novel problems which share sub-goal structures. This has been exploited to improve problem solving performance in computer-based tutors (Koedinger & Corbett, 2006) which include features to make the sub-goal structure explicit thus allowing learners to track their problem solving progress and reducing cognitive load.

There is a set of teaching-learning strategies that simultaneously target students' conceptual understanding and problem solving by engaging them in problem solving, typically of real-world problems. These include problem-based learning (Savery, 2006), model-eliciting activities (Yildirim et al., 2010), contrasting cases (Schwartz et al., 2011), productive failure (Collins, 2012; Kapur, 2008), game based learning (Hung & Van Eck, 2010) and inventing to prepare for future learning (Schwartz & Martin, 2004). The timing and type of scaffolding varies depending on the particular method. Each of these differs in the role that the problem plays in the instruction process, the scaffolds provided to the student and other dimensions. These methods have been found to work well to prepare students to transfer (Bransford & Schwartz, 1999).

In engineering education, it has been recommended that problem solving be embedded in existing engineering courses and class time be spent solving ill-structured problems so that domain knowledge and problem solving reinforce each other (Jonassen et al., 2006; Wankat & Oreovicz, 2015). There are several teaching-learning interventions focussed on developing students' engineering problem solving skills and methods (Bozic et al., 2014; Kalnins et al., 2014; Shekar, 2014; Stojcevski, 2008; Wankat & Oreovicz, 2015; M. Williams & Ringbauer, 2014; Woods et al., 1997; Zheng et al., 2013). These interventions are typically grounded in problem-based learning (De Graaf & Kolmos, 2003) and project-based learning (Perrenet et al., 2000) and include variations depending on whether students receive instruction in improving specific problem-solving skills along with, or prior to, attempting the problems (Pimmel, 2001; Woods et al., 1997). Other strategies include the use of question prompts as scaffolds while students solve engineering problems (Anand et al., 2014; Kothiyal et al., 2015; Zheng et al., 2013) and developing students' problem solving method by using a seven step problem solving strategy to design instruction (Wankat & Oreovicz, 2015). There are also software tools available to teach different types of engineering problem solving, modelling and design (Basu, Kinnebrew, et al., 2015; Blowers, 2009; Heidweiller et al., 2011; Mauer, 2001; Shacham & Cutlip, 2004) which offer some guidelines on how to design such TELEs.

We propose to draw on this literature while designing supports for estimation problem solving. However, given that we consider estimation as situated, distributed and embodied, we must specifically consider the interactivity and epistemic actions allowed by the scaffolds and other environmental resources, and the role of problem-specific knowledge (Kirsh, 2009; Sedig & Parsons, 2013) during design.

2.4.4 Synthesis of ill-structured problem solving literature

Based on our survey of ill-structured problem solving, we argue that estimation is a situated, distributed and embodied process, rather than a linear process of representation followed by search. We conjecture that the interaction between the estimator and his/her environment leads to the solution; however the nature of this interaction remains to be understood. External representations, problem-specific knowledge, metacognition, epistemic cognition and intuition will play a role in this interaction. However, the exact role and the manner in which these are employed in the interaction is not yet understood. Next, we review literature from model-based reasoning to further develop our understanding of the estimation process.

2.5 Parent discipline 2: Model-Based Reasoning

As synthesized from literature in section 2.1, creating simplified models is the first step of estimation. The process of creating and reasoning with models is referred to as model-based reasoning in science and engineering (Hestenes, 2013; Jonassen et al., 2005; Magnani, n.d.; Nersessian, 1999, 2009). In this section, we review literature on model-based reasoning in science and engineering, expert-novice differences in model-based reasoning and scaffolding learning of model-based reasoning. Finally we synthesize this literature to refine our conjectures regarding estimation.

2.5.1 Nature of Model-Based Reasoning

Models are "conceptual systems consisting of elements, relations, operations, and rules governing interactions that are expressed using external notation systems and that are used to construct, describe, or explain the behavior of other systems" (Jonassen, 2004). It is a simplified version of an object or process under study, descriptive or explanatory and has predictive power and limitations (Etkina et al., 2006). A model has also been defined as "...a representation of structure in a material system, which may be real or imaginary" (Hestenes, 2006) where structure may be systemic (composition, environment, connections), geometric, object properties, interaction and temporal events. Considering the nature of estimation problems however, for the purposes of this thesis, we adapt the definition given in (Nersessian, 2007), *Models are representations of objects, processes, or events that capture structural, behavioral, or functional relations significant to understanding the interactions between the parts of a system.* Model-based reasoning includes construction and recall of a model and making inferences, that are either specific or general, through manipulation of the model (Nersessian, 2007).

Conceptual change is the mechanism by which meangingful learning happens (Jonassen et al., 2005). Nersessian (Nersessian, 1999), (Nersessian, 2009) argues that conceptual change and innovation begins with manipulating mental models in imagination. When dealing with a novel concept or problem, these mental models may be very rudimentary and correspond to the "intuition" or common sense understanding of the concept or problem. These mental models are then "coupled" with external representations such as diagrams, equations and computational models creating a distributed cognition system (Aurigemma et al., 2013; Chandrasekharan & Nersessian, 2015) so that further understanding about the concept or problem emerges which leads to conceptual change or discovery. Thus "[T]he component processes, which when assembled make the mosaic of scientific discovery, are not qualitatively distinct from the processes that have been observed in simpler problem-solving situations. (Simon, Langley, & Bradshaw, 1981, 2)" (as quoted in (Nersessian, 2009)).

The nature of model-based reasoning in engineering is different from science. Given the sophistication of requirements from current technological innovations, it is non-trivial that the nature of systems will simplify. Sub-systems have become more complex and every element has a finite contribution to the system. Thus the goal in engineering is not to build a simple explanatory or predictive model, but to capture the many rich interactions among these elements that give rise to certain desirable behaviours, which is instantiated in an artefact (Kant & Burns, 2016). Literature suggests that the conventional conceptual framework of engineering, which is based on the physical sciences, is ill-suited to model this complexity inherent in current technological innovations (Franssen, 2014). In engineering design, it has been argued that a form of simulative model-based reasoning (Aurigemma et al., 2013) is used which results in an object as the end product of model-based reasoning.

Synthesis

In estimation, the solver encounters a context which he/she is unfamiliar with. The solver has to estimate a physical quantity based on a partial understanding of the given system or estimate a parameter within a system that will be designed. Thus, estimation may be considered a situation of "small innovation" and so we conjecture that solvers must apply a form of engineering model-based reasoning to solve estimation problems.

2.5.2 Expert-Novice Differences in model-based reasoning

In the previous section, we identified that estimation is likely to be solved by a form of engineering model-based reasoning. In this section, we review the differences between experts and novices to understand the expert practices which support them in model-based reasoning. To begin, literature suggests that modelling is a skill to be learned and improves with instruction and practice (Chittleborough & Treagust, 2007; Dauer et al., 2013). It has been reported that there are differences between experts and novices in how they draw and use models, beginning with the models' relationship to reality (Grosslight et al., 1991), translation among multiple models, features that are focussed on (Harrison & Treagust, 2000), flexibility, purpose, spontaneous use and metacognition (Quillin & Thomas, 2015).

In Quillin & Thomas (2015), the authors summarize this literature and report that 1) experts view models as dynamic thinking tools that can be manipulated and changed, while novices view them as static end products in themselves that can be memorized, 2) experts focus on underlying relationships, processes, functions and princples, while novices tend to focus on surface features while creating models, 3) experts spontaneously make models to solve problems, while novices tend not to make models to solve problems unless explicity instructed to, 4) experts can evaluate the quality or utility of their models, while novices tend not to be aware of the quality or utility of their models and 5) experts spend more time and effort in using their models to find solutions, while novices spend more time and effort creating models.

Synthesis

This literature highlights that the main differences between expert and novices in model-based reasoning is that experts focus on salient features in making models, evaluate their models and spontaneously use them as flexible tools to think with and solve problems. Based on this literature we revise our conjecture to: the process of estimation involves focussing on salient features of the problem context to create and evaluate models, and then use them to obtain an estimate. What we still need to understand is what is the nature of these models for estimation and what are the cognitive mechanisms that support model-building.

2.5.3 Scaffolding learning of model-based reasoning

Model-based learning, which involves students creating models of a problem or concept or phenomenon, has been extensively adopted as a teaching-learning strategy in science, engineering and mathematics (Basu et al., 2013; Blikstein, 2012; De Jong & van Joolingen, 2008; Hamilton et al., 2008; Jonassen et al., 2005; Lehrer & Schauble, 2000; Lesh & Lehrer, 2003; Löhner et al., 2005; Schwarz et al., 2009; Sun & Looi, 2013; B. Y. White & Frederiksen, 1998; Wilensky & Reisman, 2006). The learning goals for which model-based learning have been employed include improving conceptual understanding (Jonassen et al., 2005; Lehrer & Schauble, 2000), improving scientific inquiry (De Jong & van Joolingen, 2008; Löhner et al., 2005; Sun & Looi, 2013), improving understanding of complex systems (Blikstein, 2012; Wilensky & Reisman, 2006) and improving students computational thinking skills (Basu et al., 2013). Models in these contexts range in meaning from causal models of a concept or phenomenon (Basu et al., 2013), agent-based models of emergent processes (Blikstein, 2012; Wilensky & Reisman, 2006) and models of ill-structured problems (Hamilton et al., 2008). Many TELEs have been designed based on model-based learning such as (Avouris et al., 2003; Fretz et al., 2002; Govaerts et al., 2013; Slotta & Linn, 2009; Sun & Looi, 2013; Swaak & De Jong, 2001; B. White et al., 2002; Wilensky & Reisman, 2006) and these have different strategies and affordances in order to scaffold the model construction and learning processes. Common features of such environments include variable manipulation simulations, modelling tools for creating models which depend on the exact system such as causal map vs. equations, collaboration via chatting or online discussions, process maps, text box, drawing tools, explanations and structured tasks.

We elaborate on this literature in Section 6.2 and we will draw from this literature in the design of scaffolds for model-based reasoning for estimation.

2.5.4 Synthesis of model-based reasoning literature

From the literature on the nature of model-based reasoning in science and engineering, we conjecture that estimation is a process of model-based reasoning, that involves focussing on the salient features of the problem context to build a simplified model of the problem system that can be used to obtain an estimate. This model is evaluated as it is being used to do the estimation. Together with the literature in Section 2.4, we conjecture that the process of creating, evaluating and using the models to solve the estimation problem will involve interaction with resources in the environment. We however do not understand the underlying cognitive mechanisms by which this interaction with the environment facilitates this process. In the next section, we review literature related to the cognitive mechanisms underlying both ill-structured problem solving and model-based reasoning.

2.6 Cognitive mechanisms underlying ill-structured problem-solving and model-based reasoning

We learned from literature that ill-structured problem solving and model-based reasoning is distributed, situated and embodied. Specifically, we learned that both these processes are done by interacting with resources in the environment (external representations). Therefore it is necessary to understand the cognitive mechanisms by which interaction with external representations leads to "breakthroughs" in both ill-structured problem solving and model-based reasoning. This understanding will enable us to conjecture what are the cognitive mechanisms underlying good estimation.

2.6.1 On the Role of External Representations

The theory of distributed cognition suggests that cognition emerges from the interaction between internal and external (environmental) resources (Hollan et al., 2000; Kirsh, 2009, 2013; T. Martin & Schwartz, 2005) because external representations allow processing that is not possible in the mind. One of the ways in which external resources are used to offload processing is by performing "epistemic actions" (Kirsh & Maglio, 1994) which are actions that do not move the agent towards the solution, but make the task easier to perform by reducing cognitive demands. Another way is by agents adapting the environment (Chandrasekharan & Stewart, 2007; Kirsh, 1996, 2009) by creating "epistemic structures", which are structures that do not change the nature of the task but make its execution more efficient in terms of load on working memory, perception and attention. Kirsh (1995) proposed three ways in which physical space is used in every day tasks to reduce cognitive demands: space arrangements that simplify choice, space arrangements that simplify perception and spatial dynamics that simplify internal computation. It has been further argued (Chandrasekharan & Nersessian, 2015) that the *process of building* external representations integrates the actions in imagination and on the external representation, thereby creating a coupled cognitive system and discoveries emerge from this process. All of these results together show that the actors and their environments form a coupled system which amplifies cognition.

In the domain of problem solving, Zhang (1997) showed that external representations are more than merely memory aids and/or stimuli to the internal mind. He argued that the form of the representation determines what information is perceived and how the problem is solved. In

Mathematical problem solving, research (Edens & Potter, 2008; Hegarty & Kozhevnikov, 1999) found that using schematic spatial representations rather than pictorial representations improves problem solving performance. L. Martin & Schwartz (2009) found that experts take the time to create external representations before starting because it improves their overall performance on a medical diagnosis task. Similar benefits for external representations in problem solving have been found in other domains as well (Bodner & Domin, 2000).

The creation and use of representations is central to modelling (Buckley, 2000; Löhner et al., 2003, 2005; Quillin & Thomas, 2015). The model-based learning framework (Buckley et al., 2004) suggests that model use and evaluation is mediated by interaction with representations such as simulations, diagrams, explanations, graphs etc. Recently the role of representations in engineering has received a lot of attention (Aurigemma et al., 2013; Diefes-Dux et al., 2013; Johri & Lohani, 2011; Johri, Roth, & Olds, 2013; Johri, Williams, & Pembridge, 2013; Moore et al., 2013) and it has been reported that fluency with the creation, use and transformation of representations is required in the practice of engineering (Johri & Lohani, 2011). Research has found that solvers reason about modelling tasks by building and using multiple external representations and translating across these representations (Aurigemma et al., 2013; Moore et al., 2013). In Moore et al. (2013) the authors examined how engineering students' reason during a complex modeling task and found that they use multiple representations and translate across representations. In Aurigemma et al. (2013), the authors studied how the building, use and integration of multiple external representations supports the engineering design process and found that external representations support the simulative model-based reasoning process of design in more ways than offloading.

Synthesis

Based on these results we conjecture that creating, using and integrating multiple external representations will support the process of building models for solving estimation problems. It is the coupling between the internal representations and the external representations that will lead to "breakthroughs" in model building.

2.6.2 On the Role of Mental Simulation

The role of non-verbal or visual thought in engineering has been long documented from case studies of engineers (Ferguson, 1977). An example of this is given by Nelson (E. A. Nelson, 2012) when he says, *"Engineers are visual or non-verbal thinkers in general. Not only do we represent physics in our minds, we are also able rotate static objects to understand them better."* A recent study also found that visualising and improving by manipulating materials, mental rehearsal of the physical space, sketching and doing thought experiments are described by practicing engineers as an engineering habits of mind (Lucas et al., 2014).

The process by which mental models are manipulated is called mental simulation. The role of mental simulation in science and engineering reasoning has been well documented (Christensen & Schunn, 2009; Clement, 2009; Hegarty, 2004; Nersessian, 1999; Trickett & Trafton, 2007). Clement (2004, 2009) argued that "imagistic simulation" (mental simulation) played a role in the thought experiments used by experts in solving problems outside their domain and that these simulations generated new knowledge. Nersessian (1992, 1999) studied the artefacts produced by scientists as they developed new concepts and argued that mental simulation is the cognitive process by which model-based reasoning leads to conceptual change and discovery. Christensen & Schunn (2009) found that mental simulation was a strategy to reduce uncertainty in design and Chandrasekaran (1990) observed that visual simulation of artifacts is done by designers during verification. The role of simulation in engineering design has also been studied in (Aurigemma et al., 2013) and it has been argued that the final object is the result of a simulative model-based reasoning process. Finally Hegarty (2004) presents a review of research which provides evidence for the use of mental simulation in mechanistic reasoning and suggests that mental simulations are constructed piece-by-piece and are often used in conjunction of processes such as task decomposition and rule-based reasoning. Thus we see that mental is one of the cognitive mechanisms underlying problem solving and model-based reasoning in science and engineering.

Synthesis

Estimation requires an understanding of how the problem system behaves, and then modelling the problem system for estimation. Based on the above literature, we conjecture that in the case of situations which are unfamiliar to the solver (such as the ones presented in estimation problems), this process begins by mentally simulating the system for identifying the working of the problem system. These mental simulations are coupled with external representations to build models.

2.7 Conjectures emerging from theory

In this chapter, we reviewed literature related to engineering estimation and its parent disciplines of ill-structured problem solving and model-based reasoning. We surveyed models for each of these, along with typical differences between experts and novices and ways of scaffolding novices do these tasks better. Finally we identified that the cognitive mechanisms underlying these complex tasks are mental simulation and creation and manipulation of multiple external representations. Thus literature leads us to the following conjectures regarding our research goals of understanding the estimation process and supporting estimation problem solving.

2.7.1 Conjecture 1

The expert process of estimation is based on model-based reasoning and uses mental simulation and multiple external representations, along with engineering conceptual knowledge, numerical sense and experience, as suggested by current theories of problem solving and model-based reasoning. The process begins with the experts' prior experiential knowledge of the problem context; mental simulation and coupling with external representations would enable him/her to generate more knowledge about the context, create and evaluate models for estimation.

This is a conjecture regarding the research goal of understanding the process of estimation. In this work, we will detail out the expert process of model-based reasoning and the roles of mental simulation, external representations, conceptual knowledge and experience in doing estimation. This conjecture is examined in Chapter 4.

2.7.2 Conjecture 2

Novices would focus on obtaining an equation connecting the quantity to be estimated to known quantities. They would not try to understand the problem context and instead focus on identifying the engineering conceptual knowledge which would give them the right equation.

This is a conjecture regarding the research goal of understanding the process of estimation and it highlights the differences between expert and novice estimation processes, because of which novices need support while solving estimation problems. In this work, we will identify the process that novices follow to arrive at an equation and their challenges in doing so. This conjecture is also examined in Chapter 4.

2.7.3 Conjecture 3

A learning environment that triggers modelling, that has resources for mental simulation and model-building, and prompts for model evaluation, would support novices in estimation problem solving.

This is a conjecture about the research goal of designing a TELE to support estimation problem solving. In this work, we will design such a TELE and evaluate how it supports novice estimation problem solving. In addition, we will also use the TELE to refine our understanding of the estimation process and address our research goal of understanding estimation processes. This conjecture is examined in Chapters 5, 6, 7 and 8.

2.8 Summary

A comprehensive literature survey of estimation led us to identifying the gaps in estimation literature. In order to begin our research towards addressing these gaps, we stepped back into two parent disciplines of estimation, ill-structured problem solving and model-based reasoning. Based on the literature in these disciplines, we developed three conjectures regarding our research goals of understanding the estimation process and supporting estimation problem solving. In the next chapter, we describe the methodology that we adopted in order to systematically study these conjectures.

Chapter 3

Methodology

As explained in Chapter 1, our research goal is two-fold; firstly, to understand the estimation process and secondly, to design a TELE to support novice estimation problem solving. In chapter 2, our literature review led to three conjectures regarding these two research goals that we want to examine in this research work. In this chapter, we describe how we chose a research method to align with these research goals, the characteristics of the chosen method and the details of our research process.

3.1 Choosing a research methodology

The overarching research methodology must be chosen to align with the research goal and the researchers' philosophical worldview. These two together guide a researcher in choosing appropriate research methods and designs for their data collection and analysis. So we begin by articulating our research goals.

3.1.1 Research Goals

Based on our conjectures in Section 2.7, our two research goals can be further divided into sub-goals as follows, and also shown in Figure 3.1.

1. Understand the expert process of estimation and the cognitive mechanisms underlying it.
2. Understand the novice process of estimation and novice challenges in solving estimation problems.

3. Create a design (and an associated TELE) for supporting novice estimation problem solving.

4. Evaluate how the features in the TELE scaffold novice estimation problem solving.

5. Refine our understanding of the novice estimation process.

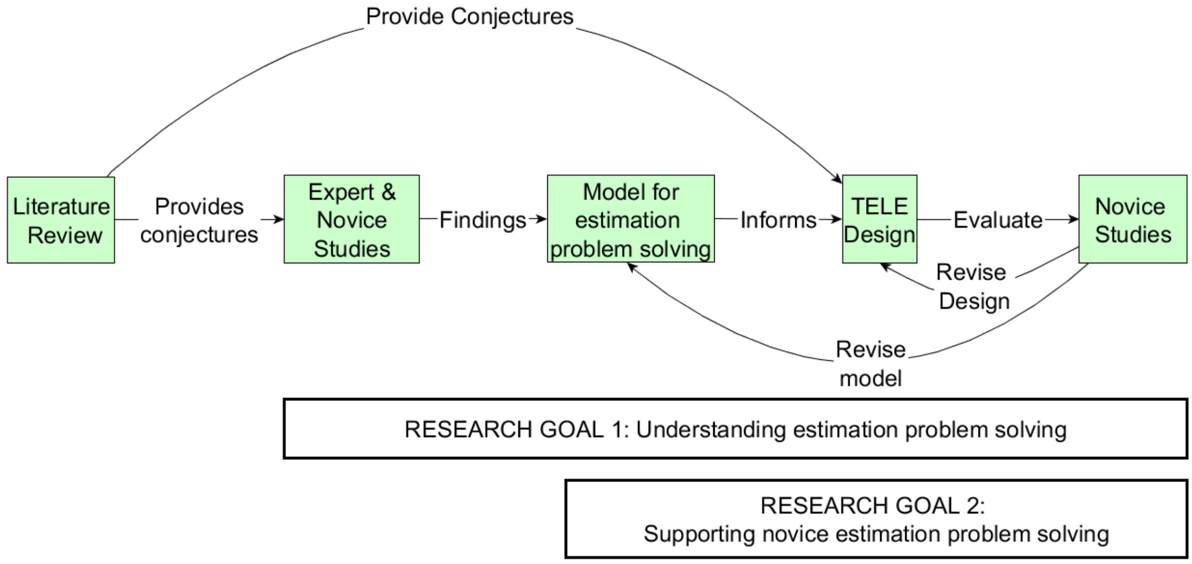


Figure 3.1: Research goals and conjectures

Our research goals focus on the understanding of processes - how people take actions in order to achieve an objective and what are the resources (cognitive and physical) that support them in doing so. This question requires the researcher to interpret a series of actions taken by a participant within a context, with a particular theoretical lens. The researcher thus needs to inductively make meaning of the estimation processes of participants.

Overarching our goal of understanding estimation processes is our approach of doing so by creating designed environments for supporting novice estimation and investigating novice estimation processes within such environments. The goal is to refine the design based on the data to improve novice estimation processes. We do so by systematically studying the novice estimation process, the role of the designed features in this process and then reflect on the revisions needed in order to modify the estimation process. By revising the design, we iteratively build a set of design principles for supporting novice estimation problem solving. Simultaneously, we build rich descriptions of the novice estimation process.

We conjectured at the end of Chapter 2, that solving estimation problems depends on an interaction between several factors such as conceptual and contextual knowledge, external representations, mental simulation and metacognition. So, the TELE will need to have several interconnected supports for solving estimation problems. Therefore, we require a methodology which is systematic, yet flexible to allow for consideration of the complexity of the research problem and studying the effect of the interplay of multiple features.

3.1.2 Our philosophical worldview

The broad assumptions/beliefs about the nature of reality that a researcher holds when they do research is referred to as the researchers philosophical worldview (Creswell, 2002; Petersen & Gencel, 2013). There are four worldviews defined in literature, namely, positivist, constructive (or interpretive), participatory and pragmatist (Petersen & Gencel, 2013).

1. The positivist worldview holds that truth is an objective reality that exists "out there" to be found. This typically leads to quantitative research methods whose goal is hypothesis falsification.

2. The constructive (or interpretive) worldview considers truth to be a subjective reality that is constructed by human beings as they see and interpret the world in their own context. This worldview typically leads to using qualitative methods.

3. The participatory (or transformative) worldview holds that research is meant for bringing out transformation in society and has an action agenda to engender change through intervention. This worldview leads to adopting a mix of qualitative and quantitative methods.

4. The pragmatic worldview emphasizes the truth as "what is practically useful and whatever works at that time." The emphasis among pragmatists is on the research problem, and therefore they use all available methods to understand and research the problem.

As our research goals show, our research problem has aspects of understanding and bringing about change in estimation processes. Both of these goals emerged from a real-world problem, the teaching-learning of estimation. Thus our focus is on the problem of estimation, rather than on finding truth or reality. Therefore we hold a pragmatic worldview in our research. Next, we identify a set of candidate methodologies that are aligned with our research goals and the pragmatic worldview and choose one among them for this work.

3.1.3 Choosing an appropriate methodology

Based on our research goal and philosophical worldview, we need a research methodology that allows for,

- the use of different methods to address different parts of the research goal
- the use of a TELE as an intervention to simultaneously support and study estimation processes
- evaluating the effect of multiple features of the TELE on the estimation process

These criteria align with the goals of the family of research methods falling under the umbrella of "educational design research" (Van den Akker et al., 2006). Educational design research differ from other research methods in education because of their emphasis on the design and development of an intervention as a solution to a complex, real-world, educational problem, with the purpose of furthering knowledge about the features of these interventions and to develop or validate theories (Plomp, 2013). Educational design research includes methods such as Design-based research (DBR) (Barab & Squire, 2004), design experiments (Cobb et al., 2003), design and development research (Richey & Klein, 2014) and design-based implementation research (Fishman et al., 2013).

Design and development research (Richey & Klein, 2014; Richey et al., 2004) refers to the "systematic study of design, development and evaluation processes with the aim of establishing an empirical basis for the creation of instructional and non-instructional products and tools and new or enhanced models that govern their development." This method does not align our goal of developing a set of design principles and theories of estimation problem solving. Design-based implementation research (Fishman et al., 2013; Penuel et al., 2011) is an approach to collaborative design, research and development in which "research on the implementation of reforms drives iterative improvements". This approach thus represents an expansion of design research, because of its emphasis on problems of practice, a concern with developing theories related to both classroom learning and issues of implementation through systematic research, and a focus on developing capacity for sustaining change. This method is not applicable to our goals because we are not focussing on issues of implementation. Design experiments have "both a pragmatic bent - "engineering" particular forms of learning - and a theoretical orientation - developing domain-specific theories by systematically studying those forms of learning and the means of supporting them" (Cobb et al., 2003). Their main characteristics are, developing a set of "humble" domain-specific theories about the process of learning and designs that support that learning; being testbeds for innovation; both prospective and reflective, and iterative. While design experiments align well with our research goals, we observe that they have typically been used in classrooms and other teacher-led instructional contexts, where the teacher is a participant in the design process. Our designed intervention will take the form of a self-learning TELE and so this methodology is not entirely appropriate for our work.

Design-based research has been defined as "a systematic but flexible methodology aimed to improve educational practices through iterative analysis, design, development, and implementation, based on collaboration among researchers and practitioners in real-world settings, and leading to contextually-sensitive design principles and theories" (F. Wang & Hannafin, 2005). The main feature of DBR is that its central goals of designing learning environments and developing theories of learning are intertwined (Design-Based Research Collective, 2003). In that sense, DBR is not "an" approach, but a series of approaches which share the goal of "producing new theories, artifacts and practices" that impact teaching-learning in certain contexts (Barab & Squire, 2004). Thus DBR aligns with all the criteria listed above (3.1.3), and so we chose DBR for this research work.

3.2 Design Based Research

DBR is a pragmatic, grounded, interactive, iterative and flexible, integrative, and contextual research methodology (F. Wang & Hannafin, 2005) for interventionist research in education. It is pragmatic because, as mentioned before, it focusses on solving real-world problems by designing interventions and refining both theories and design principles (Barab & Squire, 2004; Design-Based Research Collective, 2003; Van den Akker et al., 2006). The design is based on theories, that are refined through the process of research, so that the theories "do real work" in practice (Cobb et al., 2003).

DBR is grounded in both existing theory and the real world context (F. Wang & Hannafin, 2005) and the research process is interactive because participants work together with designers. Further, the process of analysis, design, enactment, evaluation and redesign is iterative and flexible, so that researchers can make deliberate changes if and when necessary. DBR is integrative because researchers adopt a wide array of mixed methods depending on the specific phase of the research and its requirements, to maximize rigour and credibility. Finally, DBR is contextualized because the identified design principles and theories are connected to the context and the design process.

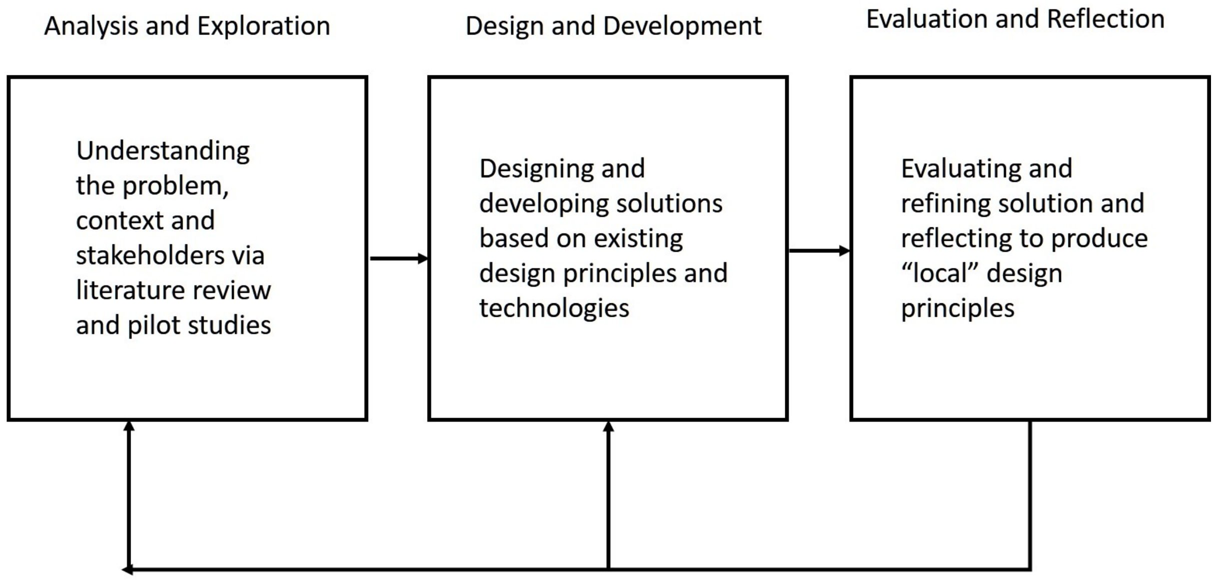


Figure 3.2: Design-based research as applied in this dissertation

DBR proceeds via iterations with each iteration having three phases (McKenney & Reeves, 2014) namely Analysis/Exploration, Design/Development and Evaluation/Reflection (see Figure 3.2). The results of one iteration inform the next iteration and the design is revised in order to improve learning. The research begins (McKenney & Reeves, 2014; Reeves, 2006) with a detailed analysis of the problem, the context and the participants. This includes an analysis of existing solutions in order to address the problem, perhaps in other contexts and with other participants. It often includes pilot studies and/or ethnographies of the context and participants in order to understand the specifics of the context and the requirements of the participants. Designers and researchers then draw from these theoretical and empirical findings in order to create preliminary LE designs which are then evaluated using various qualitative, quantitative or mixed methods in order to understand the mechanisms by which learning happens in the LE. This is followed by reflection on these learning mechanisms in order to identify how the learning effectiveness of the design could be improved and finally produce design principles and local instructional theories (Cobb et al., 2003). By local instructional theory we mean a domain-specific instructional theory or a "humble" learning theory that describes how learning happens in our specific context using our designed LE (Cobb et al., 2003).

3.3 DBR iterations in this thesis

In this thesis, we performed two iterations of DBR; the goal of the first was to understand estimation processes and identify novice challenges and the goal of the second was to support estimation problem solving. The details are described in this section.

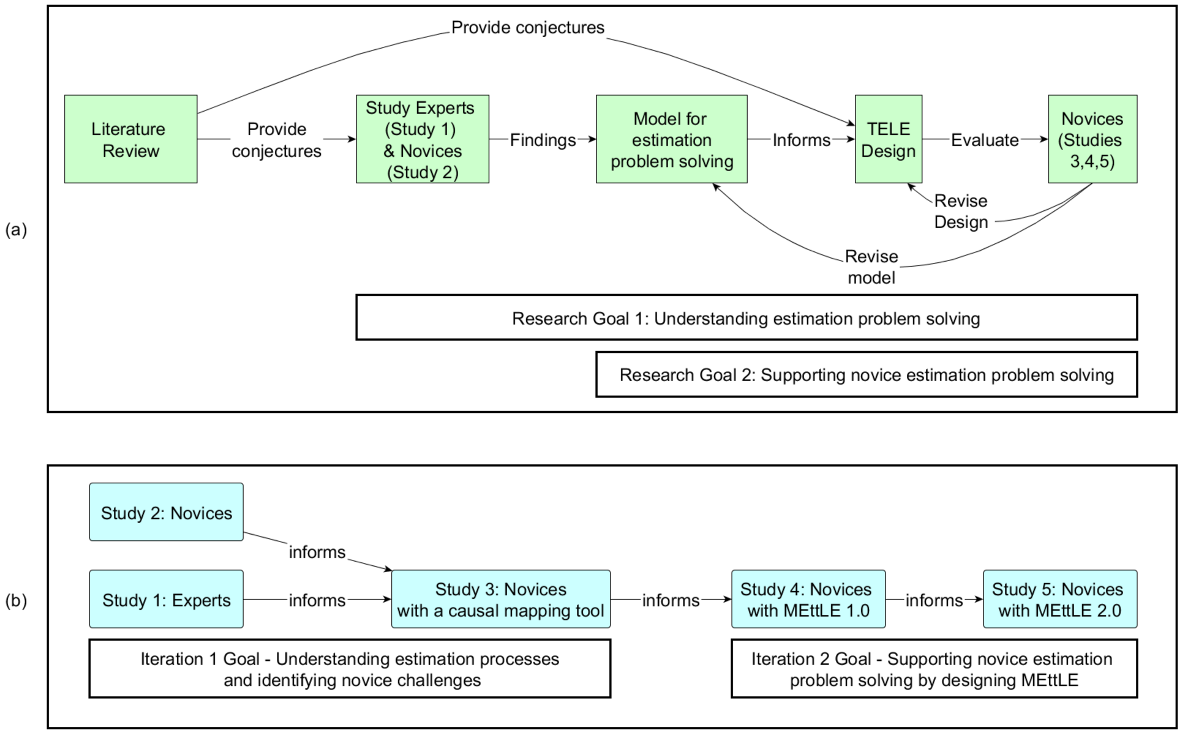


Figure 3.3: Overview of DBR iterations: (a) conceptual solution approach of this thesis (b) mapping of solution approach to DBR iterations of this thesis

The two parts of Figure 3.3 depict the conceptual solution approach of this thesis (Figure 3.3a) and how it mapped to our DBR iterations (Figure 3.3b). As seen in the Figure 3.3b, we had two DBR iterations and five studies. There were three studies in the first iteration with the goal of understanding the estimation process and identifying the challenges faced by novices in solving estimation problems. In the second iteration, we had two studies with the goal of designing a TELE to support estimation problem solving. Thus in the first iteration, the emphasis was on theory building and so the designed intervention was rudimentary, while in the second iteration the emphasis was on design principles and so the designed intervention was revised in order to better support novices' estimation processes. The details of the research studies and their methods are described in the next section.

3.3.1 Research Studies

Broadly, the two iterations of DBR in this thesis are shown in Figure 1.4, reproduced here for clarity. The details of each phase in each iteration are shown in Figure 3.5.

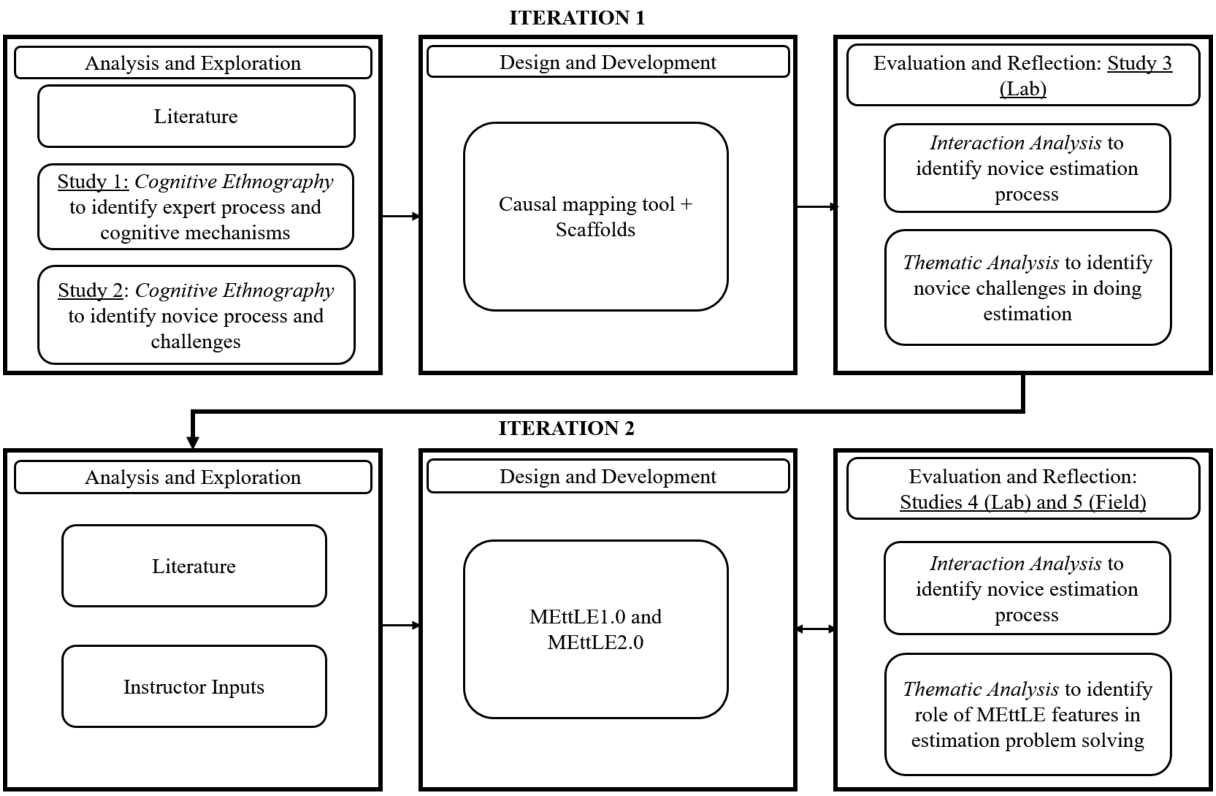


Figure 3.4: Overview of Design-based research as applied in this thesis

DBR 1: Understanding estimation processes and identifying novice challenges

The goal of this iteration was to understand the estimation process and the features needed in a TELE for supporting estimation problem solving. In order to understand the estimation processes and its underlying cognitive mechanisms, as part of the problem analysis phase of DBR1, we studied both experts (study 1) and novices (study 2). Together, these contributed to our preliminary model of estimation problem solving. To identify the features needed in a design to support novice estimation processes, we studied the challenges faced by novices while solving estimation problems, under two conditions: without any support (study 2) and while using a causal mapping tool (Study 3). This gave us our preliminary design principles for supporting novice estimation problem solving. The RQs of this iteration and its associated methods are described below, and the details of the studies are also shown in Figure 3.5.

1. **Study 1:** Broad RQ - How do experts solve estimation problems?

   RQ1a What is the expert estimation process?

   RQ1b What are the cognitive mechanisms that play a role in good estimation?

   Our research goal is to obtain a detailed understanding of the process of estimation through the lens of distributed cognition (Brereton, 2004; Hollan et al., 2000). Specifically, we want to understand what experts do as they solve an estimation problem, both in their mind and with their natural environment. We are especially interested in understanding how they use the resources in the environment and integrate them with their mental resources while solving estimation problems. We are not merely interested in the sequence of steps that they took; rather we are interested in "productive actions" that experts took that led to "breakthroughs" in solving the estimation problem.

   Cognitive ethnography is a method which is based on traditional ethnography but is concerned with identifying how members of a cultural group make meanings (Hutchins & Nomura, 2011; R. Williams, 2006) by interpreting observed behaviors. The emphasis is on the micro-level analysis of specific episodes of activity to understand how cognitive activities are accomplished in real-world settings. Thus cognitive ethnography is an appropriate method to answer this research question. So we did a cognitive ethnography of two experts who each solved three estimation problems and then analysed the data using microgenetic analysis (Siegler, 2006) to answer these research questions.

2. **Study 2:** Broad RQ - How do novices solve estimation problems?

   RQ2a How is the novice process of solving estimation problems different from the expert process?

   RQ2b What are the challenges that novices face while doing estimation?

   Our research goal, similar to with experts, was to understand what novices normally do as they solve estimation problems, both in their minds and with their environments. Like with experts, we want to understand how novices integrate resources from the environment with their mental resources in the solving of the problem. Specifically, in the case of novices, we are interested in focussing on episodes where they were stuck and identifying the challenges that they were facing, which prevent them from moving forward. Thus the cognitive ethnography method is also a good fit to answer this research question. We did a cognitive ethnography of ten second year engineering students who each solved one estimation problem. The data was analysed using microgenetic analysis (Siegler, 2006) to answer the research questions.

3. **Study 3:** How do novices solve estimation problems using a scaffolded causal mapping intervention?

RQ3a How does the scaffolded causal mapping intervention support novices in solving estimation problems?

RQ3b What challenges do novices face in doing estimation using a scaffolded causal mapping intervention?

From studies 1 and 2, we built an understanding of the estimation process which gave us preliminary insight into how to support estimation problem solving among novices. Based on this we designed a causal mapping intervention, which consisted of a causal mapping tool and researcher scaffolds. The research goal was identifying how the intervention supported novices in solving the estimation problem and what challenges they continued to have. We wanted to understand how novices used the causal mapping tool and our scaffolds in their estimation problem solving. We were interested in how the interaction between the tool, the scaffolds and novices mental resources helped them "come unstuck" while solving estimation problems.

Interaction Analysis is a research method for empirical investigation of the interaction among human beings and between human beings and their environment (Jordan & Henderson, 1995). It investigates human activities, including talk, gestures, the use of artefacts and technologies, for the purpose of identifying normal practices, their problems and possible solutions. It is based on ethnography and one of its main assumptions is that knowledge and practice is not confined to the heads of certain individuals but situated in the interactions among members of a community and their engagement with the environment. Thus this research method is aligned with our lens of distributed cognition and our research goals. So we chose the interaction analysis method for this study. We did a lab study with six first and second year engineering students, who each solved three estimation problems, and performed interaction analysis on the data to answer the research questions.

DBR 2: Supporting novice estimation problem solving by designing MEttLE

The goal of this iteration was supporting novice estimation problem solving by designing a TELE that triggers modelling, called MEttLE. We began with our understanding of the estimation process, its underlying cognitive mechanisms and the challenges faced by novices in solving estimation problems, as identified from studies 1, 2 and 3 in DBR 1, to generate a set of requirements from the TELE. Next we surveyed literature to identify pedagogical features and scaffolds to satisfy the set of requirements. These pedagogical features and scaffolds came together in our design of MEttLE1.0. We employ the conjecture mapping framework (Sandoval, 2014) to generate a set of design and theoretical conjectures regarding how the design of MEttLE1.0 leads to the desired estimation problem solving process and performance. We evaluated MEttLE1.0 by studying novice estimation processes, the role of the designed features in this process and the challenges that novices continued to face in solving estimation problems using MEttLE1.0(study 4). Next we revised MEttLE1.0 based on our findings to obtain MEttLE2.0, which we conjectured would better support novices' estimation problem solving. We evaluated MEttLE2.0 (study 5) and the results of this evaluation contributed to refining our model of estimation problem solving and design principles for supporting novices. The RQs of this iteration are shown below, while the details of the study are in Figure 3.5.

1. **Study 4** Broad RQ: How do novices do estimation in MEttLE1.0?

   RQ4a What is the novice process of solving an estimation problem in MEttLE1.0?

   RQ4b How do novices use the features in MEttLE1.0 to solve the estimation problem?

   As seen from our research questions, in this study our goal was to understand how novices solve estimation problem in MEttLE1.0 and the role played the features in MEttLE1.0 in this process. Thus we are interested in the interaction between the novice and the environment, MEttLE1.0; we want to understand how this interaction facilitates novices in solving the estimation problem and what challenges they continue to face. As described above, interaction analysis is an appropriate method for addressing these research questions. We did a lab study with ten second year engineering students, who each solved one estimation problem, and performed interaction analysis of the data to answer the research questions.

2. **Study 5:** Broad RQ: How do novices do estimation in MEttLE2.0?

RQ5a What is the novice process of solving an estimation problem in MEttLE2.0?

RQ5b How did the features of MEttLE2.0 support novices in doing good estimation?

As seen from our research questions, in this study our goal was to understand how novices solve estimation problem in MEttLE2.0 and the role played the features of MEttLE2.0 in this process. Again we are interested in the interaction between the novice and MEttLE2.0; we want to understand how this interaction facilitates novices in solving the estimation problem successfully, thus identifying design principles for supporting estimation problem solving and refining our model of estimation problem solving. As described previously, interaction analysis is an appropriate method for addressing these research questions. We did a field study with twelve second year engineering students, who each solved one estimation problem, and performed interaction analysis of the data to answer the research questions.

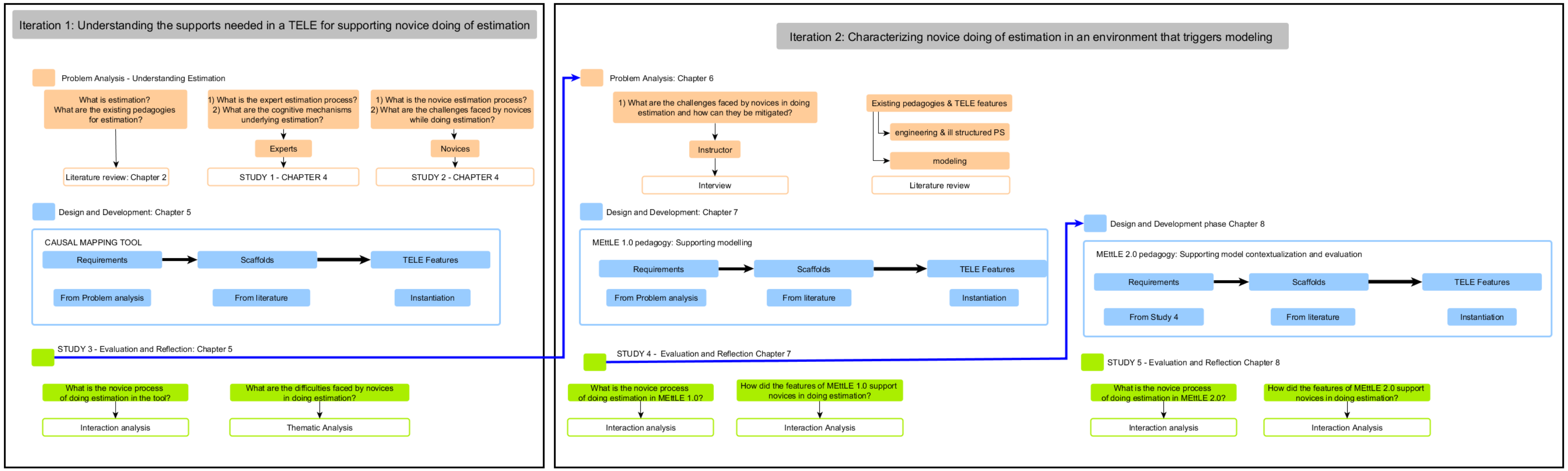


Figure 3.5: Details of Design-based research as applied in this dissertation

3.4 Ethical Considerations

The following issues were taken into consideration while finalizing the research methods and data analysis techniques:

- **Consideration of ethical issues:**

  As the research studies involved human participants, detailed guidelines for administering the studies were prepared for ethical consideration based on (Cohen et al., 2002). These guidelines primarily include:

  - Preparing documentation for taking informed consent from the participants: Participants were given a consent form before every research study detailing the objective and the procedure of the study. They were offered clarification by the researcher in case they had any queries. Once participants had clarity regarding the above points, they were asked for their consent. They had the option to discontinue the study at any point of time. Additionally, they were assured that participation in the study would have no bearing on their grades and academic performance. The consent information given to the learner is shown in the Appendix A.
  - The anonymity of all the participants was maintained throughout, and all the data was collected, preprocessed, and stored for this appropriately. No one apart from the primary and secondary researchers on the project had access to the computer data and written artefacts of the participants.
  - Permission for publication: The necessary permissions for publication were sought from the participants.

- **Deciding constraints on the research:**

  As the research studies involved undergraduate learners from engineering colleges, it was important to synchronize the research studies with their academic calendars. This was even more important because our research required those participants have already undergone courses in mechanics and electrical machines. This brought in the constraint to recruit participants who were in their third or fourth semester of undergraduate engineering.

  The necessary permissions and consent from the concerned college/institution authorities for conducting research studies were obtained in advance. Various details related to actual execution of studies were discussed with the instructors of the participants. These involved: availability of computers, working local area network, internet, video player software, working audio jacks and earphones, server, number of learners to be recruited for the study, requirement of supporting staff, etc. Student participation was voluntary, and they were provided with (workshop) participation certificates for attending the sessions.

3.5 Summary

In this chapter, we argued for our choice of DBR as an overarching research methodology and described the details of the two iterations of DBR undertaken in this thesis, DBR1 and DBR2. We also described the studies done as part of each of these iterations and their research methods. DBR1 is elaborated in chapters 4 and 5, while DBR2 is elaborated in chapters 6, 7 and 8. In the next chapter, we begin by describing the problem analysis phase of DBR1 which includes two studies, study 1 and 2, namely, the expert and novice studies.

Chapter 4

DBR 1 Problem Analysis: Understanding Estimation Processes

As described in chapter 3, DBR begins with a phase of problem analysis which includes understanding the problem and the context. This phase includes literature reviews and preliminary studies. Our literature review described in chapter 2 led to conjectures regarding the process of estimation. In order to examine our conjectures, we first studied experts to characterize their estimation process and its underlying cognitive mechanisms. Next we compared the expert process and cognitive mechanisms with the novice process and cognitive mechanisms to identify differences. Additionally, we also identified the challenges faced by novices in while solving estimation problems. In this chapter, we describe the details of these two studies.

4.1 Study 1: Characterizing Expert Process of Estimation

In Chapter 2 we conjectured that the expert process of solving estimation problems is based on model-based reasoning, and the underlying cognitive mechanisms are mental simulation and multiple external representations. Further, experts use engineering conceptual knowledge, numerical sense and experience while making estimates. In this section, we describe a study to examine this conjecture, the analysis and results obtained.

4.1.1 Methods and Materials

Our goal for this exploratory study was to investigate our conjecture regarding the expert estimation process and obtain a detailed understanding of the process. As explained in section 3.3.1, our goal is to understand what experts do as they solve an estimation problem, both in their mind and with their natural environment. Specifically, we are interested in understanding how they use the resources in the environment, integrate them with their mental resources and obtain good estimates. Cognitive ethnography method is based on traditional ethnography but is concerned with identifying how members of a cultural group make meanings (Hutchins & Nomura, 2011; R. Williams, 2006) by interpreting observed behaviors. The emphasis is on the microgenetic analysis (Siegler, 2006) of episodes of activity to understand how cognitive activities are accomplished in real-world settings. This aligns with our goal of focussing on and analysing episodes when experts obtained breakthroughs while solving estimation problems, and inferring what cognitive processes and environmental resources led to the breakthrough. Thus cognitive ethnography with microgenetic analysis is an appropriate method for our research goals. We do not expect to generalize the process of estimation, but understand the cognitive basis of a process of obtaining good estimates.

Research Questions

The broad research questions guiding this study was, "How do experts solve estimation problems?" and the specific research questions are,

RQ1a What is the expert estimation process?

RQ1b What are the cognitive mechanisms that play a role in good estimation?

Participants and Procedure

Two experienced engineers specializing in electrical engineering were chosen for the study. These experts are faculty members at a premier technology university in India, and have several years of industry experience as well. They have active research programs in their respective areas of research. The study was done separately with each expert, and conducted in a location of the experts' choosing. Each expert was given sheets with the problem written on it. They were told to write as many details while solving the problem. They were free to use any books or other materials they wanted to consult in solving the problem, including looking up supporting

Expert 1	Expert 2
Suppose I told you that the pit spacing on an ordinary CD is 2 micro-m, would you agree with me? Why/why not?	How far apart are the pits on a CD?
What is the output power of the human heart?	Could a human heart run a wine opener?
The hand cranked radio is for use far from supplies of domestic electricity or batteries. For decent sound performance (say a single 5 W speaker) how heavy would you expect the radio to be?	Consider radios used far from supplies of domestic electricity or batteries. They have to be cranked by hand for them to work. How heavy would such a radio have to be to be heard within a tent at a campsite?

Table 4.1: Problems given to experts in Study 1

information needed to solve the problem on the Internet on their personal laptop/computer. In permitting the experts to use any resources they needed to solve the problem we were trying to recreate an authentic work environment as it exists in the engineering workplace so that we obtain experts authentic estimation practices.

The experts were free to solve in their natural mode, silently or talking aloud as they felt comfortable. The researcher didn't interrupt except to offer a new problem sheet. We did not require experts to think aloud as doing this effectively without placing a cognitive load on the solver requires extensive practice which was not possible with the experts. We did not want to distract from their natural practices.

Estimation Problems Used

The problems given to the experts are shown in Table 4.1 and were chosen after pilot studies, based on their potential to elicit a wide range of problem solving behaviors from the experts. We also ensured that none of the problems would be directly from their academic domain, so that we could understand how experts solved problems that were new to them. The first problem required estimation based on the structure of an object, while the remaining two required estimation based on function. The problems progressed from simple to complex, and from requiring little to more domain knowledge. Each problem had two versions which were conceptually similar but worded differently as we believed that this would elicit different estimation behaviors from each expert. For example, one of the versions of problem 2 is formulated as an evaluation question, while the other is a numerical estimation problem. We randomly assigned one of the problem sets shown in Table 4.1 to expert 1 and the other one to expert 2.

We conjectured that the expert process would involve mental simulation; however we wanted to test whether the triggering of mental simulation depended on the nature and wording of the problem or if it was automatic. For instance, it is known that a fictive motion word, which is “a motion verb but express no explicit motion or state change”, can trigger mental simulation (Matlock, 2004). So we used fictive motion words in one of the versions of the problem and avoided them in the other. For instance consider the problem “Could a human heart run a wine opener?” It has the fictive motion word *run*. Therefore it is plausible that rather than estimate the power of the human heart and then compare it to the power required by a wine opener, experts would consider the human heart and wine opener as a system and evaluate whether the heart could drive wine opener. Thus we may observe different problem solving behaviors from both experts, which would throw further light on our mental simulation conjecture.

Data Sources

Our data sources were:

1. Video recordings: In order to record every action that the participant took towards estimation, the entire session was recorded using two video cameras. The first was focused on the task area (i.e. the sheet of paper and surrounding area on the desk) to capture their sequence of writing and small hand gestures. The second was focused on their face in order to capture facial expressions and large body movements.

2. Screen captures: Their interactions with the computer were captured using the screen capture software CamStudio (http://camstudio.org/).

3. Researcher observations: The researcher recorded regular unstructured observations while the participant solved the problems, marking events which would require elaboration in the follow-up interview.

4. Participant generated artefacts: This included the written solutions to the problems and anything else they wrote as part of their rough work, if any

5. Retrospective think aloud (stimulated recall) interviews: We interviewed the participants immediately after they had completed all problems using a semi-structured interview protocol and showing them their video if their memory needed to be stimulated. The goal was to have them describe their thinking while solving the problem and reasons for the actions that they took. So we required them to explain and elaborate their actions at several points, especially the events marked by the researcher. Some sample questions are shown in Appendix B.

4.1.2 Data Analysis

We adopt a distributed cognition lens in our analysis, i.e., we believe that cognition emerges as a solver interacts with the resources in his/her environment (Hollan et al., 2000) and therefore we analyse the data with the lens of examining the interactions of the participant with his/her environment to understand how it led to solving the problem. The data was analysed using microgenetic analysis (Siegler, 2006) using the following steps.

1. Familiarizing with the data: The researcher went through her runtime observations of both participants, focussing on events when there appeared to be a shift in the participants' flow of actions. An example of such a critical event is,

   > *Staring at the ceiling. Turns to computer. Searches for something on internet. Reads a wiki page. It had animations on it?*

   Here the participant changed modes from "thinking" in his head to searching on his computer. The researcher then listened to the interview for the explanation of this action and made notes about the actions and explanations. This first pass through the data gave us a sense of types of actions that participants had taken.

2. Transcription of the data: The researcher created detailed transcripts of all the data sources (two videos plus the screen capture and the follow-up interviews) using ELAN (https://tla.mpi.nl/tools/tla-tools/elan) for each expert. An example of such a transcript is shown in Figure 4.1. As seen in the figure, the data was annotated along four dimensions, namely, writing, gestures, computer screen, speech and interview. The speech dimension was present only for E1 as E2 did not speak aloud while solving. We initially annotated 30

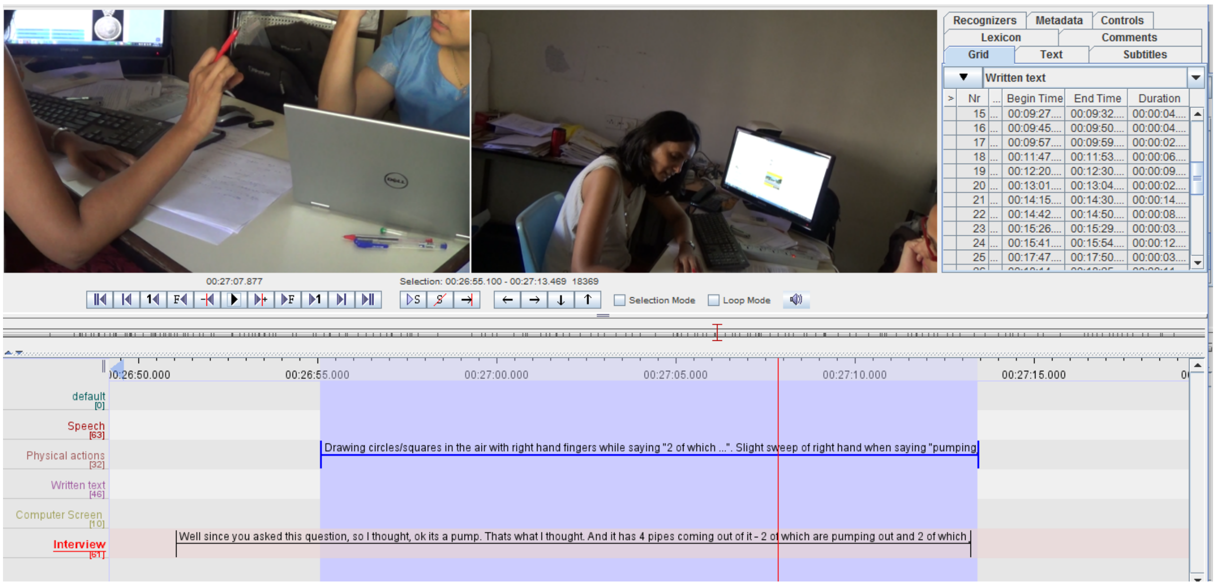


Figure 4.1: ELAN transcript for the Study 1 with experts

seconds of data at a time; later all the segments between two critical events were merged together.

3. Creating workflows: Threading these transcripts together, we created for each problem, a detailed description of the problem solving process as it happened sequentially in time. This description was authentic to participants self-reported process and actions, without any inferencing from the researcher at this point.

4. Identifying "change" points: We divided the workflow into episodes, and the boundaries of these episodes were participants self-reported "change" points, or points when their thinking changed. We focussed on specific episodes which were interesting in the larger context of the study because they allowed the expert to move forward in the problem. These were typically at the start of the problem solving, and at points when the participant was stuck. An example is shown below,

   E2 spent some time reading the problem and after this while he was "thinking" about it the index finger on his left hand moved forwards and backwards. Then he searched for "ratchet" on the Internet, briefly scrolling through results and changing the search term to "to and fro" before returning to the results for "ratchet" search. He clicked on the Wikipedia link and read the "theory of operation". While reading he made a turning movement with his right hand which seemed to correspond to the motion in the animation *of a ratchet shown on the Wiki page. During the interview he reported "The first thing that I did is that I assumed that the wine opener we mean a corkscrew. And I thought of what does the human heart do that can help me? Which is that it beats. So there's a rhythmic motion. So then I assumed that - I ofcourse had to assume that its a beating heart. And umm I have to assume some sort of structure and geometry. So I assumed that it is inside a person who is sitting or standing. So I have (pause) an anchor so to say. So then it's a question of converting that rhythmic motion into the rotational motion of a corkscrew."*

Here the two underlined phrases are two change points at which the participant changed his thinking and moved forward in the problem. We focussed on the episode between these two change points.

5. Abstracting Process: We abstracted out the conceptual actions of the participants during each episode between two change points. The theoretical lenses through which we looked for conceptual actions were ill-structured problem solving and model-based reasoning. For instance, the conceptual action associated with the snippet above is *"modelling the behaviour of the heart"*. These conceptual actions were combined together to identify the phases of the problem solving.

6. Abstracting cognitive mechanisms: We identified what were the mental and physical activities that contributed to forward progress during each episode. Specifically, we analyzed the roles that gestures, talk, writing, drawing and computer search played in these episodes. From these we were able to identify the underlying cognitive mechanisms. For example, in the above episode, from the participant's self-report and the observed gestures, we concluded that the cognitive mechanism was "mental simulation".

7. Ensuring validity: We collaboratively did multiple passes through the data until there was agreement and refined our abstractions based on discussions. We detailed out the definition of each abstraction as we re-analysed the data. For example, consider the following episode

   For the next minute E2 looked away, either staring straight ahead or at the ceiling, placing his hands on his head, closing his eyes, etc. During the follow-

up interview he described that

"...the first maybe whole minute I was thinking about a connection to weight. And I also sort of (...) decided that it would have to be the magnet that was contributing most of the weight. (...) But it took me quite a bit of time, at least that first one minute definitely, to figure out - or to - not figure out - but ***to make some connection to the weight of the radio.****"*

Then he moved his fingers to the computer but did not type and held the pen over the paper but did not write. Finally he edited his search to "weight hand cranked radio" and looked at the results without clicking on any one. Next he edited the search to "weight permanent magnet" and again looked at the results without clicking.

In the first pass this was abstracted out to *"fleshing out the structure"*. However in subsequent passes we realized that fleshing out the structure required the conceptual knowledge of the working of the radio. This was not stated explicitly by the participant at this point, but a little later in their interview. So this episode was re-abstracted out as *"fleshing out the physical and conceptual structure"*.

4.1.3 Workflows

We found that for two out of three problems the experts obtained order-of-magnitude estimates. The third problem was left incomplete by both experts because they could not solve it despite their efforts. We elaborate the reasons for their inability to finish below. Here we report sample workflows for each expert. While we have analyzed all the problems solved by each expert, in this section we only provide a description of the second problem as solved by each expert. We chose the second problem because this involved estimation based on the dynamics of a system, rather than its structure as is the case with problem 1. Further, both experts successfully and correctly solved this problem, unlike problem 3 which both experts were unable to solve and left incomplete.

Workflow of Expert 1

Expert 1 (E1) is an academic with three years' experience in academia and eleven years' experience in industry. She spoke out loud intermittently while solving the problems. A depiction of her workflow while solving problem 2 is shown in Figure refE1workflow.

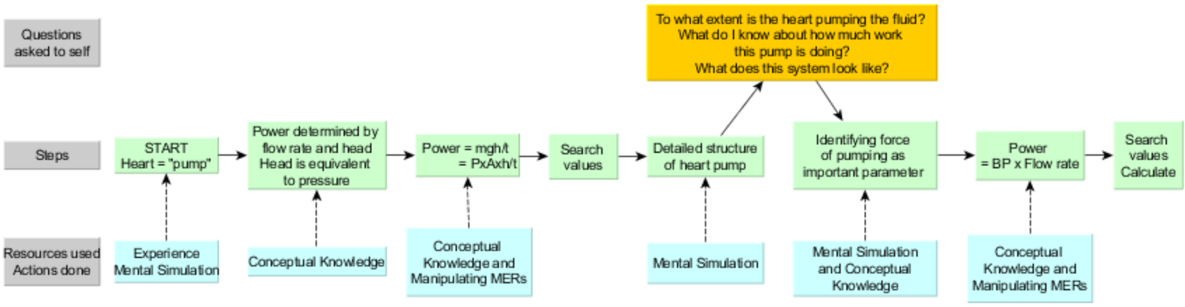


Figure 4.2: Workflow of E1 for problem 2

After reading the problem, E1 almost immediately searched *"Flow rate of blood"* on the Internet. She scrolled through the results, highlighted two links related to blood velocity, but did not click either. She picked up the pen to write, dropped it and then picked it up again and began writing. Initially she started writing "$Pressure = F\times$", but after a while she struck through that and wrote "$Power = \frac{mgh}{t}$", then after a pause added another equality "$= \frac{F\times h}{t}$". After a long pause, she wrote "$=\frac{P\times A\times h}{t}$". After another pause, she searched for *"Blood pressure"* on the Internet and clicked on the first search result that popped up called *"Normal Blood pressure"* and read it. She spoke aloud that there were two readings given for blood pressure whose meaning she didn't know so she chose a value between the two which is 100 mm Hg and wrote down that value.

Next, she wrote down "$F = P \times A$", said *"r is the distance - the head that it pushes the blood around"* and added "$\times h$" next to the equation "$F = P \times A$". She identified pressure by underlining the value she had written down, *"100 mm Hg"* and area as *"the cross-section of the two blood vessels"*. This she estimated to be "$2cm^2$". Next she said that *"h"* was hard to determine *"because the diameters of the pipes keep changing"*. She added "it's a closed loop system" and went silent for a while. For part of that duration her pen was hovering over the equation "$=\frac{P\times A\times h}{t}$". After this, she added *"Okay flow rate. That's what I need to know"* and searched for *"Flow rate of the blood from the heart"* on the Internet. She clicked on the Wikipedia page titled *"Blood Flow"* and read the section *"Velocity"*. She noted down the cross-sectional area of the aorta and the blood velocity and calculated flow rate and then power as "$flow\ rate \times pressure$". She decided to convert all values into MKS units and for that searched *"100mm Hg Pascal"* on the Internet. She noted down the value, 13332 Nm^2 and completed the calculation arriving at the result of 6 Watts. Her problem solving process (as drawn by her during the follow-up interview) is shown in Figure 4.3

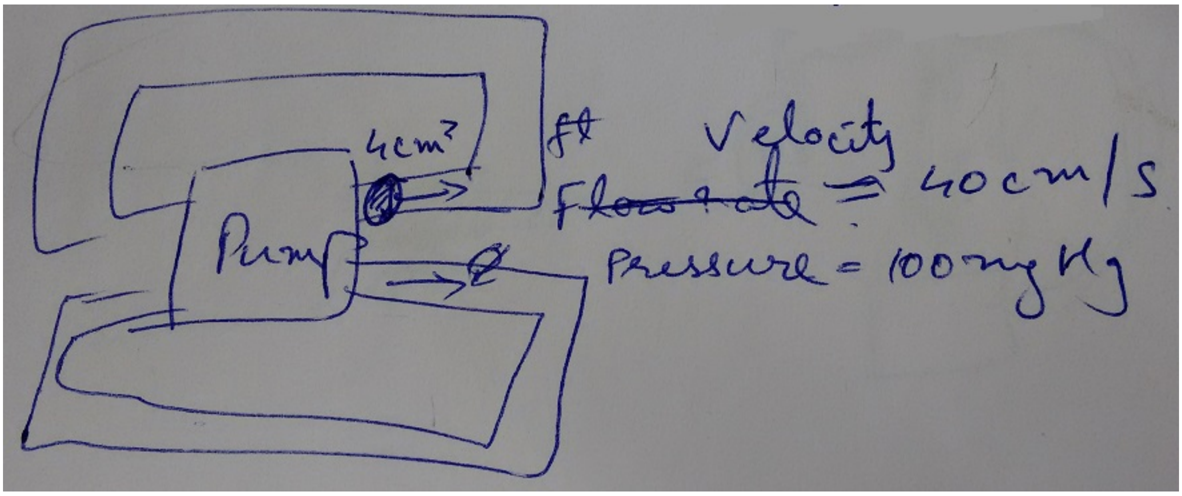


Figure 4.3: Diagram of E1 for problem 2

This problem was followed up with the other version of the same problem *"Could a human heart run a wine opener?"* E1 began by saying that she was going to consider the work done as the work against friction between the cork and the bottle neck. So she needed to determine this force of friction since work done is "$force \times displacement$" and she estimated distance to be 2cm. For a while she was silent and then said *"Work done is just power × time"*. After a brief pause she added that *"...given the right contraption it could take forever and still open the cork"*. She wrote this down and ended. Her solution approach (as drawn by her) is shown in Figure 4.4.

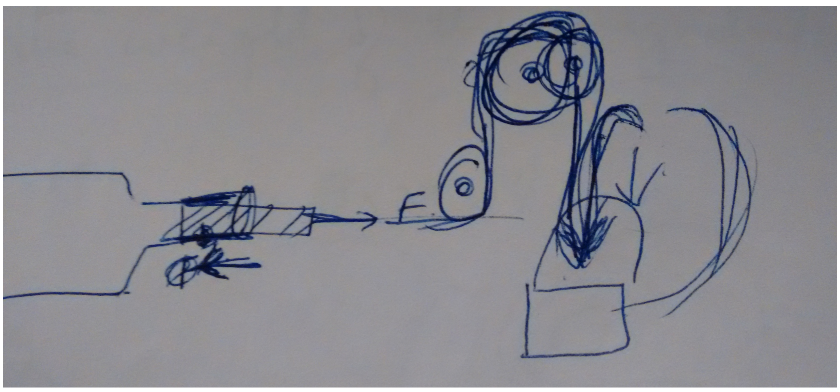


Figure 4.4: Diagram of E1 for follow-up problem 2

Workflow of Expert 2

Expert 2 (E2) is an academic with seven years' experience in academia and three years' experience in industry. He worked silently and only spoke to report that he had finished a problem. His workflow for this problem is shown in Figure 4.5.

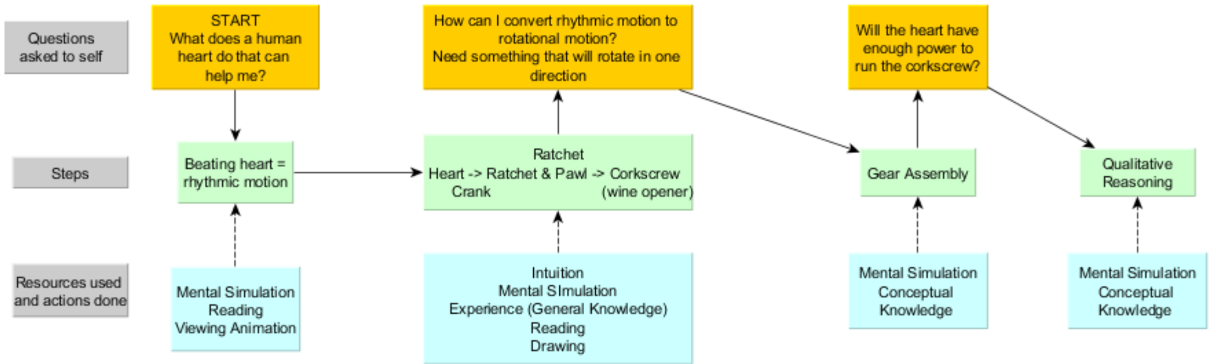


Figure 4.5: Workflow of E2 for problem 2

E2 spent some time reading the problem and after this, while he stared straight ahead silently, the index finger on his left hand moved to and fro a few times. Then he searched for *"ratchet"* on the Internet, briefly scrolling through results and changing the search term to *"to and fro"* before returning to the search results for *"ratchet"*. He clicked on the Wikipedia page for *"ratchet"* and read the *"theory of operation"*. While reading, he made a small turning movement with his right hand. Then he wrote down two assumptions, *"Assumption 1: It is a beating heart. Assumption 2: It is inside a human body."*

After this E2 spent some time reading the computer screen and then he drew a part of the diagram shown in Figure 4.6. Next, he air drew what seemed to be a straight line between the man and the ratchet. He formed a "C" with his right hand and rotated it about his wrist. He again drew straight lines and circles in the air. After a while of looking away, he searched for *"to and fro motion to rotational motion"* and read the first link titled *"reciprocating motion"*. As he read the screen, he intermittently looked at paper and looked away. Next he searched for *"crank machine"* and read the Wikipedia link for *"Crank (mechanism)"*. Then in Figure 4.6, he drew the straight line from the rectangle to ratchet and labeled it *"crank"* and completed the rest of the drawing. He drew the flow chart below this diagram to depict his solution approach *"Beating heart $\rightarrow$ Crank (turns gear on ratchet) $\rightarrow$ Ratchet & pawl $\rightarrow$ cork-screw"*. This concluded his solution.

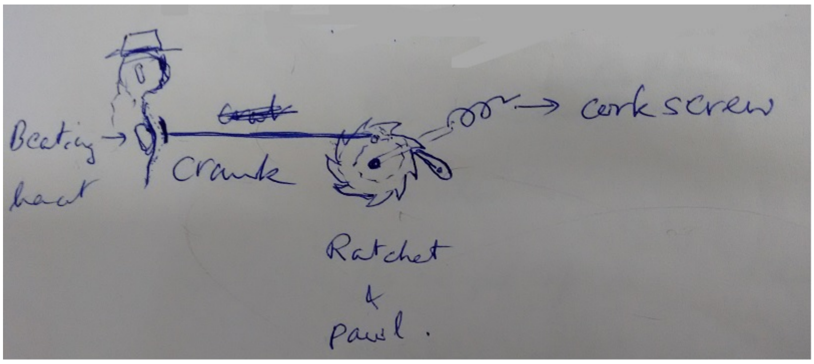


Figure 4.6: Diagram E2 for problem 2

4.1.4 Results

Engineering Estimation as a form of model-based reasoning

In this section, we present the answer to our research question RQ1a. Based on our analysis of the entire corpus of data, we identified three phases in the estimation process of experts, namely functional, qualitative and quantitative modelling which were integrated to obtain an estimate. Next we describe each phase individually and then the integration.

1. **Create a functional model**

   When faced with an unknown system, experts first focussed on the dynamics of the system and modeled the dynamics in terms of those of a known system as in the case of problem 2,

   > E1: *"...the first thing that came to my mind was the heart is a pump."* E2: *"...thought what does the human heart do that can help me? Which is that it beats. So there's a rhythmic motion."*

   In both cases, the experts began by modeling the function of the heart. Its dynamics gave experts a way to identify an object or system with similar dynamics. For E1, the similar object which immediately emerged was the pump and for E2 the heart was reduced to an object that executes repetitive motion. These converted systems that experts began working with were their functional models and their function was similar to the given problem system.

   In problem 3, which required estimating the weight of a hand-cranked radio, the experts reported that

> E1: *"the initial part I was actually thinking of it in mechanical terms. So if you have this crank shaft that you're trying to turn. Then there's a mass sitting here thats turning with some velocity then what would be the power etc"* E2: *" I had some image of a real hand-cranked radio. And I was trying to imagine I think lifting one of those and I realized that I have actually no intuition. I might have seen those, I don't think I tried to lift them up. So then the next thing that I know is okay I am lifting up a radio from our childhood."*

E1 connected the hand-cranking function to the familiar system of a crank shaft. E2, on the other hand, tried to connect to an actual (hand-cranked) radio. Again experts were triggered by the dynamics of the system and identified similar systems which served as their functional models.

2. **Create a qualitative model**

   Experts developed a model of the structure of the system, how its various components work together and how the various parameters of the system affect each other. We call this the qualitative model. The functional model was constantly evaluated in the mind until it aligned with the problem requirements. It was broken down into components to see which component could be modified to get the solution.

   In the case of E1, she had modeled the heart as a pump and she needed to determine the power of this pump. She identified that the power of a pump is determined by the flow rate and head. Thus her task changed to determining the flow rate and head of this heart *"pump"*. She was aided in this restructuring by her knowledge and familiarity with pumps due to her recent experience with them. However, when she looked for *"flow rate of blood"* on the Internet, she fleshed out the details of her model of the heart *"pump"*. This was her qualitative model, as she described,

   > *"...what do I know about how much work this pump is accomplishing in this system ... so what does the system look like? So first I started to think of the lengths of veins and arteries and their widths - their diameters and things like that. [pause] And then the pressure."*

   In E2's case, because he had modeled the heart as something which moves rhythmically, his task was to find a way to *"run"* the wine opener (or cork screw as he assumed) using that motion. Thus his problem reduced to converting the rhythmic motion of the heart to the rotational motion of a corkscrew; thus he restructured the problem. Next, E2 had to identify the components of a mechanism to convert the beating motion of the heart into the rotation of the corkscrew. He recognized that the heart goes to-and-fro but he wanted the corkscrew to only go in one direction.

Here he recalled the ratchet and that it had something to do with one-way rotation. So he looked it up and decided that it was suitable to the task of turning the corkscrew in one direction. He indicated his partial solution by drawing the heart and the ratchet & pawl. At this point he realized that before the corkscrew could be turned, the linear motion of the heart would need to be converted to rotational motion. As he didn't know what mechanism could accomplish this, he looked it up on the Internet, learned of the crank and inserted it into drawing of the mechanism that he had already drawn (Figure 4.6). Thus E2 also re-examined and restructured his functional model resulting in his qualitative model.

During qualitative modelling, in addition to detailing the structure and working of their functional model, experts also identified the causal relationships between the parameters of the system and focussed on the problem requirements (model contextualization). This aspect of qualitative modelling requires conceptual knowledge, often of multiple domains depending of the problem. This aspect is critical, because it is at this stage when the possibilities of the functional model are constrained.

In order to estimate the weight in problem 3, E2 tried to identify the parameters that would affect weight in the hand cranked radio as he reported,

> *"What was [pause] difficult in this problem I would say is to link - is to find out a connection to the heavy. Where is the weight coming from? Umm electronics is not heavy. Umm the mechanical part of it - the crank handle etc- those I mean you have materials these days that would make that not heavy. So umm it look a little while to see that okay the weight would have to be - I think the weight would have to be in the magnet."*

E2 constrained his functional model using conceptual knowledge and comparisons to focus on the aspects which are important for estimation.

Summary of Functional and Qualitative Modelling: A summary of functional and

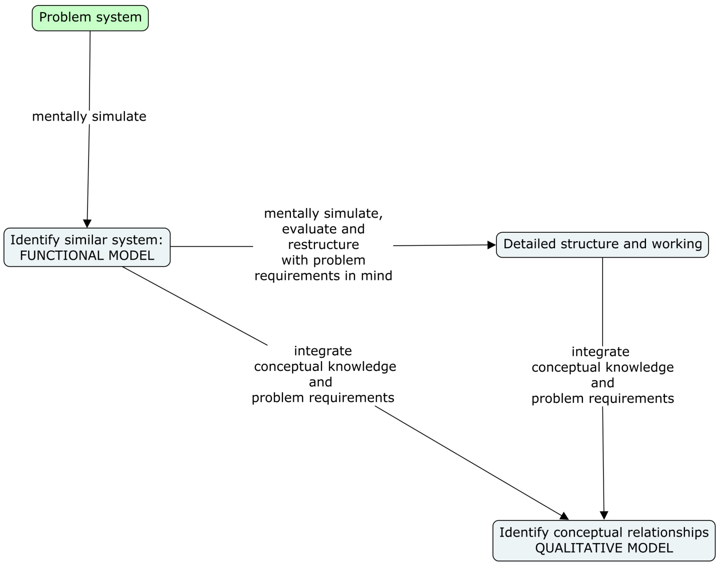


Figure 4.7: Summary of Functional and Qualitative Modelling

qualitative modelling is shown in Figure 4.7. We found that experts enacted the problem system in order to identify a similar system (functional model), its components, their connections and working, and this helped them expand the problem space. They integrated the problem requirements and conceptual knowledge in order to narrow the problem space and create a contextualized qualitative model of the problem system.

3. **Create a quantitative model**

   In this third phase experts developed (if necessary) a quantitative model or equation corresponding to their qualitative model to calculate the estimate. E1 wrote out the general equation for power and restructured that to arrive at the equation for the power of the heart **"pump"** in terms of the blood pressure of the heart, namely "$Power = \frac{P \times A \times h}{t}$" where "P" is the blood pressure that she looked up. In this new structure, she still did not know "h" in the equation. She evaluated the qualitative model with the system working in mind to determine what "h" was,

   > *"...basically to what extent is the heart pumping the fluid. So I was trying to think, ok then what are the various diameters of the various arteries and how long are they and all that. But then I was thinking whatever the energy with which it pushes the blood out is expended by the time the blood comes back to the heart."*

   By re-examining the equation she realized that $\frac{A \times h}{t}$ was actually flow rate and that the distance through which the heart pumps the blood, “h” doesn’t matter. She restructured the equation again and arrived at an equation in which all the parameters’ values could be looked up. She then looked up the standard values on the internet, namely blood pressure and velocity of blood in the veins and completed the estimate. Thus the functional and qualitative models were built upon to create the equation and the enacted problem system was converted to numbers via equations.

E2 did not develop a quantitative model of the system in problem 2 or calculate power of the heart to compare it with the power of the corkscrew. Recall that we had expected this to happen due to the wording of the problem given to him. During the follow-up interview, when he was asked to evaluate whether the heart had enough power to turn a corkscrew, he qualitatively reasoned that it probably didn’t. He added that by including two gears – a small one and a large one – which would together turn the corkscrew *“very slowly”*, he would be able to open the wine bottle, though *“it would take forever”*. Thus by restructuring his qualitative model he was able to evaluate this alternative scenario and develop another solution.

In problem 3, both experts reported that, because they did not known the equations involved, they were unable to solve the problem. Thus conceptual knowledge of multiple domains is necessary at this last stage of estimation to obtain a numerical estimate or do qualitative reasoning by comparison.

Summary: Experts used their functional and/or qualitative models and conceptual knowledge to create equations or make comparisons in order to freeze upon an estimate or a judgment regarding feasibility.

4. **Integrating functional, qualitative and quantitative models**

Our results suggests that engineering estimation is an instance of model-based reasoning shown in Figure 4.8. Experts begin by mentally simulating the problem system in order to identify a similar system which is their functional model. This functional model is iteratively evaluated and detailed multiple times, culminating (in the case of a numerical estimation problem) in the calculation of the estimate and, if necessary, revision of the models (Figure 4.8). We also observe that experience or familiarity with certain systems (either the problem system or related ones) played a critical role in estimation as experts began the process by considering systems from their experience as functional models. Further we observe that the problem context is always kept in mind while creating and revising models.

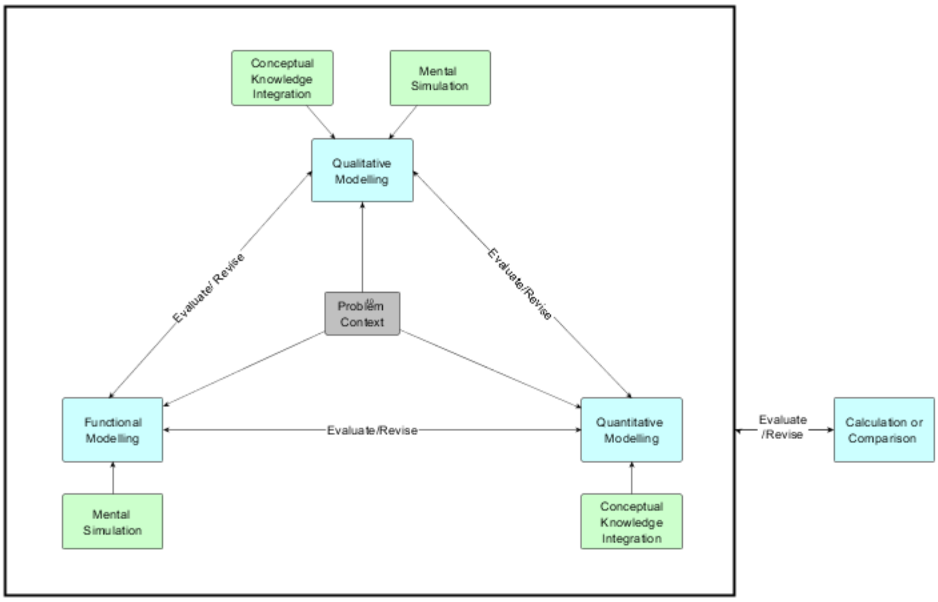


Figure 4.8: Engineering estimation as a form of model-based reasoning

As seen in Figure 4.8, there are three models in the model-based reasoning process, the functional, qualitative and quantitative modelling. The green rectangles in Figure 4.8 indicate the cognitive mechanisms supporting each phase of modelling, and the problem context is incorporated in each phase of model-building. While it may appear logical to go through the sequence of functional, qualitative and quantitative models and build on the models, we found that experts did not always do so. They always began with functional models and ended with qualitative or quantitative models depending on the problem. In the interim, they went back and forth between the three models, as shown in Figure 4.8. What was clear was that, experts integrated all three models in their final solution. That is, the dynamics of the system (functional model) is aligned with the physical structure and causal relationships (qualitative model) and the equation describing the system (quantitative model). The problem context serves as the integrating factor of all three models. Once integrated, depending on the problem at hand, one of the models along with numerical sense, calculation, comparison and decision-making lead to the estimate or judgment. For instance, in case of a numerical estimation problem, values are substituted in the equation, calculated and evaluated. However an expert may directly use the qualitative model to make a judgment when needed.

Summary: Experts solve estimation problems by enacting the problem system, incorporating the problem requirements and conceptual knowledge to create contextualized models and then freezing that model to numerical estimates or judgments. In the next section, we elaborate on the cognitive mechanisms underlying estimation.

Cognitive Mechanisms Underlying Estimation

In this section, we answer our second research question and elaborate the roles of mental simulation and external representations in engineering estimation.

1. **Mental Simulation**

   The data shows that when experts read a problem they mentally simulated the dynamics of the problem system, entirely or in part. Some system the expert knew about was used to "instantiate" the simulated dynamics (e.g. heart is a pump). Experts simulated the end point (e.g. the wine opener/corkscrew) or the entire system (e.g. working of the heart) in sufficient detail to evaluate whether their instantiated functional model achieved the desired result. Thus the requirements from system are always kept in mind while mentally simulating its dynamics.

   Evidence for this comes from both experts.

   > E1: *"it has 4 pipes coming out of it - 2 of which are pumping out and 2 of which are pumping in. So essentially if it has 2 pipes ...I mean, if it's pushing water out..."* E2: *"It's something that is executing repetitive motion."*

   This simulation helped them to develop their initial functional model of the situation. Further evidence for this mental simulation comes from experts' gestures. When E1 described the heart, she gestured dynamically with her hands to indicate the flow of water in the pipes (Figure 4.9), while E2 had been moving his index finger to and fro in the initial phase of the problem solving when he was developing his model (Figure 4.10). As known from literature (Hostetter & Alibali, 2008), gestures are evidence of mental simulation.

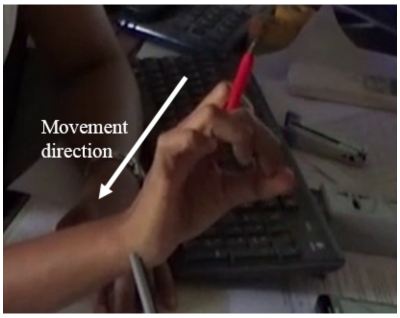


Figure 4.9: E1's gesture

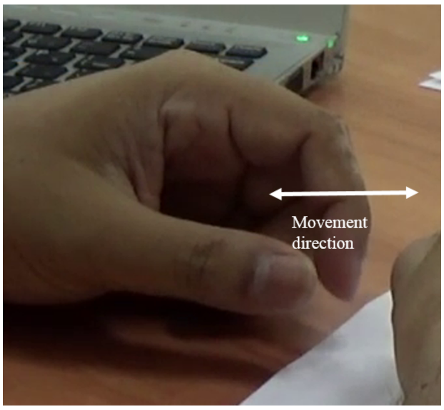


Figure 4.10: E2's gesture

These mental simulations did not stop with functional model building; as experts created the qualitative model, the functional model was simulated and constantly compared to the desired behaviour required from the system to ensure that it was still valid. Experts were willing to modify their models if they did not give the desired result. For instance, in the case of E1 while solving problem 3, she initially developed a functional model of a crank and mass attached to it. However, re-simulating the model helped her realize that the radio works on electricity and *"turning the crank means you are running a generator"*, so mass meant the mass of the magnet. Thus constant evaluation of the functional model led to a breakthrough in problem understanding.

Summary: Mental simulation of the problem system helps expand the problem space by generating many variations of possible dynamics and structures for the problem system as shown by the "blob" in Figure 4.11. These variations are then evaluated using mental simulation keeping the problem requirements in mind. Conceptual knowledge supports this evaluation process and helps to productively constrain the mental simulation to the realm of causality. As seen in Figure 4.11, the arrows indicate that the expanded problem

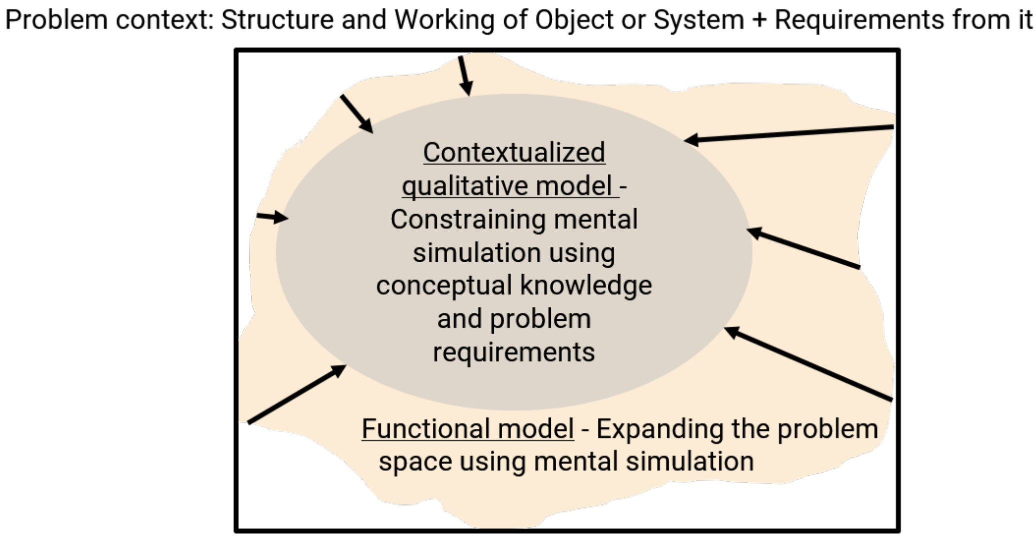


Figure 4.11: Mental Simulation and conceptual knowledge in modelling

space is narrowed using mental simulation and conceptual knowledge. This evaluation results in a contextualized qualitative model.

2. **External Representations**

   (a) **Diagrams**

   We found that E1 did not draw diagrams while solving problems. However she had imagined very clear models for problems 1 and 2 while solving them as was evident from the diagrams she drew when asked during the follow-up interview. We argue that because of these clear imagined models she was able to easily restructure and solve these problems. From her rudimentary diagrams and her verbal reports for problem 3, it appears that she did not have very clear imagined models of this problem, which could have been the reason for her difficulty with this problem, especially because the system was more unfamiliar than the previous two problems.

   E1 drew diagrams while solving problems 1 and 2. For problem 1, since the question was to estimate pit spacing, by drawing a diagram of his model of the CD he was able to create the other models required for solving the problem, namely the equations for pit spacing. For problem 2, the final diagram that he drew was his solution (Figure 4.6). After he drew the first and third parts of his solution, the diagram helped him identify that the solution was incomplete and he needed something in the middle to convert the linear motion to the rotational motion. Thus drawing the diagram supported his mental simulation. For problem 3, he did not draw a diagram but a flow chart describing his approach to the problem.

(b) **Equations**

E1 and E2 both used equations extensively, which is not surprising in engineering. Equations were the way to assign numerical values to physical quantities. However equations served other purposes besides this in the estimation process. For instance, in problem 2, E1 used equations as an external representation that can be rearranged and reformulated (Kirsh, 2010) and arranged them into a form that was conducive to further action. Equations helped her in mapping the details of her model with the given problem system. Originally she thought that to calculate power she would need to know flow rate and head, but later realized that head was not a valid parameter in this context. Thus working from the basic equation of power ($mght$) she was able to rearrange and reformulate it to a form in which everything was known to her ($\frac{P \times A \times h}{t}$). In the follow-up to problem 2 and in problem 3, she used equations as persistent objects to think with (Kirsh, 2010), as equations helped her in splitting the problem into factors, and in identifying a clear path to the solution.

E2 used equations as persistent objects to think with and for restructuring the problem when he was trying to arrive at an estimate for the weight of the magnet in problem 3. He wrote down a set of equations and then tried to assign approximate values to the physical quantities involved in them in order to determine the volume of the magnet and hence weight. This restructuring of the problem from weight to volume was aided by the equations, which again helped in factorizing the problem and identifying a path to the solution.

E2 very often transitioned between text (written by himself and on the computer screen), equations and diagrams in the solving of problems. An instance of this was seen in problem 1 when his pen went back and forth in the air between the diagram and the equation before he wrote. This indicates that he was making a connection between the equation and diagram or using information from one in the other. Thus experts translate across representations while solving estimation problems.

Summary: Experts use different kinds of external representations such as diagrams, flow charts and equations. These representations support their mental simulation, evaluating their models and translating between models. In addition, they serve as persistent objects to think with and support problem restructuring and reformulation. Experts frequently translate between representations.

Metacognition in expert process

The expert process consists of both cognitive and meta-cognitive mechanisms as shown in our descriptive model of an experts' estimation process. The cognitive mechanisms are those involved in creating functional, qualitative and quantitative models, and include mental simulation by connecting to prior knowledge, experience and intuition, and manipulating external representations such as figures, equations, videos and simulations as elaborated above. Experts are able to identify and use the appropriate cognitive mechanisms for modelling and employ physical resources from the environment as needed.

The meta-cognitive mechanisms are those that trigger the evaluation of models and reflection on estimation process. We identified that experts proceed by setting goals for themselves which include identifying how the system works at deepening levels of detail (model building) and then evaluating whether the model meets the problem requirements. For instance, as E2 reported for problem 2 (Figure 4.6),

> *"okay there were two things, one is repetitive motion on this side and on the other side was that there has to be some sort of rotation on the cork screw or whatever it is that you need to or opening of a lid. So rotational motion. So the question in my mind effectively became very quickly how do I convert this to the other? I mean ...repetitive to rotational."*

Here we see that E2 is evaluating his emerging model of how the system works by comparing it with the problem context (the problem system of heart and the problem requirements of running a wine opener).

Experts evaluated that all the parameters which affect the system performance in the given operating conditions are included. They made appropriate assumptions and approximations to simplify the model if necessary. Finally, they ensured that the model is in terms of known parameters (useful model). This is elucidated in the following snippet of E1's think aloud while solving problem 2,

The distance - the head that it pushes the blood around. So let's say, this is the pressure, area is the cross section of the two blood vessels probably
Blood in 2 so that's probably 2 cm^2
and h would be the (pause) this is hard, because the diameter of the pipes keep changing
I guess that ...okay ... it's a closed loop system
(unclear) pressure ...ok flow rate...yeah that's what I need to know
So the aorta is 3-5 cm^2*. So* $x2$*. Blood velocity is* $40cms$*. So flow rate =* $5cm^2$
...$10cm^2x40cmsec$*. That's the flow rate.*

Here, E2 is trying to assign numerical values to the parameters in her equation of the power of the heart and then she realizes that the parameters do not translate one-on-one to the features of the heart *("the diameter of the pipes keep changing")*, so she further fleshes out her model *("it's a closed loop system")* and manipulates it until she has it in terms that align with the problem context *("ok flow rate ...yeah that's what I need to know")*. Thus, the metacognitive self-questioning led to evaluating and revising her model.

Finally, we also observed that experts reflected on their process and changed their approach if they perceived it to not be useful or appropriate to solving the problem. For instance, in problem 3, after E1 had built an initial model of a mechanical system, she reflected *"why am I doing this"*,

"Then I stopped and said, No that's wrong because the radio probably works on electricity and turning that shaft means you are running a generator. So then that's completely different. It's not about mass..."

Summary: The expert process of estimation is an intertwining of cognitive and metacognitive mechanisms which together lead to good estimates. The metacognitive self-questions that experts ask themseleves serve as triggers to evaluate and revise their models and solution approach. Mental simulation and external representations support the evaluation and revision processes.

Role of Information Gathering and Conceptual Knowledge in Expert Estimation

In problems 1 and 2, E1 used the Internet to search for numerical values in order to calculate her estimates after she had created quantitative models. In problem 3, E1 searched the Internet to understand the working of the given problem system. Later after revising her functional model, she searched for an equation for power in the given problem context. In all problems E2 searched the Internet for information about the problem system. In problem 1, this was related to the structure of the CD and in problem 2 it was related to the working of the ratchet and crank. In problem 3, E2 first searched for the working of the hand cranked radio, and later for the relevant equations needed to calculate power in a generator. Thus experts primarily used information gathering to understand the problem system better.

Both experts E1 and E2 used conceptual knowledge to constrain and fine tune their initial functional models and create qualitative models that describe the relationships between the various parameters of the problem system (see Figure 4.11). Therefore the lack of conceptual knowledge makes it difficult to create a complete and valid qualitative model and hence get a good estimate, since in the last stage the qualitative models are converted to equations using the conceptual knowledge of the domain.

Summary: Experts used information gathering mainly to understand the problem system and find values for parameters in the equation. They used conceptual knowledge to fine tune their mental simulation and create contextualized models for estimation.

4.1.5 Discussion

We began this study with a conjecture regarding the expert process of estimation, that it would be based on model-based reasoning and mental simulation and manipulating external representations would be the underlying cognitive mechanisms. Our findings validate and elaborate on this conjecture. We identified that while engineering estimation may be performed in different ways depending on the problem and the solver, a three-phased iterative model-based reasoning process (Figure 4.8) can be identified in each problem-solver instance. The findings elaborate the roles of mental simulation and external representations in each phase of the estimation process. The process begins with experts simulating the dynamics of the given system and identifying a system with analogous dynamics as a functional model. The specifics of the functional model may change, especially during qualitative and quantitative modelling. The functional model is used to identify, refine and evaluate the structure, working and conceptual knowledge governing the problem system, by constant comparison to the problem requirements.

Our results showed that conceptual knowledge helps detail and converge mental simulation and model-based reasoning, and is not themselves generators of solutions. It is important to note that this is different from the classical case of model-based reasoning in science (Nersessian, 1999) in which models are used to infer general principles; in estimation the detailed structure and working of the models, along with causal reasoning and equations based on conceptual knowledge, are used to make estimates.

It is interesting to note that while E1 thought hearts pump and E2 thought hearts beat, both arrived at the conclusion that it would take forever to open the bottle "using" the heart, but that it can be done. Their starting dynamics and functional models were different, yet their final solutions were conceptually and functionally similar. The latter two phases contributed to this convergence. When conceptual knowledge and problem requirements are applied during qualitative modelling, it constrains the mental simulation to align with the underlying causality of the domain. Thus the expert estimation begins with problem space expansion by mental simulation and proceeds towards problem space narrowing using conceptual knowledge.

While this may seem to be obvious to do in engineering, it has been shown that students begin with the equation rather than the model (Wankat & Oreovicz, 2015). While experts used equations to converge their estimation process, which started off with the simulation of dynamics, students may start with the equation, which may not help generate the simulated dynamics or model of the system. Experts used equations to evaluate the simulated model; students may use equations as the only model.

Finally, experts seamlessly intertwine cognitive and metacognitive processes to evaluate and monitor their emerging solution (models) and thus obtain good estimates. This is consistent with literature on metacognition and reflection in problem solving and practice (Jonassen, 2000; Mayer, 1998; Schoenfeld, 1992; Schon, 1984) which highlights the importance of metacognitive processes such as knowing when to use and monitoring the cognitive processes involved in complex tasks such as problem solving and design. In summary, when experts obtain good estimates, their estimation process is based on metacognitively aware progressively higher order model building using mental simulation, manipulating external representations and conceptual knowledge. In the next section, we study novice processes and highlight how they are different from expert processes.

Even though we only had two participants, they solved three problems each, giving a total of six problems, which were designed to have diverse features and requirements. Still, we found coherence among expert estimation processes in terms of the three phases of modelling and the underlying cognitive mechanisms of mental simulation and external representations. While we obtained no agreement regarding the exact sequence of the estimation process, we identified the components of the estimation process which contribute to good estimates. We believe that there may in fact be no "optimal" sequence for solving estimation problems, and each solver may, depending on his/her personal preference and prior knowledge, integrate the components in various ways. In the next section, we describe how students typically solve estimation problems.

4.2 Study 2: Characterizing Novice Processes of Estimation

From our study of experts, we identified the model-based estimation process that is necessary for doing good estimation. Now we study novices to understand and compare their process with the expert process, and identify the challenges faced by them while solving estimation problems. Recall that in section 2.7, we conjectured that novices would focus on obtaining an equation connecting the quantity to be estimated to known quantities. They would not focus on the problem context and but on identifying the engineering conceptual knowledge which would give them the right equation. In this section, we describe a study to examine this conjecture, the analysis and results obtained.

4.2.1 Methods and Materials

This was also an exploratory study was to investigate our conjecture regarding the novice estimation process, obtain a detailed understanding of the process and examine its differences from the expert process. As in the case of experts, our goal is to understand what novices do as they solve an estimation problem, both in their mind and with their natural environment. Specifically, we are interested in understanding how they use the resources in the environment, integrate them with their mental resources and obtain estimates. Thus for the reasons elaborated in section 4.1 cognitive ethnography and microgenetic analysis is a suitable method for this study. Specifically, we analyse novice data through the lens of comparing it with the expert data and identifying differences. We do not expect to generalize the novice process of estimation, but understand the underlying cognitive mechanisms and how they differ from those of experts.

Research Questions

The broad research question for this study was "How do novices solve estimation problems?"

RQ2a How is the novice process of solving estimation problems different from the expert process?

RQ2b What are the challenges that impede novices from doing good estimation?

Estimation Problem Used

The problem given to the learners was designed so that the underlying conceptual knowledge was appropriate to second and third year engineering students of Electrical, Electronics, Mechanical, Chemical, Civil and Aerospace departments. The context was selected such that it would be relatable, motivating and engaging for novices. The designed problem was evaluated and revised based on the suggestions of an expert engineering educator with over ten years teaching experience in Mechanical Engineering at a technical institute in India. The final problem given to students was

You are participating in a competition in which you are required to design an electric car of weight 5kg with wheel diameters of 5" that can accelerate at $1ms^2$ *and traverse a track of 25m without burning out. Estimate the electrical power needed to achieve these specifications.*

The problems given to experts were not suitable because in pilot testing they were found to be uninteresting to our novice population and we did not want lack of interest to be a reason for poor performance. Further, we could not use more than one problem because pilot testing showed that the above problem would be challenging for novices and solving more than one such problem could lead to frustration.

Participants and Procedure

We performed a cognitive ethnography and participants were eleven novices (one female) from second year undergraduate engineering programs from two universities in India. They were selected by purposive sampling in order to cover a range of backgrounds - different departments (Mechanical Engineering, Aerospace Engineering, Chemical Engineering and Engineering Physics) and engineering curricula – in order to increase the likelihood of observing diverse behaviours. The average age of participants was 20 years. The participants self-reported being motivated towards extra-curricular technical activities such as robotics club.

Participants solved an estimation problem on paper, independently and without any researcher guidance. However they were allowed to use the Internet to search for resources/

information/ concepts that they needed. They were allowed as much time as they needed to solve the problem. The participants were free to solve in their natural way, silently or talking out loud as they felt comfortable. Again, we did not require participants to think aloud as this would place a cognitive load on novices disrupting their solving process. One participants data was not used as he did not complete the activity. The procedure was similar to the expert study, except that the study was conducted in our lab rather than a location of their choosing.

Data Sources

Our data sources were the same as the expert study, except we used only one video camera per participant for logistical reasons. The other data sources were identical.

1. Video recording: In order to record every action that the participant took towards estimation, the entire session was recorded using a video camera. The first was focused such that the participants entire body, especially their hands, and the task area was entirely visible.

2. Screen captures: Their interactions with the computer were captured using the screen capture software CamStudio (http://camstudio.org/).

3. Researcher observations: The researcher recorded regular unstructured observations while the participant solved the problems, marking events which would require elaboration in the follow-up interview.

4. Participant generated artefacts: This included the written solutions to the problems and anything else they wrote as part of their rough work, if any

5. Retrospective think aloud (stimulated recall) interviews: We interviewed the participants immediately after they had completed all problems using a semi-structured interview protocol and showing them their video if their memory needed to be stimulated. The goal was to have them describe their thinking while solving the problem and reasons for the actions that they took. So we required them to explain and elaborate their actions at several points, especially the events marked by the researcher. In addition, we specifically asked novices to elucidate the challenges that they faced in solving this problem. Some sample questions are shown in Appendix B.

4.2.2 Data Analysis

To answer RQ2a, as described in section 4.1.2, we again adopted the theoretic lens of distributed cognition (Hollan et al., 2000) and analysed the data using microgenetic analysis (Siegler, 2006) following the steps shown in section 4.1.2. To answer RQ2b, we analysed the workflows along with their self-reported challenges (during the interview) using the methods of thematic analysis (Braun & Clarke, 1996) to identify the themes related to the challenges faced by them.

Thematic analysis is an appropriate method for this research question because our goal is to explore the range of novice challenges in our data set. Following the methods of inductive thematic analysis we first familiarized ourselves with the data. Then we generated initial codes across the entire data set and collated related codes into categories and themes. Next, we reviewed the themes against the raw data for consistency. Finally we refined our themes by examining their details and created clear descriptions of them.

4.2.3 Workflow

We describe S5's workflow as he was a representative case of the novice estimation process. His workflow is shown in Figure 4.12. S5 began solving by writing down all the data given in the problem at the top of the page. Then after some thought he wrote down a formula for power "$P = \tau \times \omega$" (τ = torque and ω = angular velocity). He reported that his strategy was to try to relate what had to be determined (i.e. power) with whatever was given in the problem, and to do so he thought of all the formulae he knew relating the quantity to be estimated to the given data. He settled on the formula above because the question was about the car moving and the rotation of the wheels, so an equation with torque was more appropriate. Then he wrote $\tau = I \times \alpha$ (I = moment of inertia, α = angular acceleration). He did not know the formula for I so he searched for this on the Internet and found a relevant formula in which he knew all the quantities. He noted this down and then calculated that $\tau = 0.3175Nm$. Next he wrote $\omega = \alpha dt$ and after thinking for a while, calculated t using kinematics equations. Finally he calculated $\omega = \alpha dt$ and obtained the value $\omega = 55.67rads$.

After this thought for a while and searched for information on "how to estimate the electric power consumption of an electric car". He scrolled through the results and clicked on multiple links but did not find the information that he was looking for. As he reported later he was looking for more information about how the electrical power is generated and the operating conditions

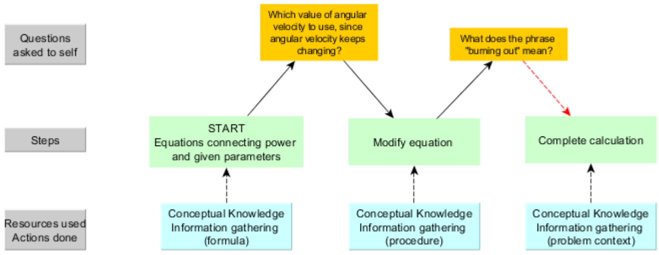


Figure 4.12: S5's workflow while solving the estimation problem

so he could decide about how to estimate ω. His confusion was because the value of angular velocity, ω is not constant and so he wasn't sure which value to consider in estimating power. Finally he reasoned that he would consider the maximum angular velocity as that would give him an estimate of the maximum power required.

Ultimately he went back to the paper, changed strategies and struck off the entire calculation of ω. He reported that he was confused about the appropriate formula for torque and though he initially chose the formula above, he later changed formulas as he was more comfortable with this one, $\tau = r \times F$ where the force, $F = ma$. He calculated $\tau = 0.635Nm$ which was different from his earlier calculation of torque. However he ignored this difference as he explained

> *"Yeah, it did, in estimating the torque, again there was a confusion whether I should use the I into sr formula, that is the moment of inertia into angular acceleration or to use the R into F formula. So, first I took I alpha, and then I was not sure about it, so I took R into F also, and then I found out that R into F gives me a larger value and I didn't think about what was wrong between them, but I took the R into F value."*

Then he re-read the problem and underlined the phrase *"without burning"*. As he reported, he did not understand what *"burning out"* meant and how it would impact the solution. He felt that this condition needs to be explained clearly in the problem statement. To understand this, he saw a few more web pages and spent some time thinking. He revised his search to *"how many kilowatts does it take to charge an electric car"* and scrolled through the results. Then he gave up on the search and went back to reading the paper and thinking.

Finally he completed the calculation for power using the formula $P = \tau \times d\omega$ since he knew all the quantities in it. He obtained a value $4.49W$ (we note that there is a calculation error in this value which S5 did not notice) for one wheel and then considering a two wheel drive, he wrote the answer as $P = 8.98W$. He appeared dissatisfied with this solution, but after spending some time reading it, he submitted his sheet.

4.2.4 Results

Engineering Estimation as an instance of Model-Searching

We found that six out of ten students obtained an estimate of the correct order of magnitude, however their equations for power were incorrect. Thus these novices obtained estimates of the right order of magnitude using inaccurate models of the system. Out of the remaining four novices, two were not able to finish the problem and two obtained estimates off by one order of magnitude.

An overview of the novice estimation process is shown in Figure 4.13. All novices began by thinking directly of equations relating power to the given quantities. The estimation was an exercise in searching for the right equation, in their minds or using *Google*, without considering the working of the car or the requirements from it given in the problem (the problem context). Novices attempted to fit the given data into an equation such that all the parameters would be known to them as reported by S2,

> *"I first made a list, like these are the problems, these are the equations I should use, these are the variables and I think this variable is not useful. So I left it aside and tried to solve from the variables I had."*

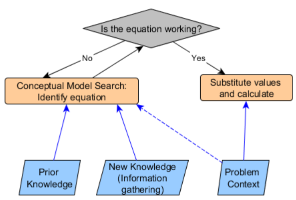


Figure 4.13: Novice Estimation Process

Some novices directly searched for the equations or conceptual relations of power on the Internet, some had prior knowledge of conceptual models (for eg, Newton's equations of motion, energy conservation and rotational motion) that they used to get equations from, while most used a combination of known conceptual models and Internet search. The identified set of equations were then applied to the given scenario and manipulated, until they were in a form where all the parameters were known from the problem statement as reported by S5,

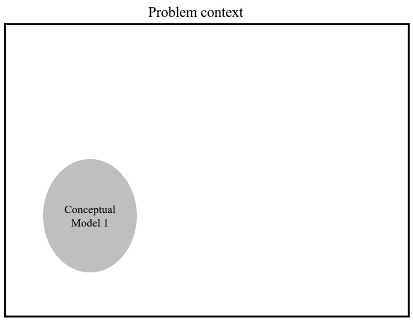


Figure 4.14: Novices use known conceptual models for estimation

> *"I tried the different forms of power that have been identified, as in force into velocity or torque into angular speed, now, given that the question was about the car moving and the rotation of the wheels, I thought that the torque one was more suited to it, so, I went with that."*

If the equation search and manipulation process was successful, which was often the case among novices with high background conceptual knowledge, then the novice quickly arrived at an estimate for power. However since he/she had not considered the working of the car and the requirements from it, the equation obtained for power was incorrect. On the other hand, among novices with low background conceptual knowledge, the search and manipulation process was long and convoluted and the obtained equation and often even the estimate was of the wrong order of magnitude.

Summary: We found that the novice process consists of searching for and fitting known "abstract and narrow conceptual models" (see Figure 4.14) to solving the estimation problem, while ignoring the reality of the requirements from the system (problem context). This is different from experts who begin by creating a model of the working of the system (functional model) and then evaluate, constrain and tune this functional model using conceptual knowledge and mental simulation to create a qualitative model, all the time being aware of the problem requirements.

Improving the model-searching process

We observed deviations from this general process of estimation in the cases of S3 and S4. Both S3 and S4 had high background conceptual knowledge of mechanics concepts.

1. **S3's Estimation process**

   S3 began by thinking of the problem requirements (Figure 4.15),

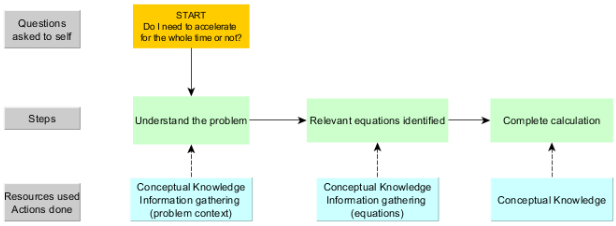


Figure 4.15: S3's Estimation Process

> *"we had to transfer this much distance and this was acceleration, so I was thinking, do I need to accelerate for the whole time or not."*

He was also confused about whether to ignore friction or not. This confusion triggered in him the need to understand more about friction constants on cars. So he searched on the Internet for *"electrical power required by cars"* and found a document that described how to calculate the power requirements of a car. He studied it and linked documents thoroughly, then applied the conceptual models of equations of motion with friction and air drag to get an estimate of power. His estimate was of the right order of magnitude and based on the correct equation, but he did not consider losses, make appropriate approximations and choose suitable numerical values. However we see that his incorporation of the requirements of the car led to identifying and applying a better model, which led to an improvement in the solution obtained based on his initial conceptual model.

2. **S4's Estimation process**

S4 began from the basic case of equations of motion without friction (Figure 4.15) as he

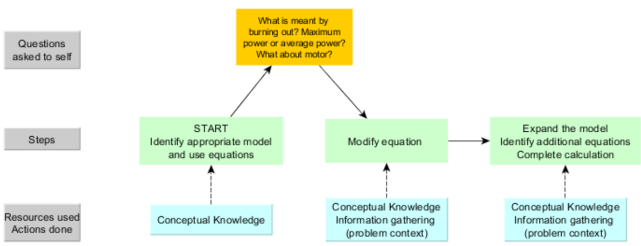


Figure 4.16: S4's Estimation Process

reported,

> *"this is something that's been built into the muscle memory, i.e. you look at*

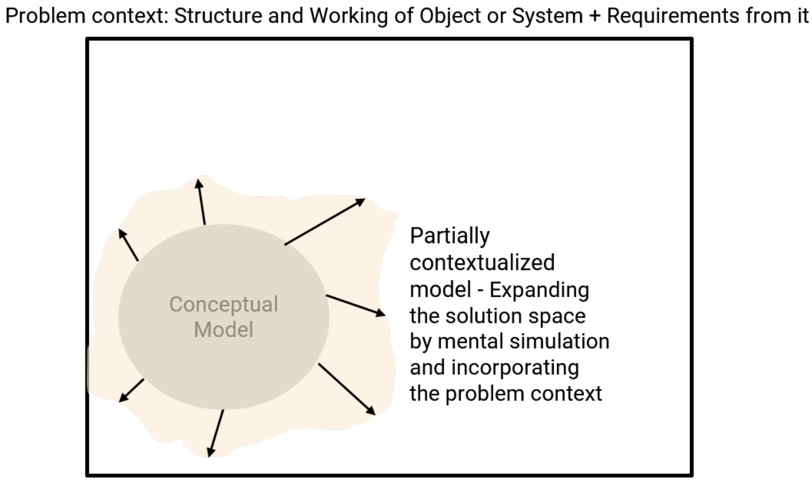


Figure 4.17: Some novices expand known conceptual models for estimation

the problem, there's a model that builds up consciously, we start working that out, we just write the few equations that are relevant, you look at those, you do some calculations, I mean you fiddle around with formulas and then you see what could be applied to the given problem, so, I started off with that,"

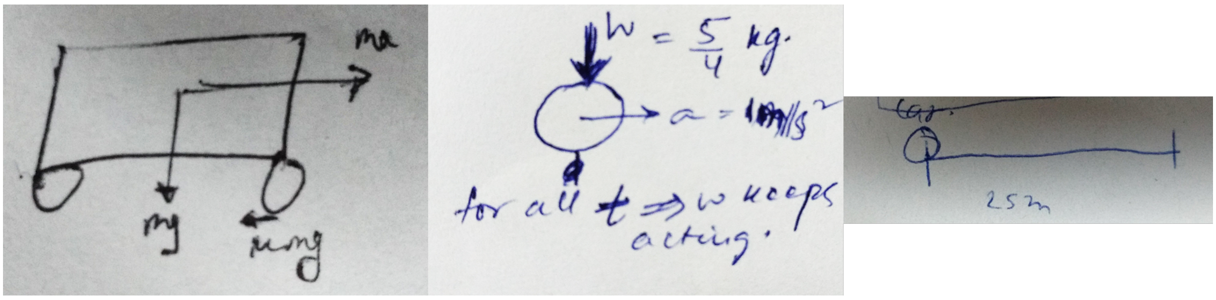
He was able to come up with an equation for instantaneous power. At this point he reflected on the problem statement and wondered why certain pieces of information had been given. He reported that he realized that he needed to consider the motor and the maximum power consumption. So he first calculated the maximum power consumption and then estimated the electric power required by studying about electric motors from the Internet. However he ignored air drag without justification. We see, however, that his incorporation of the problem system working and requirements improved the model over his initial conceptual model.

Summary: The cases of S3 and S4 show that when novices incorporate the problem system working and requirements, they expand the problem space around their initial conceptual model and improve their initial estimation model and estimate (see Figure 4.17). In principle, if they continued the problem expansion by mental simulation, they could obtain expert-like models and estimates. However we did not observe this with any of our novices.

Cognitive mechanisms underlying novice estimation

1. **External Representations:**

Figure 4.18: Novice diagrams



(a) **Diagrams:**

We found minimal use of diagrams among novice solutions. While six out of ten novices drew diagrams, we found that they were representative diagrams (4.18) of the conceptual model that they had chosen (for eg, equations of motion or rotational motion), rather than diagrams of the entire problem system.

(b) **Equations:**

We found novices used equations extensively to solve the estimation problem for different purposes. The most common purpose of equations was as persistent objects to think with and for restructuring the problem (Kirsh, 2010). As reported above, the equations representing their chosen conceptual model are used by novices to restructure the problem of estimating power. For instance, $P = mav$ as per the equations of motion model, $P = \tau\omega$ as per the rotational motion model or $E = \frac{1}{2}mv^2$ as per the conservation of energy model become the restructured problem for the novice.

The initial equations are then rearranged and reformulated (Kirsh, 2010), an interaction which allows the solution to emerge. That is, the rearrangement and reformulation allows the solver to incorporate the given problem data and convert the abstract equation of power into a form where they know all the parameters and can therefore calculate the power as reported here by S9,

> *““...first I knew this formula, I tried to somehow calculate the voltage and the current required, which was not possible from the given data, then I remembered this formula and then I tried to convert these values that have been given into torque and omega.”*

Thus equations help novices to constantly restructure the problem until a solution emerges.

2. **Mental Simulations:**

   We found no gestural evidence of mental simulation while novices were solving the problem. However it is plausible that the novices who included the operation conditions into their estimation process mentally simulated the problem system to understand it. Mental simulation may have been the cognitive mechanism that supported expanding the narrow conceptual space to the reality of the problem context (see Figure 4.17). An indication of this is seen in S4's retrospective report,

   > *"That was when I realized that the car goes ahead because of the force applied by the ground and the torque given by that force, provided by the ground, is what opposes the torque given by the motor, so, I mean, this idea, was I mean the breakthrough moment for me..."*

   Here his description of the forces on the car and its movement as a result, suggest that he may have mentally simulated the car to understand its working better and incorporate the problem requirements.

Summary: Novices primary cognitive mechanism underlying estimation is manipulation of equations, unlike experts for whom the primary cognitive mechanism is mental simulation.

Metacognitive processes in novice estimation

We found that novices rarely evaluated their work or reflected on their process; when they did, they recognized that there were several aspects of the problem context which they had ignored, such as the condition about burning out, the relation between electrical and mechanical power, air drag and whether the car constantly accelerates. However, as they reported, making changes to their estimation process to account for the problem context was often difficult for them and hence they chose to ignore them, except in the cases of S3 and S4 above.

Summary: Novices rarely question their own work; even when they do, they do not know how to evaluate and revise based on their evaluation. Experts, on the other hand, question their work often, and are able to evaluate their work and make appropriate revisions.

Role of Information Gathering and Conceptual Knowledge in Novice Estimation

We found that novices primarily used the Internet to search for the appropriate equations of power and related quantities. Secondly, novices directly searched for an approach to calculate the electric power. Thirdly, novices searched for information to understand the problem context such as meaning of the terms used in the problem, motor characteristics, friction constants, etc.

Conceptual knowledge was used to begin the estimation process and identify which model to use that fits the given problem context. It is also used to verify the equations used and rearrange them into appropriate forms.

Summary: Novices primarily used information gathering to search for the appropriate conceptual knowledge, which was the generator of solutions in estimation. This is different from experts who predominatly used the Internet at the start of their solution to search for information about the problem system to begin the mental simulation process and used conceptual knowledge to tune the mental simulation process.

Novice challenges in estimation

1. **Understanding the problem context - Model Contextualization:**
   All novices reported that they were confused by the open-ended nature of the problem statement. The problem statement was deliberately left vague, the way real world problems often are, with some extra pieces of information and so novices found it hard to identify which information was relevant and which was not. Also novices were unable to understand all the constraints given in the problem, for instance, the fact that the car has to be able to traverse a track of a particular length without burning out. This constraint translates to an implicit constraint that the motor specifications should be able to support the speed of the car at the end of the track, which novices had difficulty identifying. Further, novices had to make assumptions such as the weight distributions over the wheels, motor specifications etc and they were unsure what assumptions were reasonable to make. Finally novices were unable to make the physical connections between the various parts of the system which lead to the system working as a whole as explained by S6 **"like how was this motor how it was able to rotate the wheel."**

2. **Application of conceptual knowledge:**
   Even when novices were able to understand the working of the entire problem system (in

this case, the battery supplying power to the motor which runs the wheels), they were unable to apply their conceptual knowledge to the entire problem system. They were unable to relate the concepts associated with one part of the car (eg, motor) to another part (eg, wheels). So they spent a lot of time and effort searching for these relationships as reported by S9,

> *"See this was the ultimate formula, this is always correct, input power would be the voltage into the current of the motor, but the challenge was to convert between these two because another thing is that power is equal to torque into omega, which would help me solve the problem very easily, but finding the torque was also very easy, but calculating omega was a bit tough,"*

Summary: The main challenge faced by the novices was generating an integrated description of the system, in terms both of its physical and conceptual working. We note that this was the first task undertaken by experts, in the functional and qualitative stages of modelling.

4.2.5 Discussion: Expert-Novice Differences

The novice study highlights the differences between the novice and expert processes of estimation as shown in Figure 4.19. When faced with a new problem, experts begin in the "enaction plane" wherein they mentally simulate the problem system and then flesh out the physical and conceptual structure and working of the system, thereby expanding the problem space. Next, they integrate conceptual knowledge and the problem requirements to begin narrowing the problem space. Finally, they move to the "freezing plane" in which they further integrate conceptual knowledge and problem requirements and freeze upon a number or a judgment via equation manipulation. On the other hand, as we had conjectured, novices begin in the "freezing plane" by narrowing the problem space into a conceptual model and its associated equations, manipulating the equations to obtain a solution. They expand the space and move to the "enaction plane" only when they are unable to solve the problem. Expanding the problem space is an important requirement in solving ill-structured problem solving and failure to do so can lead to ignoring important aspects of the problem (Dennis et al., 1999).

Further, the expert process is metacognition rich in that they know which cognitive processes to use and when, how to use resources from the environment, evaluate their emerging solution and make changes if necessary. Novices, on the other hand, do not have the neces-

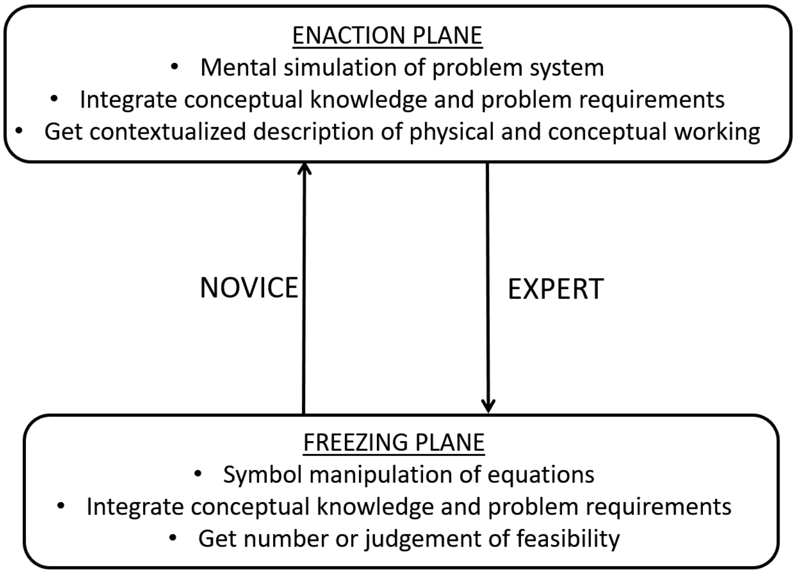


Figure 4.19: Differences between expert and novice estimation process

sary metacognitive skills (Mayer, 1998), and when they try to evaluate their solutions, they do not know which cognitive processes to use, as described in literature on the differences between expert and novice problem solvers (Adams et al., 2008; Jonassen, 2000; Maloney, 2011; Schoenfeld, 1992; Singh, 2002, 2008).

Even though novices did think about the problem requirements, they were unclear about how to use the information while solving. We believe that their inability to mentally simulate the problem system was the reason for this. We argue that the current emphasis in the engineering curriculum on equation manipulation creates a bias in students towards equations, which effectively stifles their mental simulation (Ferguson, 1977; Taylor et al., 1961).

Further, the compartamentalized learning of the students - different concepts in different courses and well-structured problems based only on a set of concepts - makes it difficult for students to integrate concepts from multiple courses in the solving of ill-structured problems such as estimation. Improving learners' conceptual knowledge structures is out of the scope of this thesis. But based on these results we conjecture that in order to support novice doing of estimation, we must support the mental simulation and modelling processes among novices.

The cases of S3 and S4 highlight how consideration of the problem system working and requirements can improve the solution based on narrow conceptual models alone. While it is true that estimation is about getting approximate values and so in certain cases the estimate based on narrow conceptual models may be accurate and reliable enough for the purposes, this can be decided only by examining all aspects of the problem space, including the actual problem requirements. Superimposing or fitting a model without exploring the entire problem space and considering the problem requirements makes it highly likely that the estimate is unreliable.

4.3 Summary

In this chapter, we described two studies to understand and compare expert and novice estimation process and identify novice challenges. These studies validated and elaborated our conjectures in section 2.7 regarding expert and novice estimation processes. In the table 4.2 we summarize our findings in terms of the differences between experts and novices in various aspects of the estimation problem solving process.

Aspect of estimation	Experts	Novices
Overall approach	A form of model-based reasoning	Searching for and fitting a conceptual model
Problem context	Integrated throughout process	Integrated at the end
Primary cognitive mechanism	Mental Simulation	Equation manipulation
Metacognition	Reflect and revise on models and process	Rarely reflect and revise
Role of information gathering	Understanding problem system	Identifying right equation
Role of conceptual knowledge	Converging solutions	Generating solutions

Table 4.2: Comparison between experts and novices

Based on the findings of this chapter, we propose that a learning environment triggering the problem space expansion via computer simulations of the given problem system and model building will seed and trigger the mental simulation and modelling processes among novices. In the next chapter, we describe a study using a preliminary intervention undertaken in order to identify the scaffolds that can support the cognitive processes of model building and mental simulation among novices.

Chapter 5

DBR 1 Design and Evaluation: Identifying Supports for Estimation

The goal of the first iteration of DBR was to understand estimation processes, their underlying cognitive mechanisms and identify the supports needed in a TELE for doing estimation. In the previous chapter, we identified the differences between experts and novices in terms of the processes of estimation (see Table 4.2). We identified the broad challenges faced by novices in solving estimation problems. We argued that the cognitive mechanisms that led to these differences are mental simulation and modelling. We conjectured that in order to support novice estimation problem solving we need to support novices' mental simulation and modelling processes. In order to identify how to support the mental simulation and modelling processes, we undertook a study where we gave novices a causal mapping tool along with additional verbal scaffolds on demand and identified the nature of the scaffolds that supported modelling and mental simulation.

We choose a causal mapping tool because a causal map is an external representation of the qualitative model, which is a critical aspect of good estimation. The novice study had already highlighted that novices try to fit abstract and narrow conceptual models to estimation problems and begin with equations. So in order to move their attention away from equations and trigger the modelling process, we gave them a goal of creating a causal map. We wanted to provide novices an affordance to build a qualitative model, while verbally scaffolding the modelling and mental simulation processes and study which scaffolds supported them in moving forward in the estimation process.

5.1 Theoretical foundations of the intervention

The design of the causal mapping tool for estimation is based on the theories of distributed and embodied cognition (Hollan et al., 2000) which argue that cognition emerges from an ongoing interaction between internal resources such as attention, memory and imagination and external resources such as the objects and artefacts in the surrounding environment. External representations facilitate this interaction as they allow processing which is difficult and often impossible in the mind (Kirsh, 2010). Research has shown that epistemic actions (Kirsh & Maglio, 1994) performed on external representations during task performance make the imagination more reliable and memory & time efficient. Therefore external representations are required for creating the causal map for estimation.

In the teaching and learning of scientific inquiry, studies have found that knowledge representations such as models, explanation frameworks and argument maps support students' inquiry and their learning of the skill of scientific inquiry (Quintana et al., 2004; Sandoval et al., 2000; Sandoval & Reiser, 2004; Toth et al., 2002). In ill-structured problem solving, the use of concept mapping (Hwang et al., 2014; Stoyanov & Kommers, 1999, 2006; Stoyanova & Kommers, 2002), knowledge mapping (Lee et al., 2005) and dual mapping (M. Wang et al., 2013; Wu & Wang, 2012) have been shown to improve problem solving performance. In the first approach, concept mapping was used for problem analysis, information organization and idea generation in problem solving. In the second approach, knowledge maps were used to represent conceptual and procedural knowledge together and in the last approach, two different maps are used namely, argument maps for describing problem solving relations and concept maps for knowledge construction. Knowledge representation such as schematic diagrams have been shown to improve performance in problem solving (Hegarty & Kozhevnikov, 1999; L. Martin & Schwartz, 2009). Jonassen (2003) has proposed the use of cognitive tools such as semantic networks, expert systems and semantic modeling tools to externalize learners' internal representations. In all these interventions students construct representations, such as argument maps, of the knowledge required for the task and are scaffolded in this process.

For qualitative modelling in engineering estimation, a causal map is a representation showing the relationship between the physical quantity to be estimated and the parameters that affect it. The causal map serves as an external representation that can be used for restructuring the problem, which would otherwise have to be done in imagination (Kirsh & Maglio, 1994). However it also requires recognizing and reasoning about several conceptual relations simultaneously. (Mahajan, 2014) also recommends creating causal maps called divide and conquer trees for the physical quantity to be estimated as it is a way of capturing the analysis with a single diagram. However, the strategies described in (Mahajan, 2014) to create the causal map are at a broad level and do not account for the role of mental simulation which we have identified. So learners will need conceptual and estimation specific epistemic scaffolds (Ge & Land, 2004; Quintana et al., 2004) to create the causal map, specifically scaffolds for mental simulation and modelling. In the next section, we describe how we designed the tool and scaffolds.

5.2 Design of the intervention

The intervention consisted of a causal mapping tool along with additional estimation problem solving scaffolds. The broad conjecture guiding the design of the tool is that using the causal mapping tool to create a qualitative model (see example in Figure 5.1) will trigger novices' model-building for estimation. Therefore, the basic feature required in the tool is the ability to create nodes and links, each node representing a parameter and the link between two parameters depicting the relationship between them. For example, in Figure 5.1 the relationship depicted is mass of air = volume × density. Similarly, there are nodes branching out from the volume node such that volume = length × breadth × height.

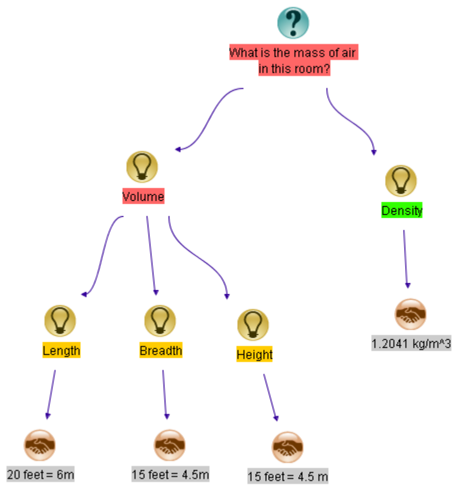


Figure 5.1: An example causal map

We used an available open source knowledge mapping software called Compendium (http://compendiuminstitute.net/) to design the mapping tool. Compendium is a software that visually represents thoughts, ideas, issues and arguments (nodes), and the connections (links) between these. It has different types of nodes and links to represent different types of ideas and connections. Compendium was chosen among several available open source software like IHMC CMAP tools, yEd, FreeMind, etc. because it had the maximum number of features needed in our design. The mapping tool (shown in Figure 5.2) was created by repurposing some of the available features in Compendium for causal mapping of estimation problems. Specifically we used the different types of nodes to create the affordance of a *"problem analysis"* map (Figure 5.3) where novices were encouraged to describe the problem system and requirements and conceptual relations as a way of externalizing their mental simulation and models while we provide appropriate scaffolds to trigger modelling and mental simulation.

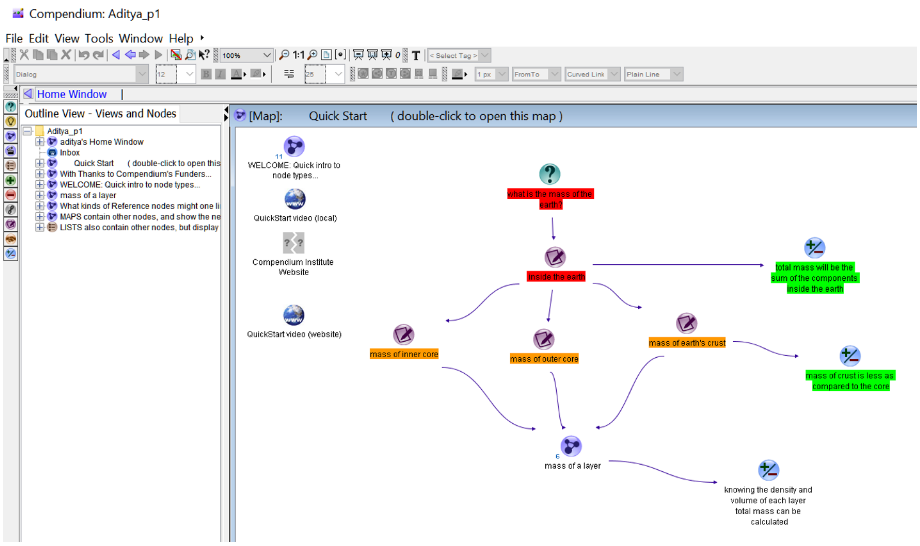


Figure 5.2: Causal Mapping tool (repurposed from Compendium)

The scaffolds given to the novices were of two types: elaboration and reflection prompts (Ge & Land, 2004) used to scaffold ill-structured problem solving. The guidelines regarding the prompts were adapted for the specific case of estimation problem solving, adding two additional kinds of prompts namely, prompts for quantity estimation and mental simulation/visualization. Examples of the prompts used are shown in Table 5.1. As a rule, the researcher always began with an elaboration or reflection prompt, before moving on to the more specific prompts for estimation, if the participant was unable to proceed.

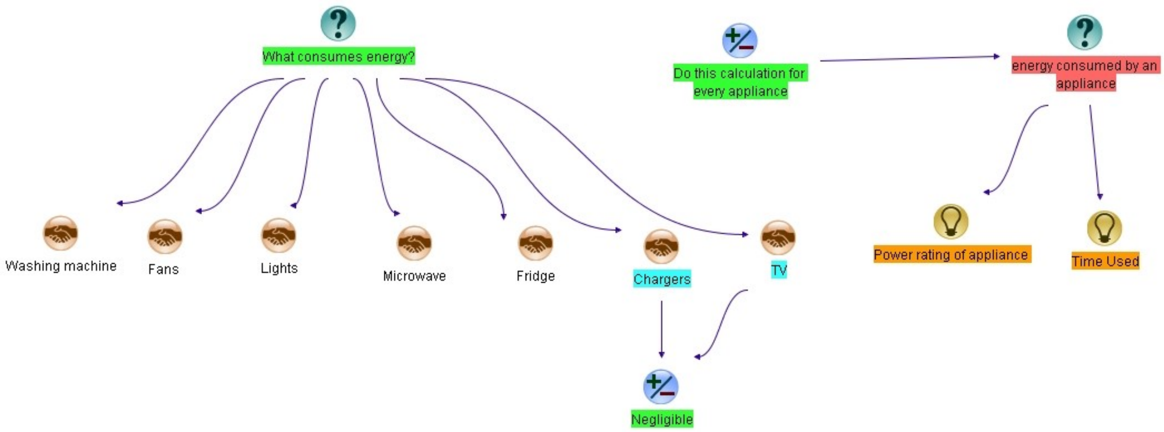


Figure 5.3: An example knowledge map

Reflection Prompts	Elaboration Prompts
To identify the parameters which affect mass, I need to know . . . Am I on the right path? Is this assumption reasonable?	What information is missing to solve this problem How are energy and power related? Can you be more specific?
Quantity Estimation Prompts	Mental simulation/ visualization prompts
How do you measure when you don't have a scale? Based on the distances that you know can you guess the radius of the earth? Can you look at it and tell me the radius of this CD?	What does the heart do? What happens when the heart beats? How is information written on a CD?

Table 5.1: Sample Prompts to Scaffold Causal mapping

5.3 Study 3: Evaluation of the Causal Mapping Intervention

5.3.1 Methods and Materials

Research Questions

The research question for this study was "How do novices solve estimation problems using a scaffolded causal mapping intervention?". This RQ has two sub-questions,

RQ3a How does the scaffolded causal mapping intervention support novices in solving estimation problems?

RQ3b What challenges do novices face in doing estimation using a scaffolded causal mapping intervention?

Participants and Procedure

The purpose of the study was to identify the scaffolds that novices needed while using the causal mapping tool to do qualitative modelling and solve estimation problems. We performed a lab study with six students (convenience sampling) from freshman and sophomore years of mechanical and electrical engineering who solved three estimation problems each. Our sample did not include any females and this is typical of these branches of engineering, wherein the gender ratio is heavily skewed towards males, with less than 10% of students female. Participants were allowed to ask questions to the researcher but not talk to each other or use any other resources. We disallowed talking to each other because our context during thesis for individual learning; we wanted to identify scaffolds when students work individually and so students talking to each other would become a confound. These students had the prior knowledge required for the estimation problems we presented. The procedure involved the following steps:

1. Watching an introductory video about estimation, causal mapping (with an example causal map) and the mapping tool (6 minutes).

2. Watching a video describing how to use the features of the mapping tool to create causal maps. Next one worked example was shown for the construction of a causal map for an estimation problem, which walked novices through the process of creating a causal map. The role of each and every node and link as it was being added to the causal map and the problem analysis map was explicated so the novice would be able to interpret its purpose. The goal was not for them to learn estimation at this point, but to understand how to make a causal map for an estimation problem, hence we only had one example problem which was explained in detail. (15 minutes).

3. Individual causal mapping of three estimation problems using the mapping tool (open ended).

The students were told to create a causal map such that all the parameters they identified affecting the quantity to be estimated were known or could be looked up. They were allowed to watch the videos as many times as they wished, including while solving the problems. They were also given a set of instructions summarizing the two videos. Students used pen and paper to do anything which the tool did not have provision for, such as drawing diagrams. If students' encountered difficulties while solving problems they asked the researcher who provided them scaffolds regarding how to proceed.

Problems

The problems were designed to ensure that they could not be solved by directly applying any conceptual model, without considering the problem context. Each of the problems required understanding the structure of the object and/or the behaviour of the given system. Given the importance of conceptual knowledge in estimation, we chose problems that required very little engineering conceptual knowledge, but rather modelling of the structure and behaviour of the object using mental simulation, so that the scaffolds for mental simulation and modelling could be tested. The problems chosen were:

1. Estimate the mass of the earth.

2. How far apart are the pits on a CD?

3. Estimate the power generated by the human heart.

Data Sources

We collected the following data in this study.

1. Audio recording of all conversations between researcher and participants. The participant asked the researcher when they needed help and the researcher asked them to think aloud about their approach and why they were stuck, before scaffolding them to proceed.

2. On-screen interaction of students in the causal mapping tool (using CamStudio).

3. Final artefacts produced in the causal mapping tool.

4. Any rough work done on paper.

5. Researchers' unstructured observations.

5.3.2 Data Analysis

In order to identify the novice process of estimation (RQ3a), we performed interaction analysis; we used the participants' screen captures and conversation between the researcher and the participant together to perform the analysis with the following steps:

1. Familiarizing with the data: We read the researchers' observations, looked at the participants final artefacts and rough work, and watched their screen captures to identify their broad approaches to the causal mapping activity.

2. Transcription: We transcribed the screen captures of the novices in terms of the nodes and links added, deleted and modified during every 1 minute. We also transcribed the conversation between the researcher and the participants verbatim.

3. Creating workflows: Next we interleaved the on-screen actions (nodes and links added) and conversations together to create each participants' workflow. This was the flow of events as it happened and there was no inferencing at this point.

4. Abstraction of Process: We used the estimation processes identified in studies 1 and 2 as the lens through which we examined participants' processes in this study. In the created workflows, we focussed on the points of conversation between the participant and the researcher. We examined the participants' actions before and after the conversation. We abstracted out the participants approach before the intervention using their on-screen actions and their self-reports during the conversation. We abstracted their approach after the intervention using their on-screen actions and the scaffolding provided by the researcher during the conversation.

5. Ensuring validity: By doing multiple collaborative passes through the data and refining our inferences in each pass, we were able to ensure the validity of our inferences regarding participant processes.

To answer RQ3b, the conversation was analysed using thematic analysis (Braun & Clarke, 1996) to identify the themes related to novices' challenges while creating the causal map for the estimation problem. First the transcripts of four students was coded and the initial codes were categorized into themes. The final artefacts and screen captures were used while analysing the audio transcripts in order to identify the context of some parts of the conversation. The initial codes emerged from the data and we did not apply any theoretical framework regarding novice challenges in problem solving. Next these themes were used to code the recording of the remaining two students. The codes and themes were revised by constant comparison until a final set of themes of challenges faced by participants in solving estimation problems emerged.

5.3.3 Workflow

We describe the workflow of Student S2 when he solved problem 1, *"What is the mass of the earth?"* as a representative case from our sample. The final map created by S2 is shown in Figure 5.4.

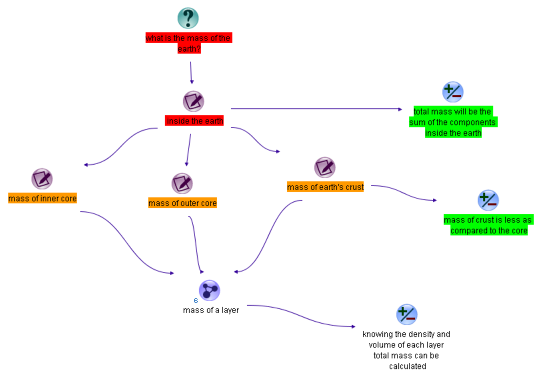


Figure 5.4: S2's causal map for problem 1

S2 began by looking at the example problem (*"What is your average monthly electricity bill?"*) again. Then he added a parameter in the map as *"mass of animals"*. He asked a question as to whether he needs to consider the weight of plants and animals. The researcher scaffolded him to consider the trade-off between ease of estimation and significance of parameter [Elaboration prompt]. When the participant was unable to respond, the researcher gave an additional scaffold to think of what the earth is made of [Visualization prompt]. S2 identified parameters *"mass of water"* and *"mass of land"*.

After this, S2 saw the example problem once again and replaced the previously identified parameters with *"mass on the earth"* and *"mass inside the earth"*. He added and deleted several nodes on the tool and watched the example problem video again, but did not move forward in the estimation. Finally he added parameters *"mass of inner core"*, *"mass of outer core"* and *"mass of earths crust"*. He argued that *"mass of crust is less as compared to the core"*. Next he watched the example problem again and moved and added nodes, but made no progress in the estimation.

At this point, S2 asked the researcher for the mass of the core layer. The researcher scaffolded him to think about the composition of the earth and its layers, and what decides mass [Elaboration and Visualization prompt]. S2 identified that he needed to know volume and density and argued that *"Earths inner core has higher density compared to outer core and crust"*. But he still was not able to proceed because he was unclear about the concept of density and the fact that the density would be decided by the material composition. So the researcher scaffolded him to try and identify the composition of each layer which would give him an estimate of each layers' density [Elaboration prompt]. S2 wrote (on the tool) that the volume of each layer would be decided by its depth and the density would depend on what the layer is made of. Finally arguing that *"knowing the density and volume of each layer total mass can be calculated"* he ended this problem.

5.3.4 Results

Answering RQ3a: Novice process of estimation problem solving using the causal mapping intervention

The overall process of novices with the causal mapping intervention, along with the scaffolds that supported them, are shown in Figure 5.5. We found that problems 1 and 3 had contexts that were a little familiar to the novices, while the context of problem 2 was completely unfamiliar to the novices.

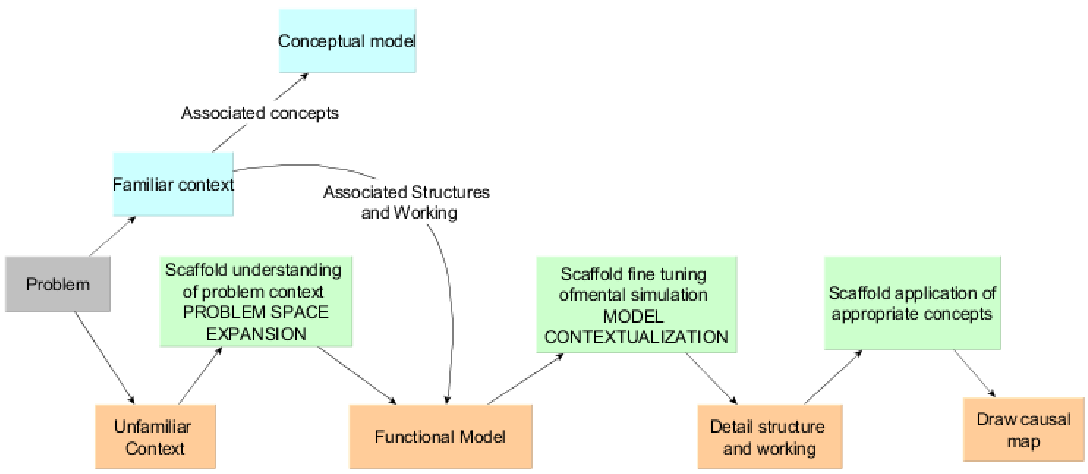


Figure 5.5: Novice Estimation Process using the Causal Mapping Tool

In problem 1 which had a familiar context, we found that three out of six novices, resorted to solving it by directly applying the equations associated with the conceptual model of Newton's law of universal gravitation. They then created a causal map to fit the equation that they had identified. The remaining three novices thought of the structure of the earth and created a causal map based on breaking down the structure of the earth into parts. However they needed scaffolds to contextualize abstract parameters affecting mass, such as density, to the given problem, for instance, *"density of nickel which is the main component of the inner core."*

In problem 3, the interplay between the functioning of the system ("heart") and the conceptual working (power, blood pressure, etc) was very strong. Novices were able to functionally model the working of the heart, as evident from their notes in the tool, for eg, S6, *"relation between power and pumping of heart"* and *"heart pumps blood at a rate"*. However, they needed scaffolds to tune their mental simulation to flesh out the structure and working of this pump. For instance, novices needed scaffolds for visualization of the area through which the blood was flowing. This is needed in order to contextualize the abstract parameter of area to *"area of the blood vessel through which the blood is flowing"*, as observed in problem 1 as well. Further, novices needed scaffolds to correctly apply the concepts of power, energy, force and identify the relationship between power and the parameters of the heart, such as, blood pressure, rate of flow of blood etc.

Problem 2 was an entirely new object to all novices and so they needed to be scaffolded using the actual object (a CD), drawings and gestures to first model the structure of the pits on the CD. Then they had to be scaffolded to identify the parameters affecting pit spacing, again using gestures, analogies and drawings. Thus, we observed productive shifts towards modelling among novices, when appropriate scaffolds for mental simulation were provided. However their familiarity with the problem system and ability to mentally simulate limited their functional and qualitative modelling, as confirmed by their descriptions and drawings. For eg, if they were not able to visualize what an object looks like, they could not determine if its area or volume would be important or not.

Answering RQ3b: Novice challenges

The themes of challenges faced by novices in doing causal mapping for an estimation problem are shown in Table 5.2. Along with the challenges, we also clarified the nature of these challenges from the analysis. The design of the mapping tool led to some usability issues such as underuse of features to do argumentation and analysis which we leave out from the Table 5.2.

[!h]

Theme	Nature of difficulty
Problem Context-specific knowledge: 1) Facts 2) Structures (Spatial) 3) Behaviours	Unknown Partially known Incorrect Unsure
Engineering conceptual knowledge	Misunderstood Partially understood Not understood Unsure
Formulas	Inappropriately applied Incorrect
Units	Incorrect
Assumptions	Inability to recognize Partially justified Unjustified Inability to judge validity Unable to make
Measurement estimation	Inability to do
Evaluation	Inability to do
Causal map	Incorrect Incomplete Unsure
Nature of estimation problem	Low information
Argumentation	Unable to write Unable to judge
Assessment of facts & numerical values	Specific enough Reasonable or not Relative significance Standard values Relevance to context
Terminology	Causes misunderstanding Unable to articulate
Miscellaneous related to ill-structured problem solving process	Inability to start Inability to proceed Inability to identify requirements Inability to reason Inability to relate Incorrect identification of problem requirements

Table 5.2: Identified types and nature of difficulties

5.3.5 Discussion

The answers to RQ3a and RQ3b together show that novices' main challenge is understanding the problem context; they need to be scaffolded to mentally simulate the structure and working of the problem system or object and create a functional model. We identified that the problem context-specific knowledge needs to be provided to novices to enable them to begin the mental simulation. Next, novices needed scaffolds to detail this mental simulation and contextualize the structures and working to the given problem requriements. Novices also needed scaffolds to apply the required conceptual knowledge correctly. Further, we found that novices need scaffolds for specific aspects of estimation problems such as making assumptions, which were provided by the researcher as they solved the estimation problem and enabled novices to move forward in the process.

An interesting finding was that even though we had ensured that students had learned the concepts and principles necessary to solve the problems, novices have difficulties in understanding and applying prior conceptual knowledge. This was because of the nature of their training that novices did not have much experience in applying conceptual knowledge. There are two ways to manage this difficulty; either we can target our TELE to advanced engineering students or we can incorporate conceptual knowledge as a scaffold in our TELE. For our next iteration, we propose to target novices who have had experience in applying conceptual knowledge, as we do not want the emphasis to shift from estimation problem solving towards conceptual knowledge acquisition. In the next section, we discuss an instructors' perspective on novice challenges in estimation and how they can be overcome.

5.4 Understanding Estimation from an Instructors' perspective

Before designing a TELE for estimation we wanted to validate a set of problems that might be used. Further, in order to identify scaffolds needed for specific parts of the estimation problem, we interviewed an expert mechanical engineering instructor (EI) with over ten years experience in a technical institution in India, who often incorporates such estimation problems in his courses even though they are not included in the curriculum. EI is also an expert engineering practitioner because he designs and develops products for automobile companies regularly.

We gave the instructor this problem to solve,

> You are participating in an electric car race in which you are required to design an electric car of weight 7kg with wheel diameters of 4" that can accelerate at $1\frac{m}{s^2}$ and traverse a track of 10m without burning out. Estimate the electrical power needed to achieve this performance and the specifications of the motor you will need.

While solving, he voluntarily spoke out loud and wrote a detailed solution. Once he had finished solving, we conducted a semi-structured interview with the goal of identifying the model contextualization that he had done in this problem. This is important because while studies 1, 2 and 3 highlighted the need for model evaluation and contextualization, the exact contextualization depends on the problem system. So, we wanted to identify the model evaluation and contextualization reasoning appropriate for this problem. His think aloud and the entire interview was recorded. We summarize his responses to our questions below.

5.4.1 On what is needed to solve power estimation problems

For the example problem above, the instructor listed the following aspects as necessary for solving the estimation problem.

1. The limits of the performance when the car is actually working will dictate the required power. In typical power cases, it is masses and accelerations.

2. The operating conditions are those which are not seen often but are seen by at least some users. The engineer should have a sense of operating conditions and what the system is required to deliver in those operating conditions. That forms the basis for the boundaries for your decision (for eg. maximum velocity attained).

3. Conceptual knowledge from different areas, for eg, Newtonian mechanics and fluid mechanics to understand drag and the underlying integrated concept map.

4. Understanding and quantifying losses and limitations, for eg, due to air drag and efficiency of machines (*"students will be hopeful everywhere"*). Knowledge of typical parameters such as drag coefficient and motor constants.

5. Practical experience (in order to learn to *"not be hopeful"*) by doing one project where they build things. Begin by doing small characterization activities in labs first.

Thus the instructor corrorborated our findings regarding the importance of understanding the problem context, as seen from points 1 and 2. Further, in these points, the instructor articulates that the model needs to be contextualized by considering the maximum velocity, mass and acceleration requirements. In addition, the instructor also highlighted the role of conceptual knowledge, which we had also identified from our previous studies. Finally, the instructor emphasized the importance of certain practical aspects of estimation, such as understanding and quantifying losses and knowing typical values for several parameters, which one gains from real-world experience.

5.4.2 Criteria of Good Estimation

Based on literature, we had identified several criteria for good estimation which was an amalgamation of the products and processes of estimation.

1. An order of magnitude estimate is obtained.
2. The parameters that affect the quantity to be estimated in the given problem is identified.
3. Appropriate assumptions and approximations are made.
4. The losses or inefficiencies in the system are considered.
5. Reasonable numerical values are chosen for parameters involved in the estimation.
6. The estimate is evaluated by comparison.

The instructor interview validated and refined these criteria, with the instructor specifically pointing out that in addition to the order of magnitude estimate, the intermediate products of the list of parameters and a correct equation are also important to measure the quality of the estimate. Therefore we revised our criteria to the following,

1. Products of Good Estimation
   (a) Final product: An order of magnitude estimate
   (b) Intermediate product 1: List of dominating parameters that affect the quantity to be estimated in the given problem

(c) Intermediate product 2: A correct equation connecting power with the list of parameters identified in criterion 1b

2. Process of Good Estimation

    (a) Appropriate assumptions and approximations are made.

    (b) The losses or inefficiencies in the system are considered.

    (c) Reasonable numerical values are chosen for parameters involved in the estimation.

    (d) The estimate is evaluated by comparison.

5.5 Reflections of DBR1

The results of study 3 showed that novices could not create causal maps for the estimation problem without additional scaffolds for triggering modelling. Specifically we found, as we had found in study 2, that novices find it difficult to mentally simulate the structure and working of the problem system and build functional and qualitative models (causal maps). They need to be provided problem context-specific knowledge to begin the mental simulation. They also need triggers to use external representations to support their mental simulation process.

We found that that even though we had ensured that participants had the required conceptual knowledge necessary to solve the problems, without the clear mental simulation of the problem context, they also had difficulty in applying familiar concepts into new contexts. Our results showed that scaffolding novices mental simulation to detail out the structure and working of the problem system or object enabled novices to suitably apply conceptual knowledge to the estimation problem. Thus, the estimation problem space expansion processes, namely model-building based on mental simulation and manipulation of external representations need to be made explicit and scaffolded for novices.

The results of study 3 confirmed the results of study 2 regarding novice processes and their challenges in solving estimation problems. Additionally, this study helped us identify a set of scaffolds for triggering and supporting novice mental simulation and model-building processes. These include (1) prompts to mentally simulate, (2) information regarding the problem context, (3) physical models, diagrams and analogies to support modelling, and (4) prompts to connect conceptual knowledge to the problem context. The instructor inputs supported our findings regarding the importance of understanding the problem context and applying the conceptual knowledge correctly in the context. Finally, the instructor articulated the importance of experience in choosing numerical values, being able to make comparisons, assumptions and quantifying losses.

The estimation problems given to participants in studies 1, 2 and 3 were chosen depending on pilot studies to align with the interests and abilities of the respective participants. As a result, the set of problems (mass of the earth, pit size of a CD, power of the heart, weight of a hand cranked radio, power of an electric car) are different in terms of contexts and underlying conceptual knowledge. The purpose and advantage of this set is that we were able to focus on the underlying cognitive mechanisms for estimation and validate the set of cognitive mechanisms required to solve any type of estimation problem. However the limitation of this is that owing to the diversity in the problem set, we were unable to obtain a detailed characterization of the estimation problem solving process and scaffolds for any one particular type of problem (for eg, power estimation problems). Thus while our results regarding the underlying cognitive mechanisms and scaffolds for these cognitive mechanisms are generalizable to any type of estimation problem, there are several nuances of estimation problems (such as what assumptions and approximations are reasonable in various problem contexts) for which we cannot generalize our findings and scaffolds. In the next iteration of DBR, we use our findings of how to scaffold the underlying cognitive mechanisms of estimation, along with findings from literature regarding how other aspects of estimation such as making assumptions might be supported, in order to design our TELE for estimation problem solving.

5.6 Summary

Our studies 1, 2 and 3 together provide support for the fact that any environment for supporting estimation problem solving needs to trigger model-building via explicit prompts and modelling affordances, provide support for mental simulation and trigger solvers' metacognition intermittently. In the next iteration, we chose one way of operationalizing these requirements. We argue that by incorporating affordances for model-building, supporting mental simulation and including scaffolds for model evaluation and contextualization, and reflection, we will create a problem-solving environment which will enable novices to solve estimation problems.

Chapter 6

DBR 2: Problem Analysis and Design of MEttLE1.0

In this chapter, we describe the problem analysis phase of our DBR iteration 2 shown in Figure 3.5. Recall that the goal of this iteration is supporting novice estimation problem solving, for which we designed an open-ended technology-enhanced learning environment called Modelling-based Estimation Learning Environment (MEttLE), which is based on triggering a model-based estimation process among novices. Before beginning the design, as is the norm in DBR, we need to understand and analyse the problem of supporting novice estimation problem solving, which is done in sections 6.1 and 6.2 of this chapter. We begin by collating all the requirements for supporting estimation problem solving that we have obtained from studies 1 (experts), 2 (novices) and 3 (novices with causal mapping tool) in DBR iteration 1 (Section 6.1).

Next based on the nature of these requirements, we review related literature (Section 6.2) from the areas of supporting model-based reasoning, mental simulation, scaffolding complex and ill-structured tasks, external representations, scaffolding metacognition and experiential aspects of estimation. In the following section 6.3 we select appropriate pedagogical features for each of these requirements from among the many choices available in literature. Then we use the conjecture mapping framework (Sandoval, 2014) to obtain a set of design and theoretical conjectures regarding how these features together lead to the desired estimation problem solving process and performance. Finally in section 6.4 we elaborate the design of MEttLE1.0 for supporting novices estimation problem solving.

6.1 Requirements to Support Estimation

From the expert study we learned that,

1. When experts obtain good estimates, they follow the three-phased model-based reasoning process. Experts expand the problem space during functional modelling and narrow the problem space during qualitative and quantitative modelling.

2. Incorporating the problem context is integral to every phase of modelling. Experts build models which are contextualized, ie, simplified and useful for estimation.

3. The primary cognitive mechanism which supports the expansion is mental simulation and manipulating non-formal external representations such as diagrams, videos and animations.

4. Conceptual knowledge is necessary to fine tune and constrain the mental simulation process to the realm of causality and narrow the problem space.

5. Experts use information gathering in the first stage to understand the problem context and at the final stages to search for numerical values.

6. Experts frequently evaluate and revise their models and reflect on their estimation process.

From the novice study we found that,

1. Novices begin by narrow the problem space to a single conceptual model, which may be sub-optimal for estimation.

2. Novices do not know how to incorporate problem context into their estimation process.

3. Novices primarily use equation manipulation to solve estimation problems.

4. Novices are unable to identify and apply appropriate conceptual knowledge in the given problem.

5. Novices search for equations rather than information about the problem context.

6. Novices rarely evaluate their chosen models or reflect on their process while estimating.

The causal mapping intervention study showed that,

1. The modelling and mental simulation processes need to be made explicit for novices.
2. Novices need to be scaffolded to find and incorporate information regarding the problem context into their estimation process, specifically on how to constrain the mental simulation by incorporating conceptual knowledge and the problem requirements.
3. Novices need to be scaffolded to apply conceptual knowledge for the problem.
4. Novices need to be scaffolded to evaluate and revise their models and reflect on their estimation process.

The expert instructor corroborated these required scaffolds and provided examples of specific scaffolds for novices to incorporate problem context and appropriate conceptual knowledge into their estimation process. He also reiterated the importance of experience for choosing numerical values, making comparisons, assumptions and quantifying losses.

The results of studies 1,2,3 and EI inputs together give the following set of requirements for the TELE.

1. Trigger and support model-building.
2. Trigger and support mental simulation.
3. Provide space for externalization.
4. Provide information regarding problem context.
5. Support incorporation of problem context in model-building.
6. Trigger metacognitive processes including evaluation and reflection.
7. Scaffold application of conceptual knowledge.
8. Support aspects of estimation that require experience.

The design of MEttLE was informed by our survey of literature regarding pedagogical theories, strategies and features that can support the requirements above, as described in Figure 6.1. We elaborate the relevant literature next in Section 6.2.

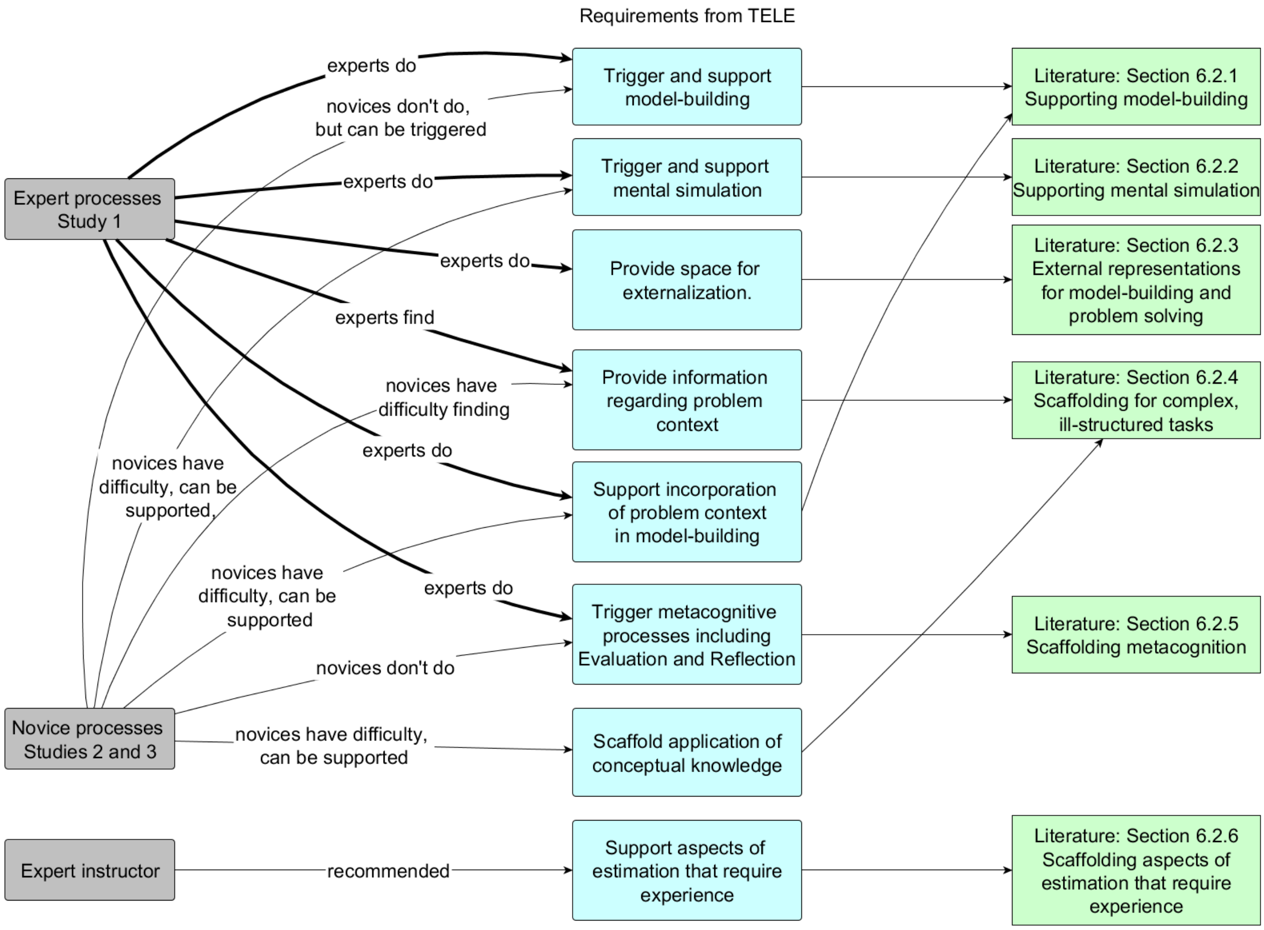


Figure 6.1: Integrating results of studies 1, 2, 3 into a set of requirements for the TELE

6.2 Theoretical Foundations of TELE design

6.2.1 Supporting model-building

From our studies 1,2 and 3, we identified that we must seed the modelling and mental simulation processes among novices by encouraging them to begin with their own mental models and building on them by interacting with appropriate affordances and scaffolds in the TELE. We also identified that model-building needs to be made explicit for learners. Research has found that model order progressions (Mulder et al., 2011; Sun & Looi, 2012; Swaak et al., 1998) wherein students create progressively more sophisticated models are an effective strategy to improve students inquiry and learning. It is also in line with the three-phased model-based estimation process we observed among experts, except that this progression (Mulder et al., 2011; Sun & Looi, 2012; Swaak et al., 1998) does not include functional modelling, which is specific to the case of estimation. So we propose to provide explicit model order progression-based sub-goals for the estimation problem, including functional modelling, in order to trigger the modelling process among novices.

Literature suggests that the nature of functional modelling in design varies depending on the domain (Eisenbart et al., 2012) owing to the lack of clarity about the term function (Vermaas et al., 2011). Additionally, as we observed that the nature of experts functional model varied depending on the problem context. Further, experts go back and forth between the phases fluidly. This makes it difficult to identify where functional modelling ends. Hence we will choose one perspective on functional modelling from (Eisenbart et al., 2012) depending on the problem chosen.

Qualitative and quantitative models are well-defined in literature (Jonassen, 2004; Mulder et al., 2011) and there are TELEs which employ model order progression by providing students with appropriate affordances at each stage of modelling (Löhner et al., 2005; Mulder et al., 2011; Sun & Looi, 2012), such as simulations for qualitative modelling to create a causal map of the system and an equation builder for quantitative modelling to create an equation representing the relationships between the variabes of the system. We propose to provide similar affordances in our TELE.

6.2.2 Supporting mental simulation

In order to support novices' estimation problem solving it is important to support their mental simulation process. The key idea here will be to get students to perform mental simulations of the working of the system rather than think of mathematical equations and do number crunching as they are prone to do (Adams et al., 2008). However, it is known that students often have difficulty in doing mental simulation (Hegarty et al., 2003). Hence the TELE will have to have the affordance for the simulation of problem systems to support students who may be unable to mentally simulate.

Ultimately though, we would also like to develop novices ability in performing mental simulations. Literature suggests that we use our sensorimotor system while performing mental simulations (Schubotz, 2007). This happens using a "forward model" which learns using sensory inputs such as sound, touch etc and is then able to make predictions regarding perceived and imagined events. Literature also suggests that *"One goal of simulation design can be to help students tune motor movements to perception, so they can recruit the motor system to help develop intuitive inferences"* (Lindgren & Schwartz, 2009).

Based on this, we argue that providing students with the affordance of fully manipulable simulations which involve their sensorimotor systems in the task will improve their ability to mentally simulate. The simulation should also get students to notice contrasts created by two runs of the simulation. But as students may create more variability that they cannot extract contrasts, boundaries may need to be created for students, either by prohibiting certain actions or providing verbal feedback (Lindgren & Schwartz, 2009). Such simulations have also been used in a number of modelling TELEs such as (Govaerts et al., 2013; Slotta & Linn, 2009; Swaak & De Jong, 2001) to improve students' modelling abilities.

Another way of stimulating novices' mental simulation is by drawing attention away from numbers and towards the qualitative aspects of the problem using language. Research suggests that while processing words which depict fictive motion such as, *"could a human heart run a wine opener"*, people tend to perform mental simulation (Matlock, 2004). This offers us a way to trigger students simulation processes by appropriate wording of the problem and the functional modelling sub-goal, which focusses novices' attention on the working of the problem system. We can provide students with a set of carefully chosen words, along with other scaffolds, that students can use to create the functional model of the system, as has been done successfully in computer supported inquiry learning (Van Joolingen et al., 2007).

6.2.3 External representations for model-building and problem solving

As already discussed in section 2.6.1, the roles of external representations in problem solving (Bodner & Domin, 2000; Edens & Potter, 2008; Hegarty & Kozhevnikov, 1999; Zhang, 1997) are more than merely memory aids and/or stimuli to the internal mind. Research has shown that the form of the representation (for example, schematic vs. pictorial) determines what information is perceived and how the problem is solved (Hegarty & Kozhevnikov, 1999). Research into the use of external representations by experts (L. Martin & Schwartz, 2009; Rosengrant et al., 2009; Van Heuvelen, 1991) found that experts take the time to create external representations before starting problem solving because it improves their overall performance, while students do not. Literature also suggests how to design computer-based interactive visual representations for complex cognitive activities that support certain types of epistemic actions (Sedig & Parsons, 2013).

In ill-structured problem solving, for example, the use of concept mapping (Hwang et al., 2014; Stoyanov & Kommers, 1999; Stoyanova & Kommers, 2002), knowledge mapping (Lee et al., 2005) and dual mapping (Wu & Wang, 2012) have been shown to improve problem solving performance. In the first approach, concept mapping facilitates the problem analysis, information organization and idea generation phases in problem solving. In the second approach, knowledge maps were used to represent conceptual and procedural knowledge together and in the last approach, two different maps were used namely, argument maps for describing problem solving relations and concept maps for knowledge construction.

In scientific modelling and inquiry, studies have found that external representations such as conceptual organizers, process maps, argument maps, causal maps, simulations, equations, graphs, diagrams and data visualization tools (often linked together) support students' in the doing and learning of scientific modelling and inquiry (Buckley, 2000; Govaerts et al., 2013; Jonassen, 2004; Löhner et al., 2005; Quintana et al., 2004; Sandoval et al., 2000; Sandoval & Reiser, 2004; Slotta & Linn, 2009; Toth et al., 2002; B. White et al., 2002). These representations facilitate process management, model building and sense-making.

Building on the above literature, we argue that the TELE must have several external representations, and affordances to build and manipulate external representations. However the central question for us is what kinds of external representations are suitable for estimation problems? Students will need to be encouraged to create and use different kinds of representations during the modelling activities. During functional modelling students need to be encouraged to draw diagrams and express their preliminary understanding of the system (Quillin & Thomas, 2015). So we propose to provide them with space in the TELE for drawing and writing.

To facilitate creation of the qualitative model, we propose to use the feature of a causal map as has been done in (Mulder et al., 2011). To facilitate the creation of the equation, we propose to provide students with the affordance of dragging-and-dropping the variables and relations to build the equation. For managing their estimation process (Quintana et al., 2004), we propose the feature of a problem map which depicts all the sub-goals of estimation and simultaneously allows the representation of the overall process and the current sub-goal/task at each stage with zoom-in and zoom-out. Such a map may serve as an *"epistemic structure"* (Chandrasekharan & Stewart, 2007) which allows offloading of the process management of estimation onto the environment and help improve speed, accuracy and robustness of estimation.

6.2.4 Scaffolding for complex, ill-structured Tasks

Students need to be able to solve estimation problem in the absence of a TELE by leveraging their own environments. However, it is known that novices at a task may be under prepared to leverage the environment productively for doing a task owing to the cognitive load that it imposes on them if they do not receive appropriate feedback from the environment (Kirsh, 2000). Hence learner interaction with the environment has to be carefully designed such that it *scaffolds* their doing process. Literature offers guidelines on how to design a TELE such that it scaffolds learners doing of complex ill-structured tasks. Scaffolding encompasses a wide range of technological affordances from variable manipulation simulations to concept maps and articulation text boxes. These have to be adapted for the specific case of estimation.

Scaffolding has been defined as the process in which a teacher or more knowledgeable peer provides supports to a novice in order to do a task or solve a problem which they would be otherwise unable to do themselves (Wood et al., 1976). With the advent of TELEs, this definition has expanded to include technological affordances which reconfigure the LE itself and enable learners to do tasks that they would have been otherwise unable to do, thus modifying their doing and learning experience (Azevedo & Hadwin, 2005; Basu, Sengupta, & Biswas, 2015; Ge & Land, 2004; Guzdial & Kehoe, 1998; Hmelo-silver & Guzdial, 1996; Holton & Clarke, 2006; Kim & Hanna, 2011; Puntambekar & Hubscher, 2005; Quintana et al., 2004, 2005; Reid et al., 2003; Reiser, 2004; Sandoval & Reiser, 2004; Sherin et al., 2004; Tugba & Pedersen, 2010). The takeaways from literature regarding the purposes which need scaffolding and the types of scaffolds for complex ill-structured tasks in TELEs is presented in Table 6.1 below.

Focus of paper	Paper title	Takeaways for design
How Scaffolding works	Scaffolding Complex Learning: The Mechanisms of Structuring and Problematizing Student Work (Reiser, 2004)	Defined two mechanisms of scaffolding, ▪ Structuring an open-ended task by decomposition, focusing and monitoring ▪ Problematizing Aspects of Subject Matter in order to elicit articulation, elicit decisions, identify gaps and disagreements ▪ Complementary tools ▪ Tension between them should be resolved

How scaffolding works	Scaffolding Analysis: Extending the scaffolding metaphor to learning artifacts (Sherin et al., 2004)	Proposed the Scaffolding Analysis Framework in which it is analysed how the differences between two situations, a "base" learning situation and a "scaffolded" learning situation, lead to changes in learner performance capability.
How scaffolding Works	Of Black and Glass Boxes : Scaffolding for Doing and Learning (Hmelo-silver & Guzdial, 1996)	Introduced the ideas of ▪ Black box scaffolding or scaffolds for performance ▪ Glass box scaffolding or scaffolds for performance and learning
Purposes and types of scaffolds for inquiry learning	A scaffolding design framework for software to support science inquiry (Quintana et al., 2004)	Presented guidelines for scaffolding different aspects of scientific inquiry such as sense making, process management, articulation and reflection. 1. Use representations and language that bridge learners' understanding 2. Organize tools and artifacts around the semantics of the discipline 3. Use representations that learners can inspect in different ways to reveal important properties of underlying data 4. Provide structure for complex tasks and functionality 5. Embed expert guidance about scientific practices 6. Automatically handle nonsalient, routine tasks 7. Facilitate ongoing articulation and reflection during the investigation

Purposes and types of scaffolds for problem solving	Scaffolding problem solving in technology-enhanced learning environments (TELEs): Bridging research and theory with practice (Kim & Hanna, 2011)	▪ Propose guidelines for incorporating scaffolding in TELE ▪ Dimensions include Scaffolding purposes, Scaffolding interactions, Scaffolding sources and Examples ▪ Scaffolding purposes include Procedural, conceptual, metacognitive and strategic ▪ Scaffolding interactions are static or dynamic ▪ Scaffolding sources are peer, teacher, technology ▪ Different scaffolding focus for each phase of problem solving corresponding to the inquiry activities in that phase
Purposes and types of question prompts for problem solving	A Conceptual Framework for Scaffolding Ill-Structured Problem-Solving Processes Using Question Prompts and Peer Interactions (Ge & Land, 2004)	Presented a framework for how to design question prompts and peer interactions for different stages of the problem solving process (eg, problem representation) and different functions (eg, eliciting explanations)
Purposes and types of scaffolding	Scaffolding and Metacognition (Holton & Clarke, 2006)	▪ Scaffolding Domain: Conceptual and Heuristic ▪ Scaffolding type: Expert, reciprocal and self-scaffolding ▪ Relating self-scaffolding and metacognition ▪ Scaffolding type × Scaffolding Domain

Purposes which need scaffolding in open-ended inquiry learning environments	A Scaffolding Framework to Support Learning of Emergent Phenomena Using Multi-Agent-Based Simulation Environments (Basu, Sengupta, & Biswas, 2015)	Scaffolds are necessary for setting up simulation, interpreting results, controlling variables, self-explanations, creating cognitive conflict, encouraging note taking and monitoring, providing resources, reminding students to refer notes and include bidirectional nature of relationships, how to reason in chains and verify their answers
Purposes which need scaffolding in apprenticeship-based learning environments	Apprenticeship-based learning environments: A principled approach to providing software-realized scaffolding through hypermedia (Guzdial & Kehoe, 1998)	Proposed three components of software-realized scaffolding ▪ Communicating process ▪ Coaching ▪ Eliciting Articulation
Purposes which need scaffolds in discovery learning	Supporting scientific discovery learning in a simulation environment (Reid et al., 2003)	Identified three types of learning support for scientific discovery learning namely interpretive support, experimental support and reflective support
Types of scaffolds for inquiry learning	Explanation-driven inquiry: Integrating conceptual and epistemic scaffolds for scientific inquiry (Sandoval & Reiser, 2004)	Framework for scaffolding epistemic aspects of inquiry integrating conceptual and epistemic scaffolds for inquiry ▪ Grounding process in products: Explanation-driven inquiry ▪ Link Explanations to Specific questions ▪ Represent theories as explanatory frameworks ▪ Link Evidence to causal claims ▪ Structured opportunities for epistemic reflection

Table 6.1: Takeaways from literature for designing scaffolds for complex ill-structured tasks

6.2.5 Scaffolding metacognition

In order to obtain a good estimate solvers must, at each phase of the model-based estimation process, evaluate their models for their utility to give the desired estimate and plan the next modelling tasks (Jonassen, 1997; Kothiyal et al., 2016). This is also consistent with the multilevel and multifacted model of metacognition (Efklides, 2008). At the end of the solution process, they must reflect on the entire model-based estimation process (Quintana et al., 2004; Sandoval & Reiser, 2004). In addition, they must learn to reason about certain aspects specific to estimation problems such as whether the estimate is reasonable by various standards, which parameters are critical in a given system and how to make assumptions and approximations without compromising on accuracy (Linder & Flowers, 2001; Mahajan, 2014; Trotskovsky & Sabag, 2016). Research has shown that students must be scaffolded in order to articulate and reflect on their inquiry (Quintana et al., 2004) and problem solving (Kim & Hanna, 2011). Elaboration question prompts have been successfully used in ill-structured problem solving to get students to elaborate and explain their thinking (Ge & Land, 2004). In scientific inquiry (Sandoval & Reiser, 2004), specific questions and "Explanation Guides" help students construct scientific explanations and learn about the epistemic aspects of inquiry. Therefore, we provide question prompts to novices in order to trigger students' evaluation of their models and estimated values and reflect on the practical aspects of estimation and estimation process.

6.2.6 Supporting aspects of estimation that require experience

While making estimates, engineers must be able to quickly choose reasonable values for certain frequently encountered quantities such as the mass and power of known systems, and the performance parameters of commonly used systems such as motors, generators and batteries. Mahajan (2014) argues that for quantities whose values we do not know directly, we must estimate them by drawing on our experience and intuition. Thus engineers require a great repertoire of knowledge about quantities and their values (quantitative facts) which they acquire as they gain experience by solving more real-life problems in any domain. This was also reiterated by our expert instructor as seen in section 5.4. This knowledge is a necessary foundation for students to reason about values, compare them, extrapolate and generalize from one situation to the next, all of which are the components of quantity sense. This has been the reason for a thrust towards deliberate practice (Litzinger et al., 2011) and incorporating situativity in engineering curricula

(Johri & Olds, 2011). Therefore the TELE must have authentic tasks that allow engineers to build their experience and intuition regarding the values of quantities that they are likely to encounter in engineering practice, along with hints regarding expert practices and how to choose values (Quintana et al., 2004).

6.2.7 Summary

The results of our studies 1,2,3 and instructor recommendations gave us a set of requirements for the TELE shown in Figure 6.1. We conducted a literature survey to identify the pedagogical theories, strategies and features that have been found to be useful to address those requirements in other teaching-learning scenarios and elaborated them in this section. We found that there are several recommendations in literature for each of the requirements we have identified. Next, we give an overview of the specific pedagogical features we chose to incorporate in MEttLE to meet each of the requirements and their underlying learning design principles.

6.3 How literature and data came together in the design of MEttLE

As seen in section 6.2, the body of literature regarding pedagogical features and strategies that can scaffold each of our requirements is vast. In this section, we describe the pedagogical features that we chose from among the available options to align with the requirements identified in section 6.1 and based on the literature we reviewed in section 6.2. Together these pedagogical features gave the first version of MEttLE, namely MEttLE1.0, which we describe in section 6.4. Broadly, we chose to convert the requirements identified in Section 6.1 to pedagogical features in MEttLE1.0 using literature in the following manner,

1. The expert study informed us that a model-based reasoning process underlies good estimates. This process has three aspects namely, functional, qualitative and quantitative modelling, all of which are important in estimation and are integrated to obtain good estimates. We chose to adopt these three aspects as a way to structure (Reiser, 2004) estimation, which is a complex ill-structured problem for novices. This is also a way to trigger and make explict the modelling and mental simulation processes for novices (Requirements 1 and 2). The three aspects together offer a natural and logical model order

progression (Mulder et al., 2011) that makes the modelling of complex systems tractable. For instance, having a comprehensive understanding of the problem context and where power is needed (functional model), will make it easier to identify what will affect power in the problem context (qualitative model) and then apply the corresponding conceptual knowledge to make the equations (quantitative model).

However, we observed even in the case of experts, that these models maybe partially built and then revised based on evaluation. Iterations are desirable to refine the models. Hence we do not enforce the model order progression, as is typically done in literature, but use it as a way to nudge novices towards beginning with enaction rather than freezing.

2. We include a variable manipulation simulator for the entire system which serves as an implict guidance for novices to consider the system working and problem requirements. Further it triggers and supports mental simulation (Requirement 2), and allows the conceptual knowledge required to solve the problem to be *"discovered"* and applied by novices (Requirement 7).

3. We include question prompts at appropriate places to trigger novices to contextualize and evaluate their models (Requirement 5 and 6).

4. We periodically incorporate planning and monitoring tasks to trigger novices reflection, which is necessary for monitoring the estimation process (Requirement 6).

The requirements to solve an estimation problem which are shown in section 6.1, the corresponding pedagogical features in MEttLE1.0 for each requirement, and their theoretical bases and justification are detailed below. In the next section, we present our conjecture map, and design and theoretical conjectures of how MEttLE1.0 supports novice estimation problem solving.

1. Process Management: For the purpose of exploring all the sub-goals in the estimation process and triggering the appropriate modelling sub-goals to be done, we included a diagram depicting the sub-goal structure of model order progression with focus questions for each modelling sub-goal. This was informed by studies 2 and 3 which highlighted the need to explicitise and trigger modelling for novices (Requirement 1). The theoretical basis for this feature is structuring and problematizing (Reiser, 2004) and the need for scaffolds for process management (Quintana et al., 2004). Specifically, it is known that

model order progression supports model-building (Mulder et al., 2011; Sun & Looi, 2012, 2013).

2. Model-Building: A specific kind of conceptual knowledge constrained mental simulation needs to be triggered and scaffolded among novices as informed by studies 1,2 and 3 (Requirements 2, 7). So we included a variable manipulation simulation of the problem system. The simulator also provides implicit guidance to incorporate problem context in the entire estimation process. The design principles guiding this feature are discovery learning (Swaak & De Jong, 2001) and perceptual learning (Lindgren & Schwartz, 2009) with simulations.

3. Model-Building: In order to scaffold functional model-building by triggering mental simulation of the working of the problem system, we included fictive motion words related to problem context (components and behaviours) in the functional modelling sub-goal. This was motivated by results of studies 1,2 and 3 where we found that experts model the system working via mental simulation, novices need support in understanding the problem system and fictive motion words trigger mental simulation among experts (Requirements 1,2,4). It is based on the theory that fictive motion words trigger mental simulation (Matlock, 2004). Further, the words serve as "interpretive support" (Reid et al., 2003) for identifying working of the system, as novices have deficiency in context-specific knowledge.

4. Model-Building: In order to scaffold qualitative model-building and represent how various parameters affect power, we included a causal mapping tool in the qualitative modelling sub-goal, as we had found from studies 1, 2 and 3 that experts have a qualitative sense of the system, while novices have difficulty in this, but can be scaffolded using a causal mapping tool (Requirement 1). The learning design principle underlying this feature is that knowledge representation such as schematic diagrams improve performance in problem solving (L. Martin & Schwartz, 2009).

5. Model-Building: To support novices in quantitative model-building by prompting them to use their causal map, prior conceptual knowledge and symbol manipulation to create an equation for estimation, we provided a set of drag-and-droppable parameters and mathematical relationships relevant to the given problem in the quantitative modelling

sub-goal. This was informed by the results of studies 1 and 2 (Requirement 1) where we found that equation manipulation is required in solving estimation problems. The underlying learning design principle is "Provide representations that can be inspected to reveal underlying properties of data. Enable learners to inspect multiple views of the same object or data" (Quintana et al., 2004) and providing "interpretive support" (Reid et al., 2003) for context-specific knowledge.

6. Evaluation during model-building: To prompt novices to examine whether their models for estimation are simplified and useful, we included model evaluation and model contextualization question prompts in the evaluation tasks of each sub-goal. This was informed by studied 1,2,3 where we found that experts constantly evaluate their models while novices do not and need to be scaffolded to do (Requirements 5,6). The guiding learning design principles come from the role of question prompts for evaluation (Ge & Land, 2004), providing opportunities for epistemic reflection (Sandoval & Reiser, 2004) and embedding "expert guidance about scientific practices" (Quintana et al., 2004).

7. Productive monitoring and planning: To support the integration of various sub-goals that novices do, reflection on tasks done and planning next tasks we included planning and monitoring question prompts. We learned from study 1 that experts plan their problem solving process and this scaffold is based on the guideline of facilitating "ongoing articulation and reflection" (Quintana et al., 2004) and the role of question prompts for reflection (Ge & Land, 2004).

8. Estimation reasoning and practice: In order to get novices to select appropriate values and evaluate their reasonableness before calculating, we included a separate calculation sub-goal which required learners to choose and justify the values that they would use to determine the estimate. This was informed by study 3 wherein we found that novices have difficulty selecting appropriate values (Requirement 8) and is based on the underlying learning design principle "Facilitate ongoing articulation and reflection" and "Embed expert guidance about scientific practices" (Quintana et al., 2004) and question prompts for elaboration (Ge & Land, 2004).

9. Estimation reasoning and practice: To trigger novices to consider whether their estimates are reasonable, of the right order of magnitude and compare them with known values,

we included question prompts for evaluating numerical values and hints for comparing. This was based on the results of studies 1,3 that experts naturally evaluate their estimates while novices need support to do this (Requirement 6,8). Again the underlying design principles are "Facilitate ongoing articulation and reflection" (Quintana et al., 2004), question prompts for elaboration (Ge & Land, 2004) and evaluating by comparison (Mahajan, 2014).

10. Productive reflection on process: To make novices reflect on the process they applied to estimate, its usefulness and applicability we included a separate reflection task with question prompts for reflection (Ge & Land, 2004) as recommended in literature, "Facilitate ongoing articulation and reflection" (Quintana et al., 2004).

11. Context-specific knowledge: To support novice understanding of the problem context using reading material and videos, we included the feature of "Info Center" which contains information regarding the problem context. This was based on the findings of studies 1,2,3 that experts gather and use information about problem context and novices need support in this (Requirement 4). The learning design principle informing this feature is to provide "Interpretive support" (Reid et al., 2003), annotated diagrams for understanding the problem system and videos for stimulating mental simulation process (Hegarty et al., 2003).

12. External representations: To encourage externalization for model-building via manipulation of preliminary mental models, we included the feature of "Scribble Pad" which is a space for writing and drawing and is informed by study 1 where we found that experts build models by manipulating external representations such as drawings and flow charts (Requirement 3). So we provided a space where novices could create and manipulate different kinds of external representations such as diagrams, equations and notes (Kirsh, 2013).

6.3.1 Conjecture Map of MEttLE1.0

In DBR, conjecture mapping (Sandoval, 2014) is the technique of identifying the salient features of a learning environment design and mapping out how they are expected to interact in order to produce the desired forms of learning. It is a way of describing the predicted learning pathways of a student working with a designed learning environment. Thus conjecture mapping explicates the implicit conjectures in a learning environment design about how learning is expected to happen. A conjecture map has,

- a *high level conjecture* about how to support learning in some context which leads to
- the *embodiment* of the specific design, namely the tools & materials, the task structures, the participant structures and the discursive practices which are expected to generate
- the *mediating processes*, including the observable interactions and participant artifacts, that produce
- the desired *outcomes*

The researchers' ideas about how the elements of the embodiment together generate the mediating processes are called *design conjectures*, while the ideas of how the mediating processes together produce the desired outcomes are called *theoretical conjectures*. Based on the designed features listed above, the conjecture map is shown below in Figure 6.2.

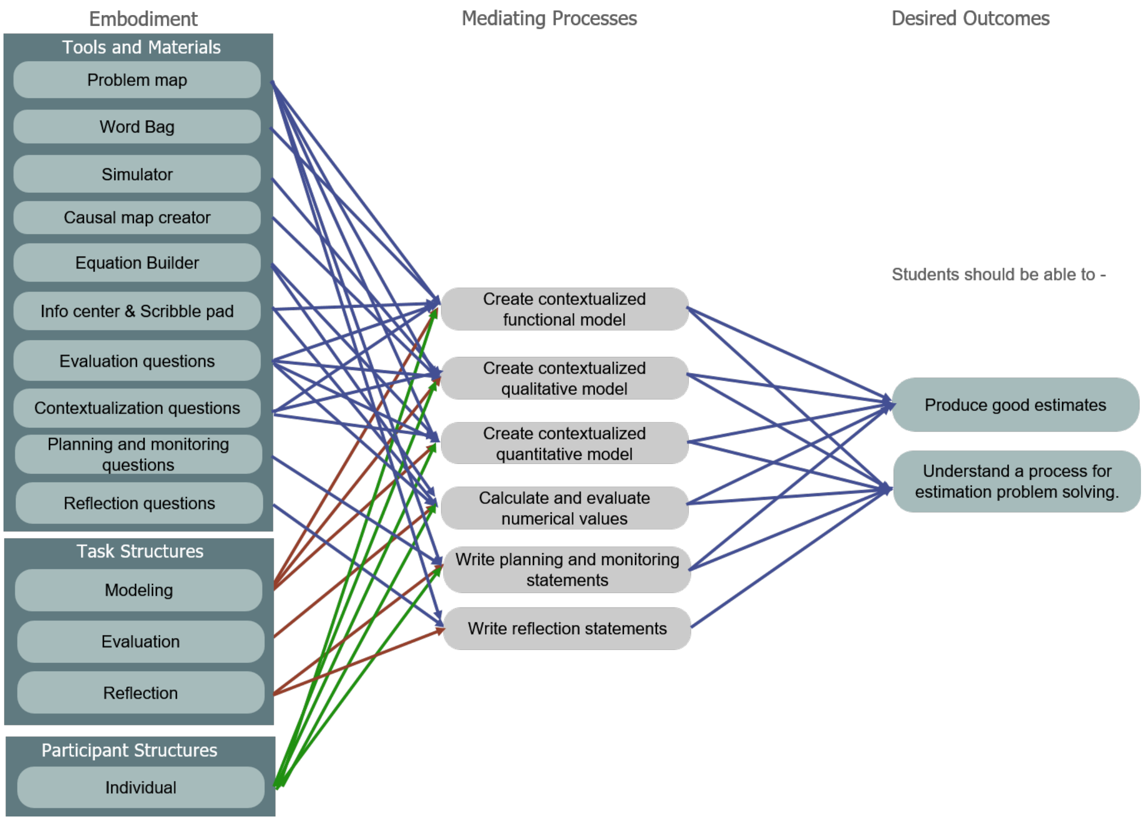


Figure 6.2: Conjecture Map of MEttLE1.0

The design conjectures for MEttLE1.0 are as follows,

1. If an individual student uses the problem map, the word bag, the info center, contextualization and evaluation questions to do modelling, he/she will be able to create a contextualized functional model.

2. If an individual student uses the problem map, the simulator, the causal map creator, contextualization and evaluation questions to do modelling, he/she will be able to create a contextualized qualitative model.

3. If an individual student uses the problem map, the equation builder, contextualization and evaluation questions to do modelling, he/she will be able to create a contextualized quantitative model.

4. If an individual student uses the equation builder, information center and evaluation questions to do evaluation, he/she will be able to calculate and evaluate numerical values.

5. If an individual student uses the planning and monitoring questions and problem map to do reflection, he/she will be able to write planning and monitoring statements.

6. If an individual student uses the reflection questions and problem map to do reflection, he/she will be able to write reflection statements.

Based on our literature survey we had proposed a conjecture related to a learning environment that supports estimation (Conjecture 3 in Section 2.7). Based on our studies 1,2 and 3 and our design of MEttLE1.0 we now propose the theoretical conjectures below (also depicted in Figure 6.3) for how MEttLE1.0 supports novice estimation problem solving. In study 4 described in Chapter 7, we evaluate the first theoretical conjecture below in a lab study by analysing novices estimation problem solving process in MEttLE1.0 using interaction (Jordan & Henderson, 1995) and thematic (Braun & Clarke, 1996) analyses.

1. **Conjecture 1:** Our first theoretical conjecture is related to a process of solving estimation problems such that a solver can obtain good estimates, ie, estimates which satisfy all the criteria for good estimates described in Section 5.4.2 and says,

   If an individual student creates contextualized functional, qualitative and quantitative models, calculates and evaluates the numerical values, and writes planning and monitoring statements he/she will be able to produce good estimates of a physical quantity.

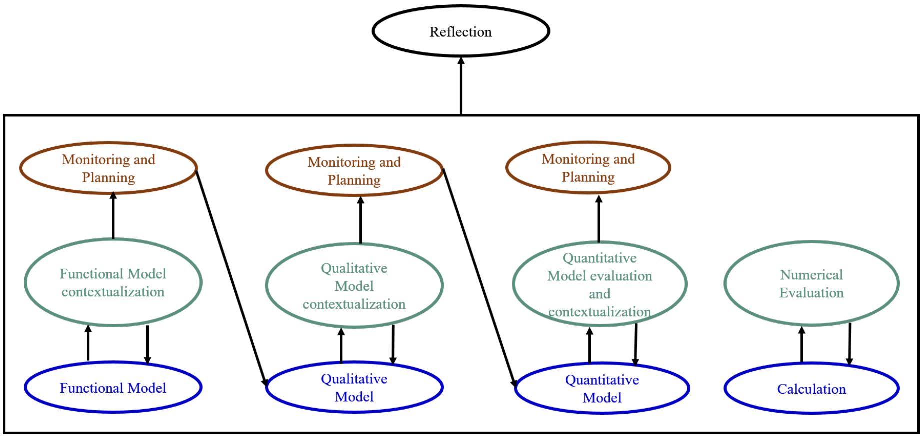


Figure 6.3: Theoretical conjectures of MEttLE1.0

Thus we conjecture that if novices go through an estimation process based on intertwining contextualized model-building and the metacognitive processes of evaluation, monitoring and planning, they will be able to obtain good estimates.

2. **Conjecture 2:** Our second theoretical conjecture is related to the learning of this process of solving estimation problems and says,

   If an individual student creates contextualized functional, qualitative and quantitative models, calculates and evaluates numerical values, writes planning, monitoring and reflection statements, he/she will be able to understand a process of estimation problem solving.

   Thus we conjecture that if novices go through an estimation process based on intertwining contextualized model-building and the metacognitive processes of evaluation, monitoring, planning and reflection they will be able to understand a process for estimation problem solving.

6.4 Modelling-based Estimation Learning Environment (MEttLE1.0)

6.4.1 An overview of MEttLE1.0

We designed MEttLE1.0 for the estimation problem of the type shown below that students in our target population need to be able to solve:

> You are participating in an electric car race in which you are required to design an electric car of weight 7kg with wheel diameters of 4” that can accelerate at 1m/s^2 and traverse a track of 10m without burning out. Estimate the electrical power needed to achieve these specifications and the specifications of the motor you will need.

Our solution to support novices in solving estimation problems such as the above is technology-enhanced learning environment (TELE) called the Modelling-based Estimation Learning Environment (MEttLE), based on progressively higher order modelling. Each problem is broken down into five sub-goals, namely, functional, qualitative and quantitative modeling, calculation and evaluation. Each sub-goal has two or three tasks and the three modeling sub-goals each have tasks of create a model, evaluate the model and plan next steps. Novices are prompted to evaluate and contextualize their models at each stage. Finally they calculate and evaluate their estimate and if necessary, revise it until the estimate satisfies the evaluation criteria. The purposes of the modelling sub-goals are,

1. Functional modelling: Novices model how the system works, i.e., what are the various parts of the system and how these parts are connected together to generate its functioning. In this sub-goal, novices expand the problem space using mental simulation and information gathering in order to identify which are the sources and users of power, and which of these users will dictate the power requirements in the problem context.

2. Qualitative modelling: Novices identify the parameters affecting power, the parameters (system performance requirements and external parameters) which have a large effect and which can be ignored in the operating conditions, and the qualitative relations between power and those parameters. In this sub-goal, novices narrow down the problem space and identify parts of the solution. Thus the qualitative model is a simplified model.

3. Quantitative modelling: Novices use conceptual knowledge to create an equation connecting power and the previously identified parameters, incorporating the inefficiencies of the system and making assumptions and approximations in order to simplify the analysis (since the goal is only to get an approximate answer). Thus the quantitative model is a simplified and useful model that leads to the solution.

MEttLE includes focus questions and affordances for building and manipulating models, supporting resources such as a variable manipulation simulation, reading material and videos for problem context knowledge and question prompts for model evaluation and contextualization, and numerical evaluation and reflection. Students manage their estimation process using a problem map. Students are free to use these resources in any manner and sequence of their choosing as long as they get an estimate that satisfies the evaluation criteria. Thus MEttLE is an open-ended environment and the philosophy of guidance is one of implicitly suggesting an order, without prescribing it. So novices are suggested to think about certain aspects of estimation which we know they do not normally focus on, without requiring them to do so. The reason for not being prescriptive is that, while we have built an understanding of some good processes of estimation via our studies 1, 2 and 3, there are several aspects regarding which we do not yet have clarity, for example, how to incorporate the problem context, system working and requirements at various stages of the estimation process. Therefore we only built in "hints" (Kirsh, 2009) into the environment regarding certain aspects and allow solvers to use them as needed. Novices were free to iterate between the sub-goals and revise their models and estimates based on their evaluation.

Given that MEttle has five sub-goals for each problem and several resources and scaffolds, novices could, in principle, create any number of learning paths leading to the solving of the estimation problem. In Section 4.1 we found that experts follow an iterative model-based estimation process and go back and forth between models, often very rapidly. The similar possible workflow for a novice in MEttLE is shown in 6.4.

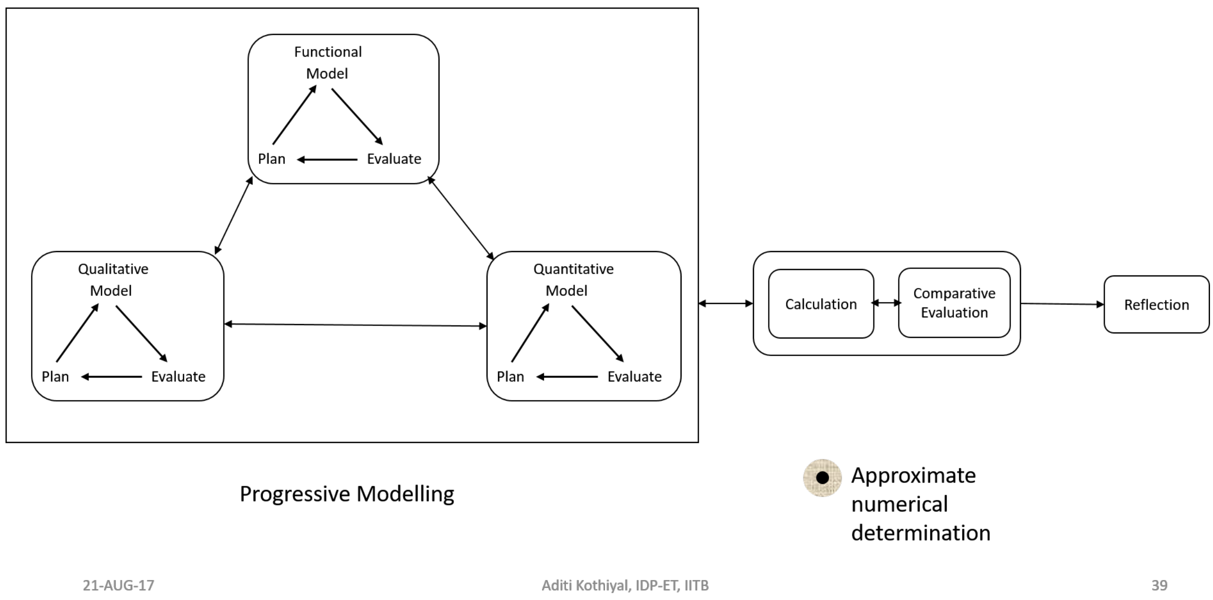


Figure 6.4: Workflow of a novice in MEttLE1.0

6.4.2 Features of MEttLE

When a novice enters the MEttLE system, he/she is presented with the estimation problem. Next they are shown a video introducing them to the problem solving method in MEttLE. The video describes how estimation problems are solved by completing one sub-goal at a time and building up to a solution until an evaluation criteria is met. This leads to a clickable problem map (Figure 6.5) with the sub-goals and the tasks within each sub-goal described in detail. Next, MEttLE presents the student with a problem map from which they select one of sub-goals to do, in any sequence they choose. The five sub-goals are: three modelling sub-goals namely functional, qualitative and quantitative modelling each with tasks of "create a model", "evaluate the model" and "plan next steps"; a calculation sub-goal in which solvers choose and evaluate the reasonableness of values, and calculate the estimate; an evaluation sub-goal, in which solvers evaluate whether the calculated estimate is reasonable by two standards, namely correctness to the order-of-magnitude and comparable with known values. This is followed by a last activity of reflection on the entire process. Each of the modelling tasks includes a focus question and a modelling affordance. In addition there are a set of tools available to the learner at all times namely, "Info Center", "Simulator", "Problem map", "Scribble Pad" and "Calculator". These features of MEttLE1.0 are described in detail below and screenshots of all features of MEttLE1.0 are available in Appendix D.

1. Estimap: This is a clickable problem map (Figure 6.5) depicting the five sub-goals of estimation and describing the purpose of each sub-goal. The solver can click on any sub-goal to see its tasks and begin doing the task. The Estimap is the central process management feature from where the solver chooses tasks and thus his/her solution path. The solver can choose the sub-goals in any sequence, but must complete all tasks of a sub-goal before proceeding to the next sub-goal. Before presenting the Estimap, the student sees a short video about the estimation process using another estimation problem as an example, which introduces the Estimap as well.

2. Modelling sub-goals and tasks: Each modelling task (Figure 6.6) is divided into three tasks namely create, evaluate and plan tasks. The overall sub-goal has a focus question, such as for functional modelling it is *"How does an electric car run?"*, for qualitative modelling it is *"How is the power required by an electric car affected by various parameters?"* and for quantitative modelling it is *"What is the equation connecting power required by an*

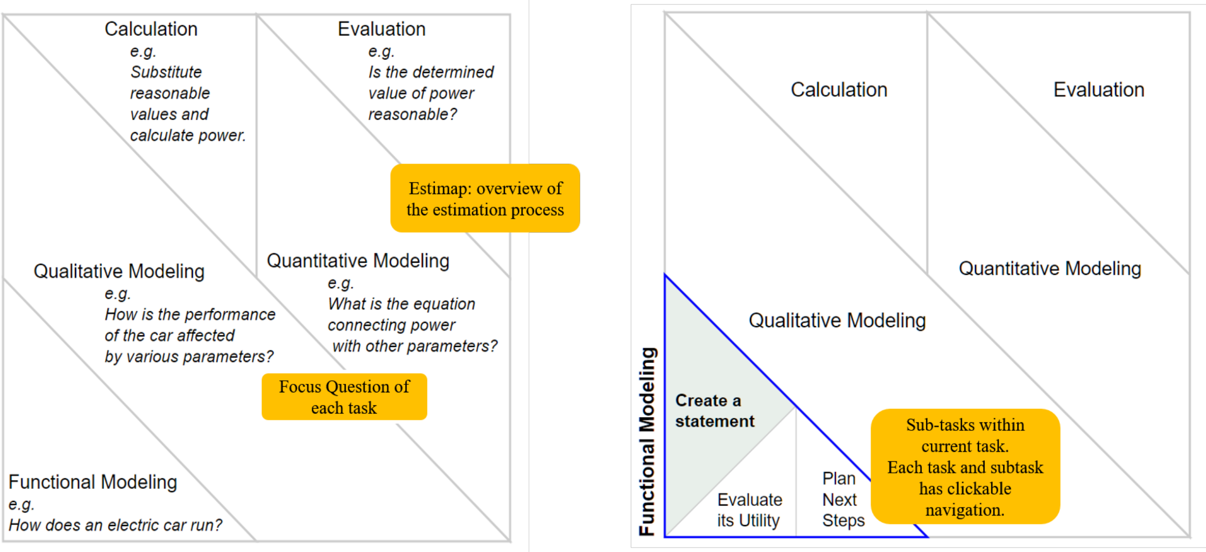


Figure 6.5: Estimap, the problem map

electric car to other parameters?" In addition, the create tasks also have a modelling affordance. For creating a functional model, the affordance is a drag-and-drop word bag containing a set of words describing actions, behaviours, parts of the car and physical parameters. Learners select words from this set to create a sentence answering the focus question, thus creating the functional model. The modelling affordance for qualitative modeling is a causal map creator and for quantitative modelling it is a drag-and-drop equation builder.

The evaluate sub-task has "model evaluation questions" such as, for evaluating the functional model *"Does the model describe how power is generated and used in this system? What is the source and user of power?"* Similarly, in the plan task there are two types of questions, the "model contextualization questions" (e.g. *"What performance requirements from the car will dictate the power requirements and choice of motor?"*) and planning questions (*"What steps will you follow to determine power using this model?"*). The model contextualization questions focus students attention on the problem context and make assumptions to simplify the models.

3. Calculation task: In this task, the student selects numerical values for parameters in their equation and calculates the power estimate. Students are prompted to think about the "reasonableness" of the numerical values and justify them.

4. Evaluation task: In this task, the student evaluates whether their final estimate is of the

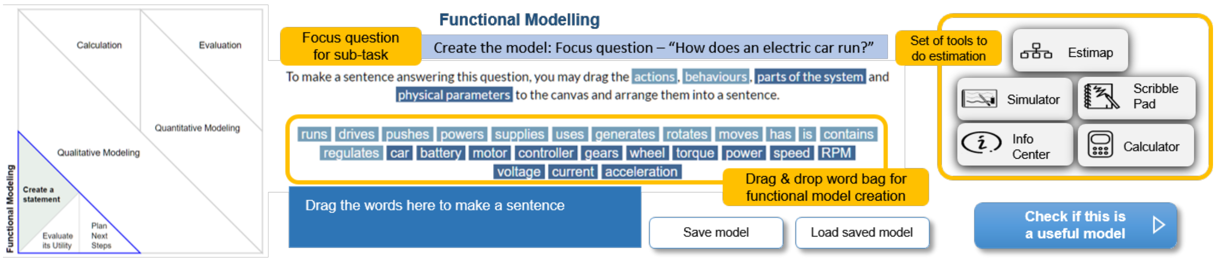


Figure 6.6: Create sub-task of Functional Modelling

right order-of-magnitude and comparable to other known values by answering a series of question prompts such as, *"What order of magnitude of power do you expect is needed to run a car? Is the power you determined of the expected order of magnitude? If not, what could be the reason?"* The students use the prompts to self-assess their estimate and are not provided any feedback by MEttLE1.0.

5. Simulator: This consists of a variable manipulation simulation (Figure 6.7) showing the problem system (a in Figure 6.7), the parameters affecting power in the system (c in Figure 6.7) and graphs showing the variation of power with each of these parameters (d in Figure 6.7). The parameters are presented to the student one-by-one in order to constrain their exploration productively (b of Figure 6.7). In this design, we chose to have a simple simulator which ignored the factor of air drag, which is a valid assumption for the given problem where the speeds required to be attained by are low enough that drag is not a dominating factor.

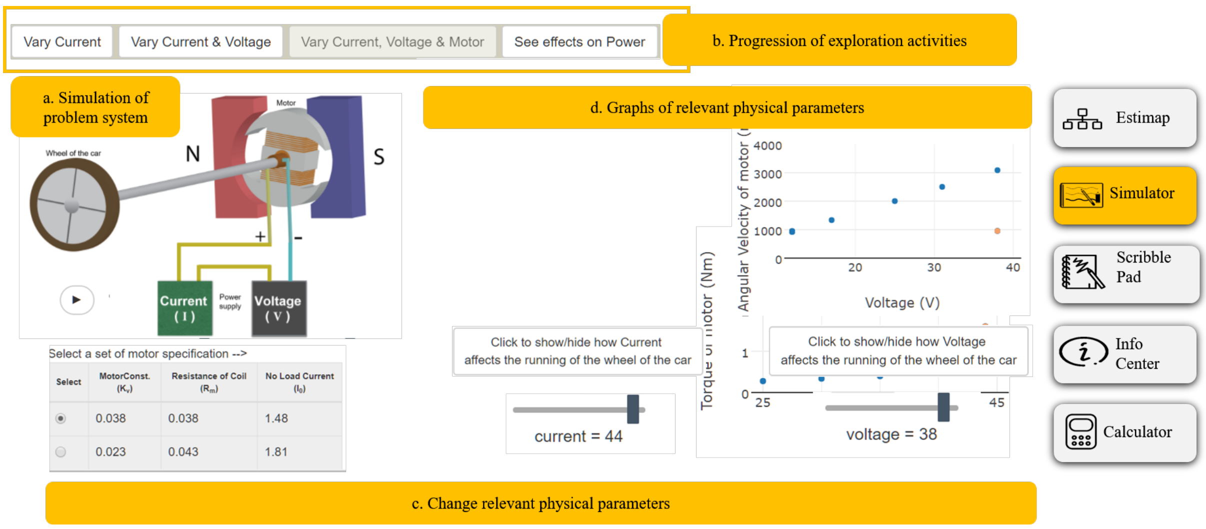


Figure 6.7: Simulator

6. Scribble Pad: In this space students can take notes and make drawings while they are doing the tasks and sub-tasks.

7. Info Center: This space has reference material including documents/webpages/videos for the student to familiarize themselves with the problem system.

8. Reflection activity: In this activity, the student answers a set of question asking them to reflect on their own problem solving process, the tasks which they did and the sequence in which they did them. An example question is, *"What tasks did I do to calculate the estimate? What was the main activity in each task?"*

6.5 Summary

We began this chapter with a list of requirements for a TELE that supports estimation. We then surveyed literature for a set of pedagogical theories, strategies and scaffolds for each of these requirements. Next we described how we instantiated the requirements using this knowledge from literature, to design our modelling-based open-ended technology-enhanced learning environment for estimation, called MEttLE. We also elucidated a set of conjectures regarding estimation problem solving that emerge from our design. Finally, we described the workflow and features of MEttLE, which include three modelling-based sub-goals for estimation, modelling affordances and focus questions for each of these sub-goals, scaffolds for model evaluation, contextualization and reflection and a problem simulator. In the next chapter, we describe an evaluation study to test our first theoretical conjecture (Figure 6.3 and Section 6.3.1) regarding estimation problem solving.

Chapter 7

DBR 2: Evaluation of MEttLE1.0

In chapter 6 we described the design of MEttLE1.0 beginning with the set of requirements that emerged from iteration 1. We then described the theoretical foundations of MEttLE1.0 and how we applied theory to design MEttLE1.0 in order to meet the identified requirements. Finally we described the design and features of MEttLE1.0. In this chapter, we elaborate the study that we did in order to evaluate our design. As is the norm in DBR, our goal for the evaluation was two-fold; firstly, to understand how novices do estimation in MEttLE, which will contribute towards the local learning theory and secondly, to understand a) how the design features are useful to solve the estimation problem, which will contribute towards design principles and b) design limitations, which will contribute towards design refinement. Since this was the first study, we only evaluated the first theoretical conjecture (Section 6.3.1) related to the novice estimation problem solving to obtain good estimates.

7.1 Methods and Materials

7.1.1 Research Questions

The broad research question was "How do novices do estimation in MEttLE1.0?" and the specific research questions were,

RQ4a What is the novice process of solving an estimation problem in MEttLE1.0?

RQ4b How do novices use the features in MEttLE1.0 to solve the estimation problem?

7.1.2 Estimation Problem Used

The problem given to the novices was designed so that the underlying conceptual knowledge was appropriate to second and third year engineering students of Electrical, Electronics, Mechanical, Chemical, Civil and Aerospace departments. The context was selected such that it would be relatable, motivating and engaging for novices. The designed problem was evaluated and revised based on the suggestions of the expert instructor, EI. The final problem included in MEttLE1.0 was

> You are participating in an electric car race in which you are required to design an electric car of weight 7kg with wheel diameters of 4" that can accelerate at $1\frac{m}{s^2}$ and traverse a track of 10m without burning out. Estimate the electrical power needed to achieve this performance and the specifications of the motor you will need.

7.1.3 Research Design and Participants

We performed a lab study and participants were eleven novices (one female) from second year undergraduate engineering programs, eight from Mechanical Engineering and one each from Aerospace Engineering, Chemical Engineering and Engineering Physics. They were selected by purposive sampling in order to include different backgrounds and increase the chance of observing diverse behaviours. So participants were selected from two different institutes. Further, we selected participants who had participated in non-curricular technical activities such as engineering design competitions. The reason was that we wanted students who would be interested in solving real-world engineering problems as we did not want lack of interest to be a confound in our study. The average age of learners was 20 years and they were familiar with the use of computers through other courses and labs in their curriculum. One participants' data was not used as the audio recording was not clear.

7.1.4 Procedure

The overall procedure for the research study consisted of the following steps:

1. Initial briefing: We briefed participants about the study and its objectives and obtained their consent for recording their audio, video and computer screen.

2. Pre-test: Participants independently solved an estimation problem on paper and were allowed as much time as they needed to solve the question. The problem given to the learners was the same one used in Study 2:

   > You are participating in a competition in which you are required to design an electric car of weight 5kg with wheel diameters of 5” that can accelerate at $1ms^2$ and traverse a track of 25m without burning out. Estimate the electrical power needed to achieve these specifications.

   We chose this problem because we had already validated it from an engineering instructor and it requires the same concepts as the problem they would solve in MEttLE.

3. Interaction with MEttLE: Participants interacted with MEttLE and solved the estimation problem mentioned earlier. During this interaction they were not allowed to use the Internet. However they were free to use all the resources in MEttLE all the time and ask the researcher any questions regarding how to use the resources MEttLE.

4. Individual semi-structured interview: After the interaction, we interviewed learners using a stimulated recall protocol wherein their screen capture was played back to them and we asked them to describe what they did at each point in the solving process and reasons for their actions. In addition, we asked them questions about the nature of estimation and the estimation process.

7.1.5 Data Sources

We collected multiple sources of qualitative data in order to examine novice performance including

1. Screen captures: Their interactions in MEttLE1.0 were captured using the screen capture software CamStudio (http://camstudio.org/).

2. Video recordings: In order to record any action that the participant took outside of MEttLE1.0 such as writing on rough paper we had a video camera focussed on their task area.

3. Researcher observations: The researcher recorded unstructured observations while the participant solved the problems, marking events which would require elaboration in the

follow-up interview.

4. Participant generated artefacts: This included any written solutions to the problems and anything else they wrote as part of their rough work, if any.

5. Retrospective think aloud (stimulated recall) interviews: We interviewed the participants immediately after they had completed the problem in MEttLE1.0 using a semi-structured interview protocol and showing them their video and screen capture if their memory needed to be stimulated. The goal was to have them describe their thinking while solving the problem and reasons for the actions that they took. So we required them to explain and elaborate their actions at several points, how they used each feature in MEttLE1.0 and what they learned. Some sample questions are shown in Appendix C.

7.2 Data Analysis

We conducted the pre-test in order to assess novices' conceptual knowledge, rather than estimation performance. So we assessed their solution based on the accuracy of the concepts and equations used in the problem. If a participant had used the correct equations and concepts to solve the problem they were assessed as having high conceptual knowledge, while participants who applied incorrect equations and concepts to solve the problem were assessed as having low conceptual knowledge. Based on their pre-test performance we found that S1, S2, S3, S4 were high conceptual knowledge novices and S5, S6, S7, S8, S9, S10 were low conceptual knowledge novices. Next we examined the estimation performance and process in MEttLE1.0 of each category of novices (high and low conceptual knowledge) separately.

In order to assess participants' estimation performance in MEttLE1.0, we used the product criteria defined in section 5.4.2 namely,

1. Estimate is of the right order of magnitude.

2. The important parameters which affect power in the system are identified.

3. The appropriate equation for power is written

In order to understand the novice process of estimation (RQ4a) we performed interaction analysis and the to understand the role of the features in the estimation process (RQ4b), we used thematic analysis. We used the participants' screen captures and their interviews together to perform the analyses with the following steps:

1. Familiarizing with the data: The researcher read her observations, looked at the participants artefacts and rough work, skimmed through their screen captures and listened to their interviews to get a preliminary understanding of their overall process. This familiarization also helps to understand what kind of actions need to be transcribed and what should be the "unit of transcription", ie, in terms of length of time or activities done.

2. Transcription: The researcher annotated the screen captures of the novices using "Elan" (https://tla.mpi.nl/tools/tla-tools/elan) in terms of the actions done in each page of MEttLE1.0. The actions include reading, typing, clicking, changing values (slider or radio buttons), dragging and dropping, drawing, adding, deleting and editing nodes and links in the causal map. At this point, when the screen was idle for more than 30seconds, we looked at the participant video to check if they were doing any off-screen actions and annotated them as well. An example of a transcript is shown in Figure 7.1.

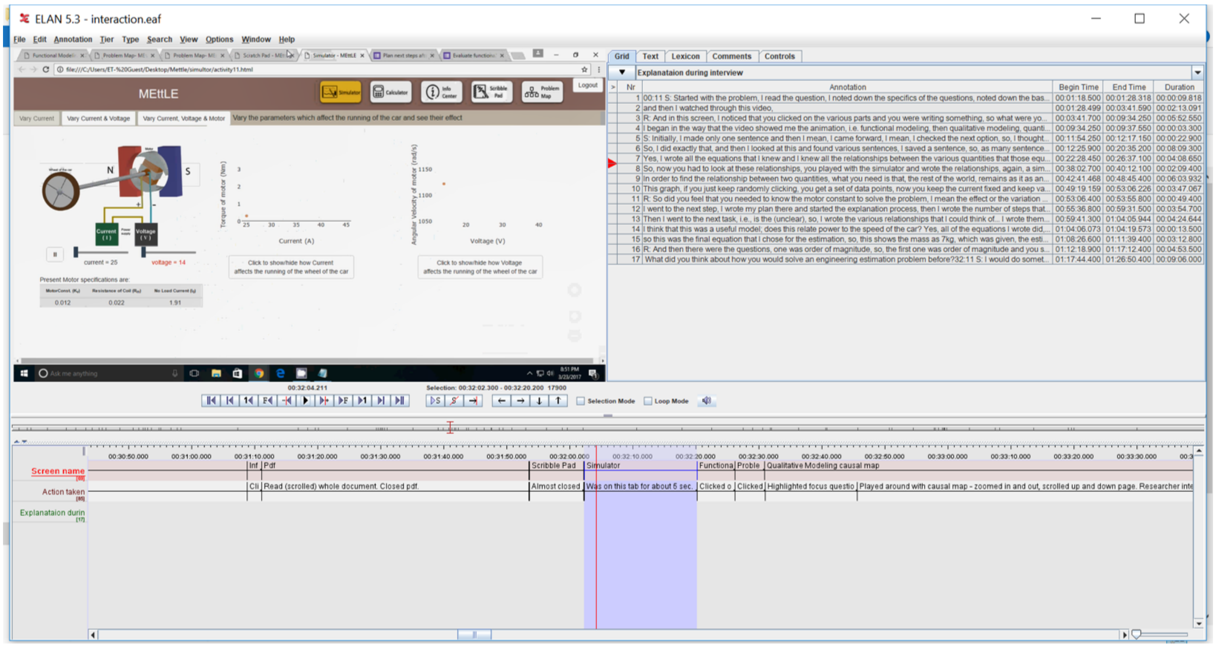


Figure 7.1: Interaction analysis method for Study 4

3. Creating workflows: The researcher transcribed the participant interviews verbatim. Next we interleaved the on-screen actions and the interviews together to create each participants' workflow. This was the flow of events as it happened and there was no inferencing at this point.

4. Abstraction of Process: We used each sub-goal of estimation as an *"ethnographic chunk"* (Jordan & Henderson, 1995) as we applied the *"analytic focus"* of *"the structure of events"* as defined in (Jordan & Henderson, 1995) to guide our analysis. In the created workflows, we focussed on the interaction between the participant and the features of MEttLE1.0 during each task. Using their actions and reported explanations for their actions we were able to abstract their process during each task and thus their overall process. When they returned to a task after the first pass through it, it was considered a separate event. In the process, we searched for two event patterns that we knew from our expert-novice studies were desirable for good performance,

   (a) Model -> Evaluate -> Fail -> Revise

   (b) Calculate -> Evaluate -> Fail -> Revise

5. Identifying role of features: To identify the themes related to the roles of the features of MEttLE in their process we began by coding their workflow in terms of the purpose that each feature was serving in the novice process as shown in Figure 7.2. The initial codes emerged from the data and we did not apply any theoretical framework to view the data. We generated initial codes across the entire data set and collated related codes into categories and themes. Next, we reviewed the themes against the raw data for consistency and generated an analysis map. Finally we refined our themes by examining their details and created clear descriptions of them. The codes and themes were revised by constant comparison until a final set of themes of the role of the features in estimation problem solving emerged.

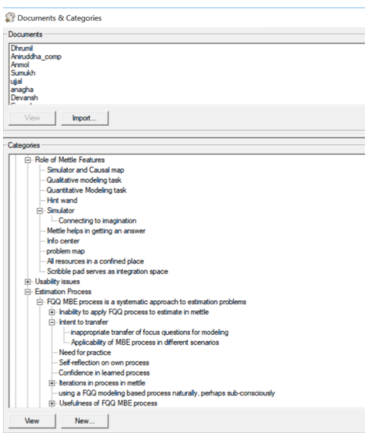


Figure 7.2: Thematic analysis method for Study 4

6. Ensuring validity: The data was viewed multiple times collaboratively by two researchers (the researcher and a colleague), comparing inferences and themes against each other and refining them during each pass. This way we were able to ensure the validity of our inferences regarding participant processes and the roles of designed features in the process.

7.3 Workflow in MEttLE1.0

We describe the workflow of S5, who had medium conceptual knowledge as an illustrative case of estimation in MEttLE1.0. Broadly, S5 solved the estimation problems by doing the sub-goals in the sequence functional, qualitative and quantitative modelling, followed by calculation and evaluation. He revised his models when he decided that the evaluation criteria had not been met. Finally based on the numerical evaluation criteria, he revised his equation and estimate as seen in Figure 7.3.

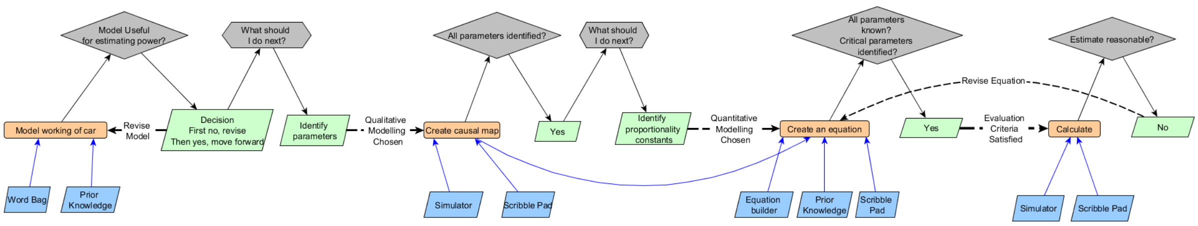


Figure 7.3: S5's workflow in MEttLE

After reading the problem in MEttLE, S5 watched the video which describes the Estimap and the five sub-goals of the estimation problem. He went forward to the detailed Estimap page and clicked and explored all the sub-goals and tasks in the map. He used the Scribble pad to take notes regarding what needed to be done in each task and wrote down preliminary answers to the focus questions of the modelling tasks. For instance, he created a rudimentary causal map depicting the relationships between power, torque, angular velocity and "safety limits".

It is interesting that though neither the video nor the Estimap specify an order in which the tasks should be done, S5 wrote down his sub-goal sequence as Functional Modelling, Qualitative Modelling, Quantitative Modelling and then Calculation. He reported that, it made sense to him that understanding the working principle first would make identifying the parameters that affect power easier. Hence functional and qualitative modelling needed to be the first two steps.

Further, when he tried to apply the sub-goals given in the Estimap to the example problem in the video "Estimate the power of the human heart.",

> *"I kind of got that idea from how, I could relate it to the blood pressure flow, and then I realized that getting an idea of what is exactly going on in the process would be more important than formulating the equations."*.

For S5 the focus questions of each modelling sub-goal served as a trigger that nudged him towards functional modelling first. He created a model in response to the focus question, "How does an electric car run?" using the words given in the word bag. He reported that the word bag helped him understand the components of an electric car and how they are connected. After creating the model, he evaluated it and because he felt that it was not clear enough regarding the source and user of power, he rewrote the model as,

> *"Car contains a battery which supplies power in the form of electric current to the motor. The motor rotates and generates RPM. Gears are connected between motor to wheel to provide sufficient amount of torque.The drive is then given to the wheels which accelerate the vehicle."*

While there are some conceptual inaccuracies, it is a rich description of how a car works and he reported that he was visualising how a conventional car works and trying to extrapolate it to an electric car. Next, S5 wrote down his plan to identify the parameters involved and their relationship to power and answered the model contextualization question regarding which performance requirements would dictate the power requirements. His response shows that he thought of the performance of the car in abstract rather than in the problem context.

Next, S5 moved to qualitative modelling and systematically explored all the parameters and graphs in the simulator by varying each parameter one by one and made note of the relations on the scribble pad. He related power to voltage and current and then to the other parameters of torque and angular velocity (see his causal map in Figure 7.4). He reported that initially he had only thought of the mechanical power and the factors that affected it, but after interacting with the simulator he realized how the mechanical parameters are related to the electrical parameters as he reported,

> *"Simulator actually helps you to think about the actual situations as in, if the motor is rotating and you have an independent current supply and an independent voltage*

supply and you're actually varying the current, then you are able to think what is the effect on the output parameters and if that is not present, I will have to go through a series of long procedures to identify that current is inversely proportional to RPM or so. So, that helped me to deduce that part quickly."

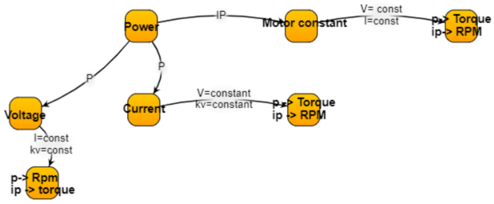


Figure 7.4: S5's causal map

While identifying the relationships between parameters, S5 was simultaneously creating the equations for them. He felt that qualitative and quantitative modelling cannot be separated as one automatically leads to the other. Next he evaluated that he had identified all the relationships in the causal map and wrote down his plan to identify the proportionality constants in the relationships he had identified.

Next S5 used the parameters and mathematical operators given in the equation builder to verify the validity of the equations he had already created ($P = k * I * VKm$ and $P = k * vtd$). The evaluation questions guided him to modify his equation in terms of the parameters that were important in the problem context. Note that even though the second equation is in terms of parameters given in the problem, it is incorrect. At this point the model contextualization question related to identifying the critical parameters and assumptions. S5's responses show that he was unable to judge what is a critical parameter and what is not. While he was able to recognize that he was making approximations by ignoring friction and air drag, he was unable to properly justify why these assumptions were valid.

Next S5 used the simulator, his qualitative model, his notes on the scribble pad and paper to calculate the constants in the power equation. Then he substituted the given data and determined power. Here he again observed that he was making the assumption of using the maximum velocity but was unclear as to why it was a valid assumption. He spent a long time determining the constants and used the simulator extensively, effectively trying to find the equation of the graph relating torque and current, and angular velocity and voltage by curve fitting. This was an unintended use of the simulator.

Finally he evaluated his estimated power by the two standards of order-of-magnitude and comparing with known values and his self-assessment showed that his value was incorrect. He went back and checked his equation and realized that he had included one incorrect relationship in his equation. He corrected that, re-calculated the constants and the power estimate and this time he evaluated his value to be correct. The last step was the reflection activity in which S5 described his estimation process as

> *"Identifying the working principle helped me think about the parameters affecting the power output. Earlier I was not able to formulate the effect of voltage and current. Using the simulation and graph plots I was able to identify the effect of these two and their relation with the parameters given in the problem statement.Evaluation was necessary in order to get an idea of whether the track of thinking i chose was rigth.It pointed out the error and made me look at my formulation again."*

During the interview he reiterated the importance of the first modelling stage and when probed as to why he chose that sequence he said,

> *"I don't know why but that sequence seemed important to me, following the functional modelling and then it felt like it was a natural flow of thinking,"*.

7.4 Results

To answer RQ4a, we examine the effect of the sub-goal structure along with their focus questions, the Estimap and the metacognitive scaffolds, as these were the salient features that decided the estimation process of the novices. To answer RQ4b, we focus on how learners used the modelling questions and affordances, the simulator and the metacognitive prompts as these are the salient features for solving the estimation problem.

7.4.1 Answering RQ4a: A modelling-based process is applied to solve estimation problems in MEttLE

We found that, in MEttLE, five out of ten participants obtained an estimate of the right order of magnitude while the others obtained an estimate one magnitude higher (four) or one magnitude lower (one). The data showed that the five participants who obtained estimates of the right order of magnitude also identified all the parameters affecting power and created a complete equation, except for considering the motor efficiency. Finally they were able to choose appropriate values as per the problem requirements and obtain an order of magnitude estimate. On the other hand, the remaining participants who did not obtain an estimate of the right order of magnitude, also identified the right set of parameters affecting power and had complete equations except for considering the motor efficiency. However they were unable to incorporate the problem requirements properly in their equation. These novices used the simulator to choose values to plug into their equation and calculate. However they were unable to relate the values in the simulator to the problem requirements.

In MEttLE, we presented the estimation process as a set of five sub-goals, each with a specific focus question. However the sequence of sub-goals was not prescriptive and decided by the students. Novices watched the introductory video and then chose their sub-goals using the Estimap. They reported that the sub-goal structure depicted in the Estimap (Figure 6.5), along with the focus questions of each sub-goal, made the choice of sub-goal easier. As described by S1,

> *"So, I went through this [pointing to Estimap] so I knew that evaluation needs to be the last and so ...functional modelling was something which I found to be the best part to start with because you need to know how a car runs. Before solving a problem I should know that. After that the qualitative and then the quantitative and the calculation and evaluation."*

Although MEttLE was not prescriptive in the sub-goal sequence, when faced with all the options of possible sub-goals, novices recognized the importance of beginning with a model of the working of the car. As a result, all novices chose to begin with functional modelling because it made sense to them that understanding the working principle first would make identifying the parameters that affect power easier. As S7 reported,

> *"I didn't do it before, but you should know the concept what you are actually doing, you should know that before you actually solve the problem, and you should first analyse it qualitatively, like the relationships and all, that's actually one of the most important things to do and if we just look at it as a problem and just go through the quantitative part, that way I don't think it'll be as beneficial as it was today."*

Thus the task structure in MEttLE seeded the modelling and mental simulation process among novices and we found that all novices broadly followed the path of functional modelling, qualitative modelling, quantitative modelling, calculation and evaluation. Even though some novices made errors during modelling and had to iterate between the sub-goals and their tasks until they obtained a reasonable estimate, they recognized the utility of this sequence. When asked why he chose this sequence in MEttLE S5 reported

> *"The sequence, I don't know why but that sequence seemed important to me, following the functional modelling and then it felt like it was a natural flow of thinking, that is, first you identify what is the model, then you identify what are the parameters involved in that, then you try to formulate your required output along with the parameters, then you calculate and then compare and then evaluated an iterate it till you get a good estimate."*

Novices reported that they were unaware of this sequence before working in MEttLE; however they may have been implicitly solve problems in this sequence, although they would often skip steps. Novices also reported that MEttLE made the process explicit for them and so they shifted to the progressively higher order modelling estimation process. We argue that the structure of the Estimap, with five sub-goal options only, all of which needed to be done in some order, along with their focus questions, provided the complementary mechanisms of structuring and problematizing, which helped students recognize the sequence that would be useful in solving the problem and made the progressively higher order modelling-based estimation process intuitive and easy to follow. Next we report the process of high and low conceptual knowledge novices separately.

Process followed by Novices with high conceptual knowledge (S1, S2, S3, S4)

The estimation process of high conceptual knowledge learners in MEttLE is shown in Figure 7.5. The top series of rectangles (tasks) indicates the flow of their process. The grey rectangles are modelling tasks, while the yellow rectangles are metacognitive tasks. The rectangles at the bottom indicate the cognitive/physical resource(s) that was used to do the task. The thickness of the arrow connecting two rectangles is representative of the number of times this connection was observed. The thicker the line more often this path was observed in the data.

In functional modelling, novices described the working of the car, evaluated that they had considered where power is used in this system and revised their model if necessary (S4). Then they moved to qualitatative modelling, wherein three out of four novices (S1,S2,S4) created partially complete causal maps, considering either only the mechanical or the electrical working of the car. However the part that they created was accurate. Their evaluation of the model was incomplete but they moved on without realizing it. In quantitative modelling, they all created correct equations for mechanical power only, without considering efficiency. Here the evaluation focussed their attention on an implicit problem requirement (maximum velocity attained by car) on the basis of which they revised their equation if necessary (S1). Next they substituted reasonable values and got an estimate of power.

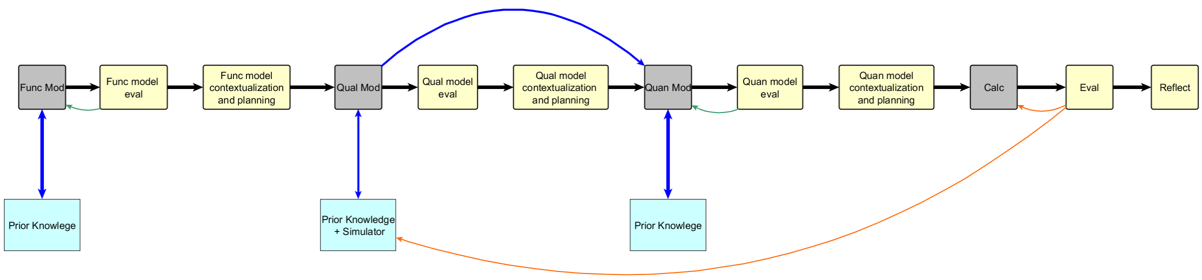


Figure 7.5: Estimation Process of High Conceptual Knowledge novices in MEttLE

All four obtained estimates of the right order of magnitude since the factor which they had ignored (efficiency) is high enough in this case not to affect the order of magnitude of electric power. However, except S4, neither of them reported that they had ignored the efficiency factor. These novices relied primarily on their prior conceptual knowledge to solve the problem as seen in Figure 7.5, using the simulator only to verify their models. Further they integrated the problem requirements into the solution at the end (in the equation) and thus did not contextualize their models at each stage. Their process shows very few desirable action patterns as seen from the Figure 7.5, ie, they did not revise their models/numerical estimate when their evaluation failed, because they did not recognize that the evaluation criteria had not been satisfied.

In summary, these novices followed an enaction-freezing process for estimation; however they did not satisfy all the criteria for good estimates because they did not do contextualization, evaluation and revision at each stage.

Process followed by novices with low conceptual knowledge (S5, S6, S7, S8, S9, S10)

The estimation process of medium conceptual knowledge learners in MEttLE is shown in Figure 7.6. In functional modelling, these novices wrote rich descriptions of the working of the car. However they were all unable to evaluate how power is generated and used in the system. In qualitative modelling, S5, S6, S10 created complete and accurate causal maps with all parameters affecting electrical power identified, while S7, S8 and S9 had accurate but incomplete maps with only some of the parameters related to each other. In quantitative modelling, S6, S7, S8 and S9 created correct equations, separately for electrical and mechanical power, without relating the two. S5 and S10 related electrical and mechanical power, but their relationship was inaccurate.

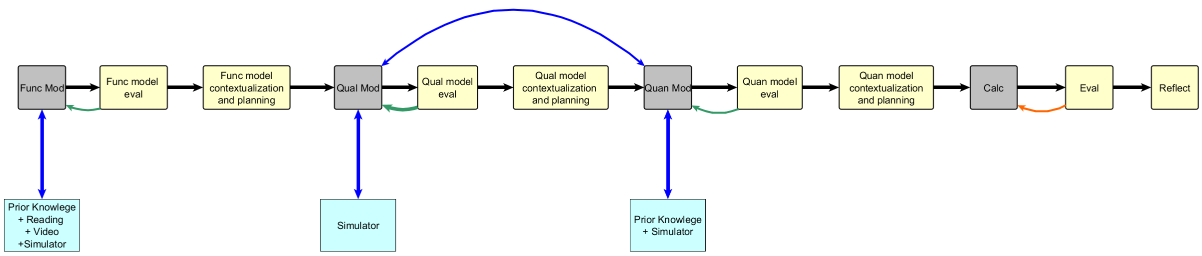


Figure 7.6: Estimation Process of Low Conceptual Knowledge novices in MEttLE

All novices evaluated that their equation had power related to the velocity of the car. These novices attempted to integrate the problem requirements into the equation, but except S9 none of the novices was able to substitute reasonable values and get an order of magnitude estimate for power, even though similar to the novices with high conceptual knowledge, he only calculated mechanical power and ignored efficiency without justification. S5, S6, S7, S8 and S10 were unable to choose reasonable values and obtained estimates off by one magnitude. These novices attempted to obtain data regarding voltage and current needed to meet the requirements of the car from the simulator and directly estimate electrical power. However, they made mistakes in choosing appropriate values and so did not obtain an order of magnitude estimate. Their process shows some desirable action patterns as seen in Figure 7.6; they recognized that the evaluation criteria had not been satisfied and attempted to revise their models, but were unable to do the revision appropriately.

In summary, these novices followed an enaction and freezing process, but were unable to satisfy all the criteria of good estimates because they did not do the model contextualization and revision well.

Comparison between expert and novice performance

In study 1 we found that there is a very strong coupling between all the phases of modelling of the expert process and we found that experts fluidly went back and forth between the phases while doing estimation, with the problem context as the integrating consideration. However we did not observe this behaviour among novices doing estimation in MEttLE1.0. Specifically, we observed that even though novices did functional, qualitative and quantitative modelling, they only iterated back and forth between qualitative and quantitative modelling using the simulator. Even though novices perceived functional modelling to be important, it was not for the designed purpose of problem space expansion. So they did not build upon their functional models to make qualitative and quantitative models, rather they used the functional modelling as a way to understand the system as reported by S3,

> *"As I told you the first thing, in the functional learning, they mentioned all the components, which will be governing, so, from that, because, in that way, I was not thinking about the motor or anything, I was just thinking what the car, like there's a big car, it's accelerating and I just have to find Fv, but, do to those, then I started thinking, deeper into the car and so, I went through that, so that I think was a big thing that was helpful"*

In the qualitative modelling novices identified the parameters affecting power and in quantitative modelling they created an equation incorporating all the identified parameters and conceptual knowledge. Finally, they substituted values into the equation and obtained an estimate. The simulator supported the mental simulation process among novices as reported by S8,

> *"I already established the how acceleration is taking place, but then with respect to current, it [simulator] supported me because I was able to imagine that how it is changing when I change the voltage or current parameters."*

Summary

Novices did estimation by a modelling-based process in MEttLE1.0, but did not expand the problem space during functional modelling and did not do model evaluation, revision and contextualization well, as a result of which their models were not contextualized and estimates did not satisfy all the criteria of goodness. Recall that our first theoretical conjecture stated that, "If an individual student creates contextualized functional, qualitative and quantitative models, calculates and evaluates the numerical values, and writes planning and monitoring statements he/she will be able to produce good estimates of a physical quantity." Thus our data does not support our theoretical conjecture because novices did not create contextualized models in MEttLE1.0. Instead the data indicates that the design conjectures are not supported because novices are unable to create contextualized models using the designed features. In the next section, we examine which features of MEttLE supported novices in estimation and why certain challenges remained as a result of which they were unable to obtain good estimates.

7.4.2 Answering RQ4b: "How do novices use the features in MEttLE to solve the estimation problem?"

Modelling Questions and Affordances

All novices used the modelling questions (focus questions, model evaluation questions and model contextualization questions) and affordances to create the functional, qualitative and quantitative models and MEttLE supported a diverse set of productive actions for each phase of modelling. In functional modelling, novices used the words (components, parameters, actions and behaviours), the information resources and simulator given in MEttLE in order to create the model, which they refined based on the model evaluation questions. Half of the novices (S1, S2, S3, S4, S5) used their prior experience of cars, their imagination of how a car works along with the set of words given to create a complete and useful model. Other novices (S6, S7, S8, S9, S10) read the material given, watched the video and explored the simulator in order to effectively use the words to create a complete and useful model. In qualitative modelling, novices created a causal map describing the relationships between power and the parameters which might affect it via multiple interaction paths. Some novices (S1, S3) used their conceptual knowledge to create a causal map, while other learners explored the tabs in the simulator, changed the variables and observed the graphs in order to create the causal map. Low conceptual knowledge novices often iterated between modelling and evaluation, all the time using the simulator in order to create a comprehensive causal map capturing the relationships between power and all the electrical and mechanical parameters.

In quantitative modelling, novices were given a set of parameters and mathematical relationships in MEttLE. In addition, their causal map, the simulator and information resources were available to them. The strategy used by high conceptual knowledge novices (S1,S2,S3,S4) was to look at their causal map and apply conceptual knowledge to create an equation. Another strategy (S8, S9, S10) was to use conceptual knowledge and the given parameters to create the equation and the simulator to verify the validity of the equations. This was described by S10,

> *"This is one of the best parts, I can say because I had all the parameters that I needed, this helps me out that I have to build an equation from this parameters because the others aren't that necessary, these are the most important parameters, and in a way I thought of voltage and current because only given in the parameters, otherwise only going the direction of mechanical power, but then with these parameters, I realized that I need to link it with the voltage and current required."*

The third strategy (S5, S6, S7) was to create an "empirical" equation for power using the graphs in the simulator and verifying it using the given parameters as described by S5

> *"Yeah, but I actually didn't know about the formulae relating I, tau and omega. (...) I didn't have an idea, so I had to think, create an idea from the data that was given in the simulator."*

Regardless of the strategy, novices were able to create an equation for power in terms of mechanical and electrical parameters. Some novices (S5, S7, S9, S10) did qualitative and quantitative modelling together, creating the equations as they identified the qualitative relationships and felt that the two cannot be separated as S7 said,

> *"When you make some changes, like to apply readily, you have to shift; you can't just do everything qualitative and then after that do the quantitative formula. So I was doing it simultaneously like if you found something, apply it somewhere. And actually, I wrote it in the scribbled notes also, the relations that I found, I tried to make the formula and also I wrote it in the notes section."*

Thus we see that the modelling questions and affordances allowed novices to create useful and complete functional, qualitative and quantitative models via different interaction paths. Depending on their conceptual knowledge and via their preferred interaction paths, novices were able to create the progressively higher order models and solve the estimation problem.

Simulator

The primary purpose of the simulator was to facilitate novice visualization and simulation of the behaviour of the problem system and identifying the qualitative relationships between various parameters, since we conjectured that novices will have difficulty doing this via mental simulation. Novices recognized these benefits of the simulator; the simulator provided a visualization of the effect of different parameters on the behaviour of different parts of the system as mentioned by S10,

> *"Like for such cases, I feel that we need to have some visualization about it, like in this we got a simulator, by which I was able to visualize how it is changing the different parameters, so, same way for solving a problem, we need to have a visualization or some factor that helps you that my this parameter is being affected by so and so parameters, so, it helps you to establish some relationships between the two."*

Further novices also reported that initially they had only thought of the mechanical power and the factors that affected it, but after interacting with the simulator they realized how the mechanical parameters are related to the electrical parameters. Articulating this S5 reported,

> *"That would have been a little difficult to identify as in you are saying that current correlation with torque and that would have been a little difficult to identify because we don't have any prior experience, working with motors, that much."*

While creating the causal map, some novices followed a systematic approach, varying one variable at a time, observing the changes and making notes; others were less systematic in their exploration and explored only a few variables and tabs before creating the map and then revising the causal map based on the model evaluation questions. We observed multiple additional uses of the simulator by the learners. Firstly, novices used the simulator to create equations after identifying the qualitative relationships. Secondly, novices used the simulator in the quantitative modelling stage to "curve fit" an equation for power using the various graphs shown. In this manner, the simulator served as a bridge enabling students with low conceptual knowledge to do estimation. The third use by novices was to directly read off from the graphs in the simulator the motor parameter values (e.g., current) that would give them the required mechanical performance parameter value (e.g., acceleration). This is standard design practice and expert engineers often use data sheets of components for the same purpose. However novices were unable to choose the appropriate values from the simulator. Finally, novices also used the simulator to evaluate their final estimate. This was a productive use of the simulator as evaluation is a good practice. **Thus the simulator served as space for integration across the sub-goals and to solve the larger estimation problem.**

Metacognitive Question Prompts

The model evaluation questions asked students to assess whether their models were useful and complete for estimation and revise if not. Further the model contextualization questions aimed at getting solvers to a) contextualize their models (for eg, which performance requirements of the car will dominate power requirements) b) assess whether their models were, in addition to being complete, simple and useful to get a good estimate (for eg, considering critical parameters only). Novices did this assessment and iterated their models based on the model evaluation questions. However novices' answers to the questions were incomplete and inaccurate. Their responses show that they do not know *how to judge* whether their models are simple and useful and how to consider the problem context in their models. This is because these judgments require a firm grasp of conceptual knowledge and skills such as comparison and decision making, which novices lack. Novices' responses indicate that their consideration was limited to parameters given in the problem, simulator and/or obvious parameters (e.g. friction), while failing to consider non-obvious, but possibly important parameters (e.g. drag). We found that novices had similar difficulties in assessing their numerical values. Most novices were unable to make judgments and comparisons with numerical values; their responses showed that they had very poor intuition for the numerical values and were unable to reason about them.

The planning questions (in the plan task) were intended as an integration activity to get novices to connect what they had done to what they will do next and learn how to monitor and plan their estimation process. However, we found that they did not entirely serve this designed purpose. Only S5 reported the purpose of planning task as,

> *"...the questions they told me to think of certain things in what I had done, so suppose it was functional modelling, then what I had actually done and what I can do in the next phase, so, what was lacking in what I had done, is addressed in those questions, what I am doing next helped me to link the two, like functional modelling to qualitative modelling, like I could relate the two because of the planning phase."*

Others perceived them as assessment or a hindrance to their estimation flow as reported by S1,

> *"...I would have thought that plan next steps is not necessary like I'm going in a particular way if I just follow it I'll just reach that place."*

For these novices, the Estimap and the set of focus questions supported the integration process rather than answering these planning questions.

The reflection activity was intended for novices to reflect on the steps in the estimation process, understand them better and abstract an estimation process applicable to other problems. It helped reiterate to novices the importance of first understanding the system working, as S6 wrote in response to the reflection question,

> *"Firstly I looked up at the theory related to the topic. Then, created a flow chart that gave a relation between all the parameters. Then created an equation that would satisfy the relations. Finally used the equation to find out the power for the given values of parameters."*

However, some novices (4 out of 10) either did not respond at all or responded superficially to the reflection questions, which showed that they did not think deeply about the role of each sub-goal and task in the estimation process. Still, when asked about the value of reflection during the interview, three out of these four novices reported that it was a valuable exercise as exemplified by S8 here,

> *"Yeah, the effect [of the reflection] was that I would actually know that whether I am using these steps while solving any problem in the future, I feel that these are the things that we generally do, but if we don't know these things step by step, you might end up skipping a step or maybe doing something that is not required."*

Thus, the reflection activity helped novices in abstracting and understanding the modelling-based estimation process.

7.5 Discussion

The goals of this evaluation were to explore how novices solved the estimation problem in MEttLE1.0 (RQ4a), and the role of the designed features in their doing of estimation (RQ4b).

Broadly, we found that novices used the modelling questions and affordances and the simulator in order to create and revise models while solving the estimation problem. MEttLE1.0 afforded a diverse set of productive interaction paths for each phase of modelling and the overall estimation process; it supported expert-like actions, such as using mental simulation (Kothiyal et al., 2016) to build a functional model and systematic use of the simulator to build a qualitative model, while also supporting novices who were unable to mentally simulate, by allowing them to use the conceptual knowledge and information resources in MEttLE1.0 in order to build models.

We found that novices used the three-phased modelling-based process to solve the estimation problem because they perceived it is a systematic and useful process to solve estimation problems. This was because of the five sub-goal structure (Reiser, 2004) provided in MEttLE1.0, which was based on model order progressions (Sun & Looi, 2013; Swaak et al., 1998) and the focus questions, which problematized the tasks (Reiser, 2004) by directing learners' attention on important aspects of modelling. Novices described the role of the Estimap in making the modelling-based process explicit and this is consistent with the benefits of external representations for process management documented in scientific inquiry (Quintana et al., 2004) and problem solving (Hwang et al., 2014). We argue that the design of Estimap, with five task options only and their focus questions, was a *productive constraint* that helped students discover a sequence that would be useful in solving the problem. As we elaborated in section 7.4, it was a constraint because learners had to choose one of the five tasks; it was productive because it highlighted the goals of each task and enabled learners to solve the problem.

The model order progression is a logical way to making the modelling of complicated systems tractable and is the typical manner in which scientific knowledge is generated (Nersessian, 2010). While iterations are desirable for evaluating and refining the models, based on our observations of experts, we know that there is a directionality bias towards beginning with functional modelling and mental simulation before going on to qualitative and then quantitative model building. In estimation (of power, for example), the role of functional modelling is generating various scenarios of the problem context that require power. One or few of these scenarios is then chosen because it (or they) dominates the power requirements. The power is then estimated in this scenario. Thus functional modelling is when problem space expansion happens, and this is important at the start of problem solving (Dennis et al., 1999). While it could be argued that MEttLE prescribes a structured progressive modelling process for solving an ill-structured problem, we argue that it is not prescriptive; novices may choose the path they wish to take depending on the problem. Indeed as some novices mentioned they would follow the three-phased process beginning with functional modelling for problems which had an unknown system, while they would prefer to go directly to equation building in the case of familiar problem contexts. In solving the given estimation problem in MEttLE1.0, we observed that novices focussed more on qualitative and quantitative modelling, perhaps because they perceived that the system was familiar and the functional model did not need to be revised. This is also consistent with expert behaviour (Section 4.1), wherein the first two phases of modelling were done implicitly when experts were faced with a familiar problem.

We found that the simulator served as a good tool for visualization and qualitative understanding of the system (Lindgren & Schwartz, 2009; Swaak & De Jong, 2001) which are necessary for the estimation process. In addition, the simulator was used in several unintended ways and we found that the simulator served as an integrator across the entire estimation process. This role is similar to experts who use mental simulation throughout their estimation process to create, evaluate and refine their models (Kothiyal et al., 2016). An issue that we observed with the simulator was that its availability drew some novices away from the main task and they spent a considerable time exploring it, trying to understand the relationships between all the parameters rather than doing the modelling tasks. Therefore we need to further investigate whether the simulator serves as "crutch" or a scaffold that can be faded. We also propose to provide a simplified version of the simulator rather than the current variable manipulation simulator for some parts of MEttLE.

Novices reported that the model evaluation, numerical evaluation and model contextualization questions provided periodically in MEttLE helped them recognize the importance of evaluating their models and numerical values. The nature of the questions guided them regarding what to evaluate, such as whether their models included critical parameters. This result is in agreement with research into the role of question prompts (Ge & Land, 2004) in ill-structured problem solving. However, novice responses to the questions were incomplete and inaccurate, indicating that they were unable to make the judgments required in the questions. This ability develops with experience and practice in solving problems with similar systems and comparisons with similar values (Linder & Flowers, 2001; Mahajan, 2014). As the question prompts were insufficient for novices to evaluate their models, explicit guidance of expert practice (Quintana et al., 2004; Sandoval & Reiser, 2004) at appropriate points maybe necessary for novices.

Finally, we had intended the planning questions to serve as integrators of the estimation process, helping novices keep track of their progress and plan the next steps. However most novices did not find them useful for this purpose, perceiving them to be assessment and choosing instead to hold their plan in memory, take notes in the scratch pad or use the simulator as the integrator. Hence we need to re-examine the need for these questions, perhaps incorporating alternate scaffolds for planning such as a checklist of possible tasks, a progress bar or a planning map.

A major challenge that we observed for novices was that when considering the system working, they were unable to break down the system into components, physically and conceptually and then relate the two parts to obtain a final estimate of power. In this case, the two parts are the mechanical and the electrical parts of the car, understanding of which was supported by the simulator. The running of the car requires some power (mechanical power) which is supplied by the battery (electric power). Conceptually, by conservation of energy these two ought to be equal, except for an efficiency factor, owing to losses in real systems. Novices of low conceptual knowledge (except S9), were unable to understand this point from the simulator. As a result, they attempted to directly estimate electric power and were unable to incorporate the given mechanical requirements from the car in their equation for electric power, as seen from their interactions in MEttLE. Thus after enacting and freezing they obtained an equation for electric power which was complete, but not simplified and useful, i.e., it was not contextualized for estimation. This issue will need to be addressed by redesigning MEttLE.

The sample size of this study is small, which is a limitation. However the larger goal of this evaluation is a rich and in-depth characterization of how novices solve estimation problems in MEttLE1.0, which features of MEttLE1.0 support them and how, and what is missing in their solving process because of which they are unable to obtain good estimates. The purpose is to identify how this solving process can then be made more productive by redesign. The current results reveal the solving process that happened in MEttLE1.0 and highlight the gaps in this mechanism for obtaining good estimates. In the next version of MEttLE, we will modify the design based on these results in order to improve novices estimation process and performance.

7.6 Reflection

As is the norm of DBR, we reflect on the results of our evaluation in order to develop theories of how estimation problems are solved, design principles for supporting estimation problem solving and what redesign of MEttLE is needed in order to improve novice estimation performance.

7.6.1 An emerging theory of novice estimation problem solving

Novices solved the estimation problem by following a two-phased model-based estimation process; they enacted the problem system to understand its working and build a functional model. The modelling focus question, simulator and word bag triggered the mental simulation necessary to enact the problem system and begin model-building; however they did not generate all the scenarios which would need power in a car and thus did not expand the problem space. They generated a single scenario for power requirement of a car and moved on to build qualitative and quantitative models based on that. Thus while novices moved away from their natural equation searching process, they still began estimation with a narrow problem space.

Next novices built, evaluated and revised qualitative and quantitative models. They used their prior conceptual knowledge, mental simulation and explored the simulator in order to identify the causal relationships underlying the power requirement of the car. The simulator supported both the mental simulation and conceptual knowledge integration necessary to build the qualitative models, by explicitizing the relationships between the various parts of the system and the parameters. Next novices used the parameter set in the equation builder, along with their causal maps as scaffolds to create an equation for power required by the car and freeze the problem system. Novices who were able to connect power required to the problem requirements (model contextualization) were able to substitute the relevant values and obtain good estimates, while those who were unable to contextualize their models were unable to do so. This points to the importance of model contextualization at each stage of solving estimation problems and obtaining good estimates. Also, we observe that despite beginning with a narrow problem space, some novices were able to obtain a good estimate for the given problem; however this may not always be the case and hence problem space expansion must also be better supported.

The results of study 4 show that MEttLE1.0 supported enaction and freezing, but not problem space expansion. Our theoretical conjectures were not supported; i.e. novices were unable to obtain good estimates by building and integrating conextualized models. This was because the design conjectures were not supported and novices were unable to use the features of MEttLE1.0 to build contextualized models. In the next section, we examine what redesign is required to support these processes among novices.

7.6.2 Redesign Required

As described in section 7.5, we identified that MEttLE1.0 supported novices in enacting and freezing the problem context using the three-phased modelling structure, but not in problem space expansion. Further, we found that while MEttLE1.0 supported novices in making complete models, they faced difficulties in simplifying them and making them useful, i.e. in contextualizing the models for estimation. Novices were unable to evaluate their models correctly, make revisions and iterate based on this evaluation. Therefore they were unable to obtain good estimates. Novices need additional supports to overcome the challenges described in Table 7.1. In the next version of MEttLE which we describe in the next chapter, we incorporated additional supports to overcome these novice challenges.

Novice Challenges identified from Study 4	Additional Supports Required
1) Inability to expand the problem space	Mental simulation and problem context-specific knowledge
2) Inability to simplify the model by breaking the system into physical and conceptual parts	Mental simulation and conceptual knowledge
3) Inability to simplify the model by identifying dominating parameters	Conceptual knowledge, comparison, decision making and practical knowledge
4) Inability to make useful models, i.e. models in terms of known parameters	Focus on requirements given in the problem statement
5) Model Evaluation and Revision	Focus on model evaluation criteria, conceptual and practical knowledge
6) Choice and Evaluation of Numerical Values	Standard values, comparison, decision making and practical knowledge

Table 7.1: From Novice Challenges to Redesign Required

7.7 Summary

Study 4 showed us that our theoretical conjecture (Section 6.3.1) was not supported. The three aspects of estimation, namely, the functional model, qualitative model and quantitative model, all of which come together seamlesslessly in an expert solution, did not integrate in the novice solution. This was because novices did not build contextualized models in MEttLE1.0. Thus our design conjectures were not supported and we need to revise the design to better support novices to build contextualized models.

Building contextualized models requires the interplay between mental simulation and conceptual knowledge, with the problem context underlying everything. It also requires practical considerations of the context, such as, what will dominate and what can be ignored. The next version of MEttLE has to provide additional supports to novices to focus on specific aspects of the problem, do mental simulation, apply conceptual knowledge, make comparisons and decisions, and gain and apply practical knowledge. In the next version of MEttLE described in the next chapter, we propose to address this by including additional scaffolds for supporting model contextualization and model evaluation.

Chapter 8

DBR 2: Design of MEttLE2.0, Evaluation and Reflection

In chapters 6 and 7 we described the design of the first version of MEttLE and the results of the evaluation study conducted to understand the novice estimation process in MEttLE1.0 and the role of the design in that process. We identified that novices chose a modelling-based process, building functional, qualitative and quantitative models and then determining the estimates. Further, we identified the roles of the modelling questions and affordances, the simulator, model evaluation and contextualization questions, numerical evaluation and planning questions on the novice estimation process. Finally we identified the challenges that novices continued to face in obtaining good estimates using MEttLE1.0. In the next section, we describe the changes made to support novices in overcoming these challenges.

8.1 Redesigning MEttLE

8.1.1 Instructor Recommendations for Redesign

In order to identify the scaffolds needed to support novices overcome the challenges identified in study 4, we began by returning to EI, our expert engineering instructor and practitioner, in order to understand how he would scaffold novices to solve estimation problems such as ours. We described the novice challenges listed above and conducted a semi-structured interview with the broad focus question “How can we help students solve problems such as this?” The interview was recorded and transcribed and below we list the specific suggestions that emerged from his responses.

1. EI believed that challenges 1,2,3,4 and 5 listed in Table 8.1 can be overcome by supporting the identification of parameters that affect power in the context by -
   - Getting students to draw force diagrams.
   - Providing question prompts, triggering mental simulation of the problem systems' working.
   - Scaffolding identification of concepts applicable to solving the problem.
2. EI believed that challenge 5 in identifying relevant numerical values and their evaluation stems from novices lack of experience which can be partially overcome by -
   - Providing real equipment data sheets.
   - Giving toy problems.
   - Providing set of values and asking them to choose.
   - Practicing on real-world "big" project.

8.1.2 How literature and data came together in the redesign

We integrated the recommendations from EI in section 8.1.1 along with suggestions from theory described in chapter 6 and chose additional pedagogical features to overcome novice challenges as shown in the Table 8.1.

The complete list of novice requirements to solve an estimation problem which have emerged from our work until now, the corresponding pedagogical features in MEttLE2.0 for each requirement, and their theoretical bases and justification is elaborated below. In the following section, we present the revised conjecture map and corresponding design and theoretical conjectures.

1. Process Management: For the purpose of exploring possible sub-goals in the estimation process and discovering the appropriate modelling sub-goals to be done, we retained the diagram depicting the sub-goal structure of model order progression (problem map) but revised the focus questions. This was informed by studies 2,3 and 4 which highlighted the need to explicitise and trigger modelling for novices and that the nature of the focus

Novice Challenges identified from Study 4	Additional Supports Required	Additional Supports Incorporated
1) Inability to expand the problem space	Mental simulation and problem context-specific knowledge	Additional animations of the problem context along with guidance of expert comparison practices
2) Inability to simplify the model by breaking the system into physical and conceptual parts	Mental simulation and conceptual knowledge	Change in modelling sub-goal focus questions and simulator design (focus on few aspects of system working at a time). Additional animations and graphs.
3) Inability to simplify the model by identifying dominating parameters	Conceptual knowledge, comparison, decision making and practical knowledge	Additional graphs in simulator along with guidance of expert reasoning and decision-making practices
4) Inability to make useful models, ie, models in terms of known parameters	Focus on requirements given in the problem statement	Small tasks within the model evaluation tasks focussing on problem requirements
5) Model Evaluation and Revision	Focus on model evaluation criteria, conceptual and practical knowledge	Additional question prompts and guidance of expert reasoning and decision making
6) Choice and Evaluation of Numerical Values	Standard values, comparison, decision making and practical knowledge	Large set of standard values along with guidance of expert comparison practices

Table 8.1: From Novice Challenges to Redesigned Features

question affects the nature of the model built (Challenge 2 above). The theoretical basis for this feature is structuring and problematizing (Reiser, 2004) and the need for scaffolds for process management (Quintana et al., 2004). Specifically, it is known that model order progression supports model-building (Mulder et al., 2011; Sun & Looi, 2012, 2013).

2. Model-Building: A specific kind of conceptual knowledge constrained mental simulation needs to be triggered and scaffolded among novices as informed by studies 1,2,3,4 and EI (Challenges 2 and 3 above). So we included a multi-part problem system simulator with animations of the problem system, graphs of power requirements and separate variable manipulation simulations of parts of the problem system. The simulator also provides implicit guidance to incorporate problem context in the entire estimation process (Challenge 4 above). The design principles guiding this feature are, as in MEttLE1.0, discovery learning (Swaak & De Jong, 2001) and perceptual learning (Lindgren & Schwartz, 2009) with simulations.

3. Model-Building: In order to scaffold problem space expansion (Challenge 1 above) and functional model-building by triggering mental simulation of the working of the problem system and the generating various scenarios, we included fictive motion words related to problem context (components and behaviours) in the functional modelling sub-goal and multiple animations of the problem context. This was motivated by results of study 1 where we found that fictive motion words trigger mental simulation among experts and is based on the theory that fictive motion words trigger mental simulation (Matlock, 2004). Further, the words and animations serve as "interpretive support" (Reid et al., 2003) for identifying working of the system and generating various scenarios, as students have deficiency in context-specific knowledge.

4. Model-Building: In order to scaffold qualitative model-building and represent how various parameters affect power, we included a causal mapping tool in the qualitative modelling sub-goal, as we had found from studies 1, 2 and 3 that experts have a qualitative sense of the system, while novices have difficulty in this, but can be scaffolded using a causal mapping tool. The learning design principle underlying this feature is that knowledge representation such as schematic diagrams improve performance in problem solving (L. Martin & Schwartz, 2009).

5. Model-Building: To support novices in quantitative model-building and prompting them to use their causal map and prior conceptual knowledge to create an equation for estimation, we provided a set of parameters and mathematical relationships relevant to the given problem in the quantitative modelling sub-goal. This was informed by the results of studies 1 and 2 where we found that equation manipulation is required in solving estimation

problems. The underlying learning design principle is "Provide representations that can be inspected to reveal underlying properties of data. Enable learners to inspect multiple views of the same object or data" (Quintana et al., 2004) and providing "interpretive support" (Reid et al., 2003) for context-specific knowledge.

6. Evaluation during model-building: To prompt novices to examine whether their models for estimation are simplified and useful, we included model evaluation and model contextualization question prompts, along with guidance of expert estimation practices in the evaluation tasks of each sub-goal. This was informed by studied 1,2,3,4 where we found that experts constantly evaluate their models while novices do not and need to be scaffolded to do (Challenges 4,5 above). The guiding learning design principles come from the role of question prompts for evaluation (Ge & Land, 2004), providing opportunities for epistemic reflection (Sandoval & Reiser, 2004) and embedding "expert guidance about scientific practices" (Quintana et al., 2004).

7. Productive monitoring and planning: To support the integration of various sub-goals that novices do, reflection on tasks done and planning next tasks we included planning and monitoring question prompts. We learned from study 1 that experts plan their problem solving process and this scaffold is based on the guideline of facilitating "ongoing articulation and reflection" (Quintana et al., 2004) and the role of question prompts for reflection (Ge & Land, 2004).

8. Estimation reasoning and practice: To support novices in estimation reasoning and practice such as comparing and decision making during model building, evaluation and contextualization, planning the estimation process and numerical evaluation we included guidance of expert estimation reasoning and practices in the form of intermittent, on-demand "Guide Me" prompts and "Hints" in every task. The basis for this was the results of studies 1 and 4 and EI's suggestions specifically that novices need support in comparing and reasoning with values (Challenges 3,4,5,6 above) and the underlying learning design principle is "Embed expert guidance about scientific practices" (Quintana et al., 2004).

9. Estimation reasoning and practice: In order to get novices to select appropriate values and evaluate their reasonableness before calculating, we included a separate calculation sub-goal which required learners to choose and justify the values that they would use to

determine the estimate. This was informed by study 3 wherein we found that novices have difficulty selecting appropriate values and is based on the underlying learning design principle of "Facilitate ongoing articulation and reflection" (Quintana et al., 2004) and question prompts for elaboration (Ge & Land, 2004).

10. Estimation reasoning and practice: To trigger novices to consider whether their estimates are reasonable, of the right order of magnitude and compare them with known values, we included question prompts for evaluating numerical values and guidance for comparing. This was based on the results of studies 1,3,4 and EI's inputs that experts naturally evaluate their estimates while novices need support to do this. Again the underlying design principles are "Facilitate ongoing articulation and reflection" (Quintana et al., 2004), question prompts for elaboration (Ge & Land, 2004) and evaluating by comparison (Mahajan, 2014).

11. Productive reflection on process: To make novices reflect on the process they applied to estimate, its usefulness and applicability we included a separate reflection task with question prompts for reflection (Ge & Land, 2004) as recommended in literature, "Facilitate ongoing articulation and reflection" (Quintana et al., 2004).

12. Context-specific knowledge: To support novice understanding of the problem context using reading material, videos and animations and providing a set of standard values to plug into the equation and doing comparative evaluation after estimation, we included the feature of "Info Center" which contains information regarding the problem context and standard values for calculation and comparison. This was based on the findings of studies 1,2,3,4 and EI inputs that experts gather and use information about problem context and novices need support in this. Further, the ability of choosing and comparing values develops with experience, so providing a set of values to choose and compare from can scaffold this task (Challenge 6 above). The learning design principle informing this feature is to provide "Interpretive support" (Reid et al., 2003), annotated diagrams for understanding the problem system and videos for stimulating mental simulation process (Hegarty et al., 2003).

13. External representations: To encourage externalization for model-building via manipulation of preliminary mental models, we included the feature of "Scribble Pad" which is a

space for writing and drawing and is informed by study 1 where we found that experts build models by manipulating external representations such as drawings and flow charts. So we provided a space where novices could create and manipulate different kinds of external representations such as diagrams, equations and notes (Kirsh, 2013).

8.1.3 Conjecture Map of MEttLE2.0

Based on the designed features identified above, we revised our conjecture map as shown below in Figure 8.1. The rectangles in olive green indicate features that were revised in this version of MEttLE. However there were no changes in the mediating processes for estimation.

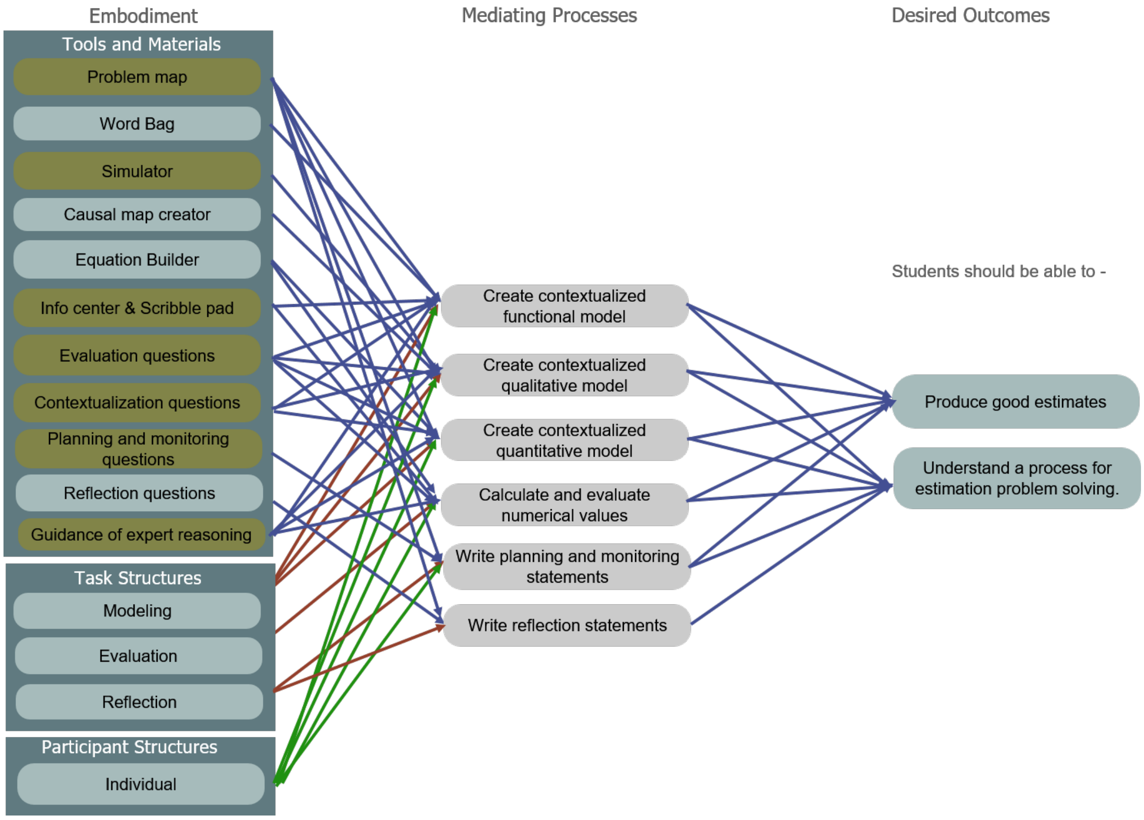


Figure 8.1: Conjecture Map of MEttLE2.0

The design conjectures for MEttLE2.0 are as follows,

1. If an individual student uses the problem map, the word bag, the info center, contextualization and evaluation questions, and guidance of expert reasoning to do modelling, he/she will be able to create a contextualized functional model.

2. If an individual student uses the problem map, the simulator, the causal map creator, contextualization and evaluation questions, and guidance of expert reasoning to do modelling,

he/she will be able to create a contextualized qualitative model.

3. If an individual student uses the problem map, the equation builder, contextualization and evaluation questions, and guidance of expert reasoning to do modelling, he/she will be able to create a contextualized quantitative model.

4. If an individual student uses the equation builder, information center, evaluation questions and guidance of expert reasoning to do evaluation, he/she will be able to calculate and evaluate numerical values.

5. If an individual student uses the planning and monitoring questions and problem map to do reflection, he/she will be able to write planning and monitoring statements.

6. If an individual student uses the reflection questions and problem map to do reflection, he/she will be able to write reflection statements.

Our theoretical conjectures, which we tested in study 5, remain the same,

1. **Conjecture 1:** *If an individual student creates contextualized functional, qualitative and quantitative models, calculates and evaluates the numerical values, and writes planning and monitoring statements he/she will be able to produce good estimates of a physical quantity.*

2. **Conjecture 2:** *If an individual student creates contextualized functional, qualitative and quantitative models, calculates and evaluates numerical values, writes planning, monitoring and reflection statements, he/she will be able to understand a process of estimation problem solving.*

8.2 Design of MEttLE2.0

8.2.1 An Overview of MEttLE2.0

Broadly Mettle2.0 has a similar workflow to MEttLE1.0 in that each estimation problem is broken down into five sub-goals, each with two or three tasks, which together lead to the estimate. Similar to MEttLE1.0, the sub-goals are functional modelling, qualitative modelling, quantitative modelling, calculation and evaluation. However in MEttLE2.0, we revised the model building process in order to help novices overcome the challenges 1,2,3 and 4 listed in 8.1. Specifically, we modified the modelling sub-goals as shown below,

1. Functional modelling: Novices identify the actions the system needs to do that require power and then focus on the actions that will dominate the power requirements according to the given problem requirements. The goal of this sub-goal is to get novices to expand and then narrow the problem space, and begin the process of building a simplified model.

2. Qualitative modelling: Novices identify all the parameters affecting power, then focus on the parameters which dominate the power requirements and the qualitative relations between power and those parameters. Thus the qualitative model is a simplified model.

3. Quantitative modelling: Learners use conceptual knowledge to create an equation connecting power and the previously identified dominating parameters, incorporating the inefficiencies of the system and making any other assumptions or approximations necessary. Thus the quantitative model is a simplified and useful model.

Similar to MEttLE1.0, the modelling sub-goals each consist of tasks of creating and evaluating the model, followed by monitoring and planning the estimation process. The other two sub-goals are calculation, in which the solver chooses and reasonable values and calculates the estimate and evaluation, in which the solver evaluates whether the calculated estimate is reasonable by two standards, namely correctness to the order-of-magnitude and comparable with known values. Once the solver has an estimate that has passed the evaluation criteria, they do the last activity of reflecting on the entire process. The TELE has focus questions and affordances for creating models, supporting resources such as animations, graphs and variable manipulation simulations, reading material, videos and a large set of standard values for problem context knowledge, question prompts and guidance of expert reasoning for model contextualization and evaluation, and finally reflection questions for planning and monitoring.

MEttLE2.0 has the following problem *"You are participating in an electric car race in which you are required to design an electric car of weight 5kg with wheel diameters of 4" that can traverse a track of 50m in less than 5 seconds. Estimate the electrical power needed to achieve this performance."* Conceptually, this problem is similar to the one in MEttLE1.0, except that the acceleration and velocity requirements are more ambitious than before. MEttLE2.0 is also an open-ended learning environment and students have agency to do the sub-goals in any order they believe useful to solve the problem. In addition they are free to iterate between the sub-goals and revise their models and estimates based on their evaluation. Thus novices create their own estimation path using the Estimap which is retained from MEttLE1.0. However, by introducing explicit guidance of expert practices, reasoning and decision-making processes, MEttLE2.0 attempts to induce a tighter coupling between the modelling phases and support the problem space expansion and narrowing, which was missing from novice performance when they worked in MEttLE1.0. The purpose is for novices to be able to iterate between and build on their models by using the feedback and doing model contextualization, evaluation and revision, thereby obtaining good estimates.

8.2.2 Features of MEttLE2.0

When a novice enters MEttLE2.0, he/she is shown an introductory text to estimation and its characteristics. Next they watch a video introducing them to the idea of breaking down a problem into sub-goals. This idea is further elaborated using the clickable problem map (Figure 6.5). Next, MEttLE presents the student with the estimation problem, followed by the problem map, from which they select one of five sub-goals to do, in any sequence they choose. The five sub-goals are: three modelling sub-goals namely functional, qualitative and quantitative modelling, each with the tasks of "create a model", "evaluate the model" and "plan next steps". Each of the modelling tasks includes a focus question and a modelling affordance. In addition there are the same set of tools as MEttLE1.0 available to the learner at all times namely, "Info Center", "Simulator", "Problem map", "Scribble Pad" and "Calculator". The features of MEttLE2.0 which are changed from MEttLE1.0 are described in detail below and screenshots of all features of MEttLE2.0 are available in Appendix E.

1. Modelling sub-goals: Each modelling task (Figure 8.2) is divided into three tasks namely create, evaluate and plan sub-tasks. The overall sub-goal has a focus question and each task has separate questions. The focus question for functional modelling is *"What are the dominant actions of the car that require power?"*, for qualitative modelling is *"What are the parameters that will affect the dominant power required?"* and for quantitative modelling is *"What is equation connecting electric power required to the dominant parameters?"* In addition, the create sub-tasks also have a modelling affordance. For creating a functional model, the affordance is a word bag containing a set of words describing

actions, behaviours, parts of the car and physical parameters. The modelling affordance for qualitative modeling is a causal mapping tool and for quantitative modelling it is a equation builder with a set of parameters that novices can choose from.

The evaluate sub-task has "model evaluation questions" for evaluating the functional models, such as, *"Have you considered accelerating and overcoming drag as actions that require power?"* and "model contextualization questions" for contextualizing the functional model, such as *"Which of your identified actions of the car do you think dominates its power requirements?"* Similarly, in the plan task there planning questions, such as *"What steps will you follow to determine power using this model?"* In order to answer the model evaluation and contextualization questions, novices had an option to use guidance of how to reason, provided as a "Hint/Guide Me".

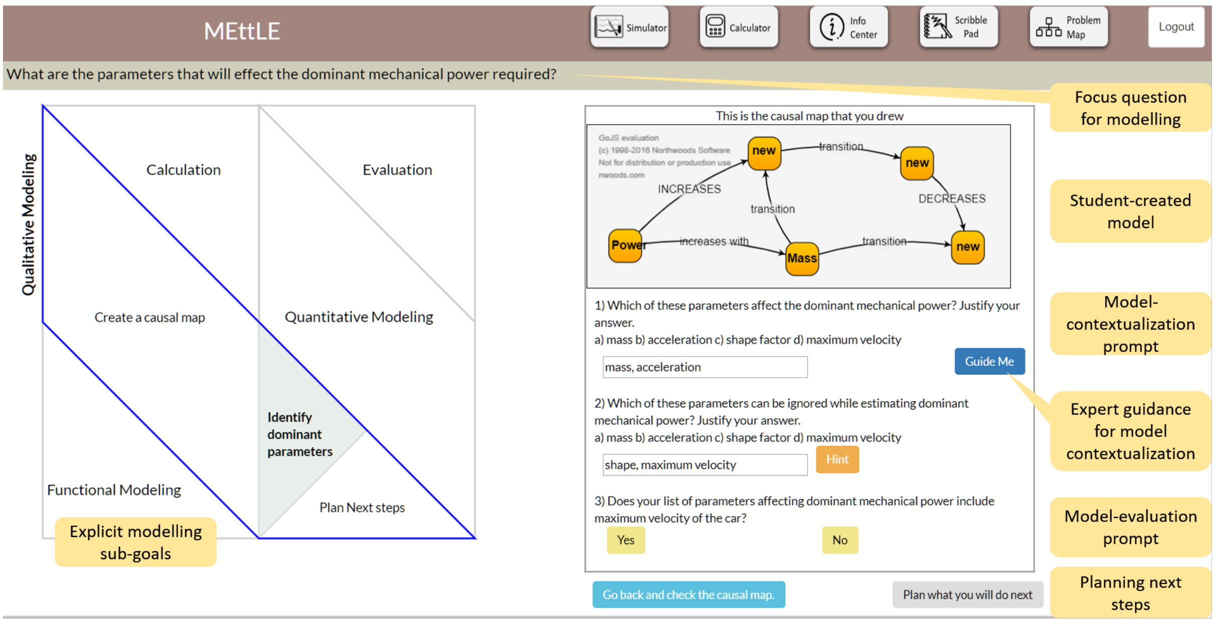


Figure 8.2: Example screenshot of MEttLE2.0

2. Evaluation task: In this task, the student evaluates whether their final estimate is of the right order-of-magnitude and comparable to other known values by answering questions such as, *"Priya and Mukesh are working on a project and propose to use the motor of an old mixie/blender to build this car. Will it be feasible? Explain how it might or might not be feasible."* The students are provided with guidance of how to do this comparison and a set of standard values are included in the "Info Center".

3. Simulator: The simulator in MEttLE2.0 consists of four parts. In the first part 8.3, as

recommended by the instructor to make students to draw force diagrams, we incorporated animated force diagrams that depict how the forces on the system change during its operation, under different scenarios. This focuses novice attention on the system actions that require power. In the second part 8.4, we included graphs showing the variation of power required for different actions that the system does, under various scenarios, to enable novices to experiment and decide which action dominates the power requirements. Together these two tabs support novices in expanding the problem space and then narrowing it by enacting the problem context. The third and fourth parts were variable manipulation simulations showing different perspectives of the problem system (wholistic 8.5 vs zoomed in 8.6), the parameters affecting power in the system and graphs showing the variation of power with each of these parameters. While the wholistic perspective is needed to understand power requirements, the zoomed in perspective is required to understand the relationship between power requirements and supply, and hence the concept of losses.

Figure 8.3: Simulator of MEttLE2.0 - Part 1

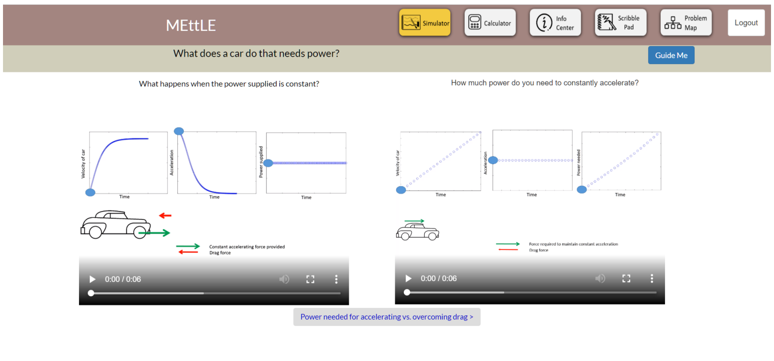


Figure 8.4: Simulator of MEttLE2.0 - Part 2

4. Info Center: This space has reference material for novices to familiarize themselves with the problem system. In addition there is set of values for determining the estimate, such as

Figure 8.5: Simulator of MEttLE2.0 - Part 3

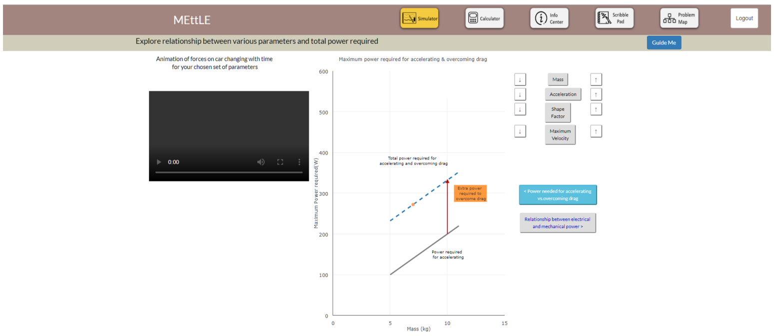
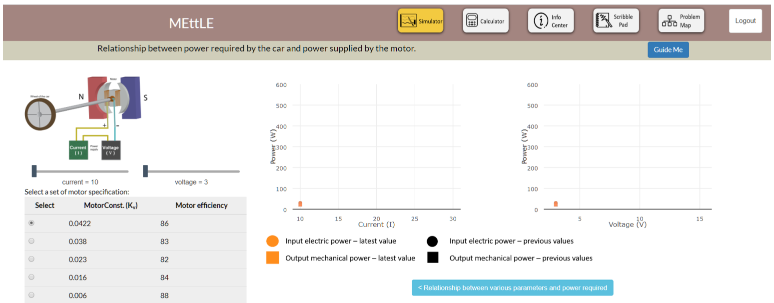


Figure 8.6: Simulator of MEttLE2.0 - Part 4



typical values of certain coefficients appears in equations and a set of values for comparing the estimate against, such as typical power consumption of vehicles and appliances.

8.3 Study 5: Evaluation of MEttLE2.0

Our goal for this evaluation was to understand how novices do estimation in MEttLE2.0 and what they learn from their interaction with MEttLE2.0 (theoretical conjectures 1 and 2), which will contribute towards the local learning theory and to understand how the redesigned features are used to do estimation.

8.3.1 Methods

Research Questions

We had two research questions in this study which were similar to the research questions of study 4. However, in this study we focussed on how the major design changes made, namely, the revised modelling focus questions, the redesigned simulator, the revised model contextualization questions and additional guidance on expert reasoning and practices, affected the novice estimation process and performance. Specifically, we wanted to understand if the revised design supported novices in building contextualized models and integrating all three models to obtain good estimates.

RQ5a What is the novice process of doing estimation in MEttLE2.0?

RQ5b How did the features of MEttLE2.0 support novices in doing good estimation?

Estimation Problem Used

As before, the problem given to the learners was designed so that the underlying conceptual knowledge was appropriate to second and third year engineering students of Electrical, Electronics, Mechanical, Chemical, Civil and Aerospace departments. The context was similar to MEttLE1.0 as it was found to be relatable, motivating and engaging for novices. The problem was checked by EI and the final problem included in MEttLE2.0 was,

> *"You are participating in an electric car race in which you are required to design an electric car of weight 5kg with wheel diameters of 4" that can traverse a track of 50m in less than 5 seconds. Estimate the electrical power needed to achieve this performance."*

Research Design and Participants

We performed a field study in an engineering college where 72 second year students of mechanical (50) and electronics (22) engineering solved an estimation problem in MEttLE2.0 as part of a lab and then did the post test. The average age of learners was 20 years and they were familiar with the use of computers through other courses and labs in their curriculum. After the post-test, we recruited volunteers for the interview and obtained twelve participants (four female, five mechanical engineering) who were interviewed and constituted our sample for this study.

Procedure

The overall procedure of this study was similar to study 4; however while study 4 had a pre-test but no post-test, in this study we had a post-test in order to examine their performance after interacting with MEttLE. The steps followed were:

1. Initial briefing: We briefed participants about the study and its objectives and obtained their consent for recording their audio and computer screen.

2. Interaction with MEttLE: Participants interacted with MEttLE and solved the estimation problem mentioned earlier. During this interaction they were not allowed to use the Internet. However they were free to use all the resources in MEttLE all the time and ask the researcher any questions regarding how to use the resources MEttLE.

3. Post-Test: Participants individually solved the following estimation problem validated by EI, *"You have to design a light aircraft of maximum take-off weight of 15000kg. It should be able to take off in 1000m and less than 10 seconds. Its air speed at 40000 ft above sea level should be about 750km/hr. Estimate the power of the engine you need to design such an aircraft."* Participants solved this problem on paper, without any additional resources or help from any other person. Further, they were not allowed to consult MEttLE for any purpose.

4. Individual semi-structured interview: After the interaction, we interviewed learners using a stimulated recall protocol wherein their screen capture was played back to them and we asked them to describe what they did at each point in the solving process and reasons for their actions. In addition, we asked them questions about the nature of estimation and the estimation process.

Data Sources

We collected the following sources of qualitative data in order to examine novice performance including,

1. Post-test solutions on paper.

2. Screen captures: Their interactions in MEttLE1.0 were captured using the screen capture software CamStudio (http://camstudio.org/).

3. Participant generated artefacts: This included any written solutions to the problems and anything else they wrote as part of their rough work, if any.

4. Retrospective think aloud (stimulated recall) interviews: We interviewed the participants after they had completed the problem in MEttLE2.0 and the post-test using a semi-

structured interview protocol and showing them their screen capture to stimulate their memory. The goal was to have them describe their thinking while solving the problem and reasons for the actions that they took. So we required them to explain and elaborate their actions at several points, how they used each feature in MEttLE2.0 and what they learned. Some sample questions are shown in Appendix C.

8.3.2 Data Analysis

In order to assess participants' estimation performance, we used the product criteria defined in section 5.4.2 namely,

1. Estimate is of the right order of magnitude.
2. The important parameters which affect power in the system are identified.
3. The appropriate equation for power is written

We began by assessing learners' estimation performance on the post-test. We graded the post-test on the basis of whether their solution satisfied the three product criteria of estimation with the following coarse rubric: Students who satisfied all three criteria got a high grade, those who satisfied two out of three criteria got a medium grade and those who satisfied one or none of the criteria got a low grade. This coarse grading and categorization of novices on the basis of their post-test grade, provided a way to categorize students as we analysed their interactions and identified their estimation process in MEttLE2.0, and assessed their understanding of the estimation problem solving process. This was different from study 4 where we categorized novices on the basis of their conceptual knowledge as assessed by their performance on the pre-test.

We used the post test primarily as a way to categorize participants, because while we can assess their performance from the post-test, we cannot infer if they actually followed a modelling-based process from their solutions. So, in order to test our second theoretical conjecture regarding understanding of estimation problem solving process, we used participants' self-reports during the reflection activity and interview to infer the extent of their understanding of the estimation problem solving process, and their intention to use it to solve other similar estimation problems, such as the post-test problem.

In order to understand the novice process of estimation in MEttLE2.0 (RQ5a) we performed interaction analysis and to understand the role of the features in the estimation process in MEttLE2.0 (RQ5b), we used thematic analysis. We used the participants' screen captures and their interviews together to perform the analyses with the same steps as done in Study 4, except that we did not have the researcher observations and participant video data sources in this study.

1. Transcription: We annotated the screen captures of the novices using "Elan" (https://tla.mpi.nl/tools/tla-tools/elan) in terms of the actions done in each page of MEttLE1.0. The actions include reading, typing, clicking, changing values (slider or radio buttons), dragging and dropping, drawing, adding, deleting and editing nodes and links in the causal map. At this point, when the screen was idle for more than 30seconds, as we did not have participant video to check if they were doing any off-screen actions, we marked it as "idle". An example of a transcript is shown in Figure 8.7.

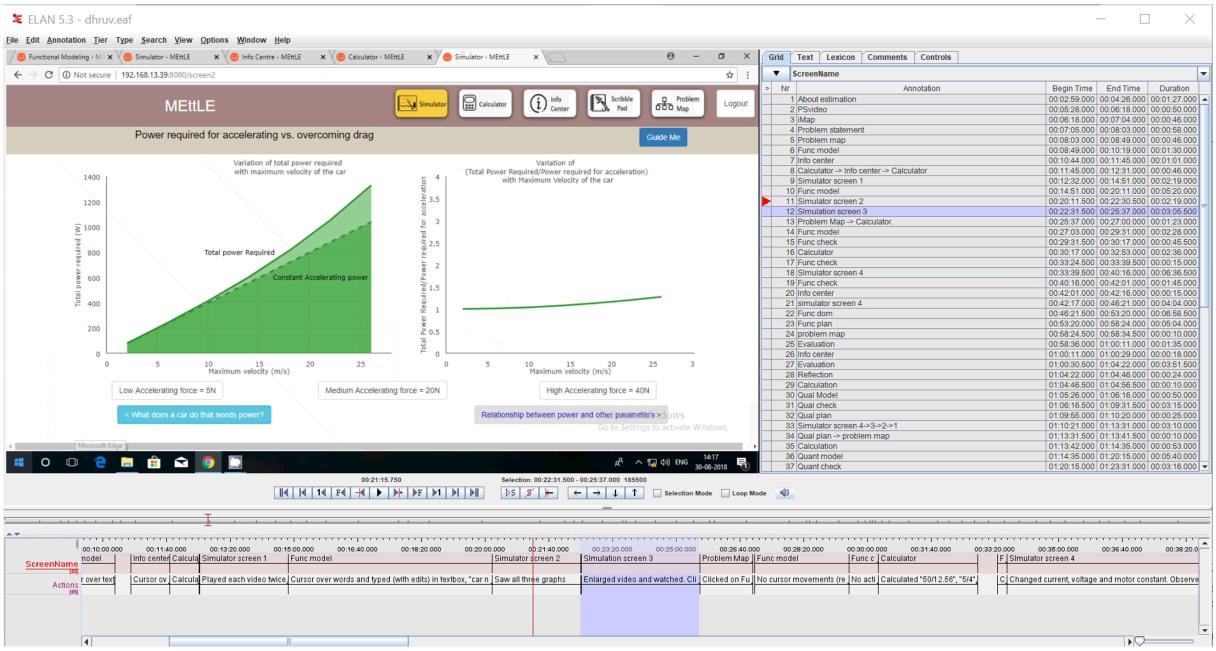


Figure 8.7: Interaction analysis method for Study 5

2. Creating workflows: We transcribed the participant interviews verbatim. Next we interleaved the on-screen actions and the interviews together to create each participants' workflow. This was the flow of events as it happened and there was no inferencing at this point.

3. Abstraction of Process: We used each sub-goal of estimation as an *"ethnographic chunk"* (Jordan & Henderson, 1995) as we applied the *"analytic focus"* of *"the structure of events"*

as defined in (Jordan & Henderson, 1995) to guide our analysis. In the created workflows, we focussed on the interaction between the participant and the features of MEttLE1.0 during each task. Using their actions and reported explanations for their actions we were able to abstract their process during each task and thus their overall process. When they returned to a task after the first pass through it, it was considered a separate event. The patterns that we searched for during the interaction analysis in study 5 changed because of the redesign of MEttLE2.0 and are shown in Table 8.2.

Pattern type	Pattern characteristics
1) Desirable	Model -> Evaluate -> Fail -> Revise
2) Desirable	Model -> Contextualize
3) Desirable	Task -> Read guidance -> Take action
4) Desirable	Evaluate -> Fail -> Revise
5) Undesirable	Jump to calculation or evaluation
6) Desirable	Quantitative and Qualitative modelling jointly done

Table 8.2: Types of action patterns investigated in Study 5

4. Identifying role of features: To identify the themes related to the roles of the features of MEttLE in their process we began by coding their workflow in terms of the purpose that each feature was serving in the novice process as shown in Figure 8.8. The initial codes emerged from the data and we did not apply any theoretical framework to view the data. We generated initial codes across the entire data set and collated related codes into categories and themes. Next, we reviewed the themes against the raw data for consistency and generated an analysis map. Finally we refined our themes by examining their details and created clear descriptions of them. The codes and themes were revised by constant comparison until a final set of themes of the role of the features in estimation problem solving emerged.

5. Ensuring validity: The data was viewed multiple times collaboratively by two researchers (the author of this thesis and a colleague), comparing inferences and themes against each other and refining them during each pass. This way we were able to ensure the validity of our inferences regarding participant processes and the roles of designed features in the process.

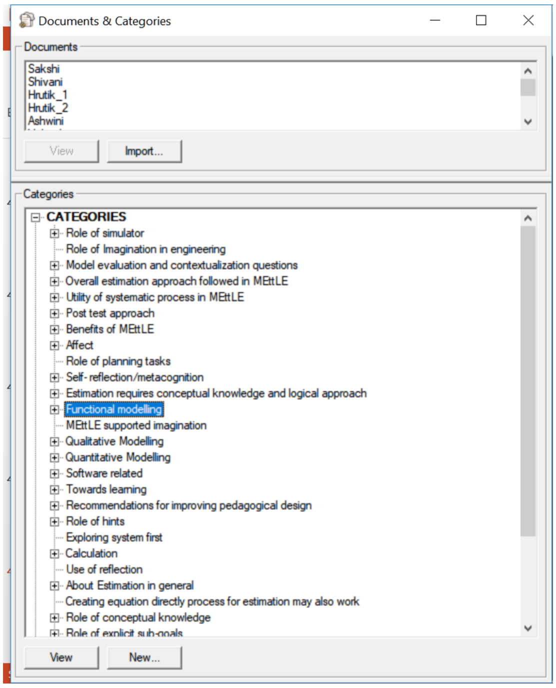


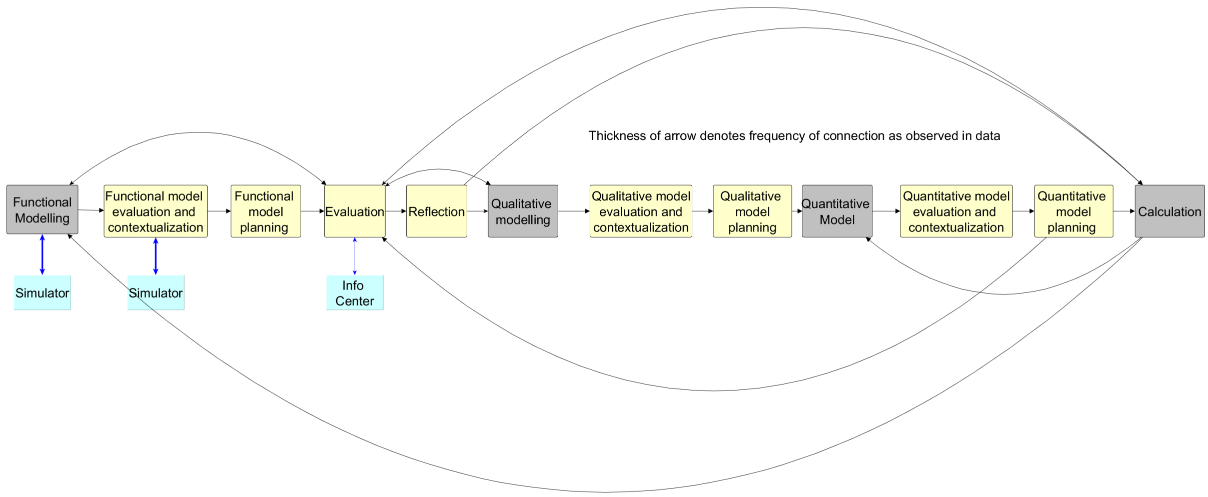
Figure 8.8: Thematic analysis method for Study 5

8.3.3 Workflow in MEttLE2.0

We begin by reporting the workflow of one student (shown in Figure 8.9) who scored a medium grade (S5) as an illustrative case. We chose S5 because his background was similar to S5 from study 4, in that both were second year mechanical engineering students from similar engineering colleges. S5 briefly read the information about estimation, its purpose and requirements. He watched only half of the video describing the sub-goal structure and did not click anywhere on the interactive problem map. Then he read the problem statement and chose functional modelling sub-goal from the problem map. He reported that he chose this sub-goal first because this was the first sub-goal chosen in the video above and that he did not understand why it was so. Thus S5 chose the sub-goal that he concluded was “prescribed”, without reflecting on the purpose of the sub-goal. After this and within each sub-goal he went back-and-forth among tasks as we elaborate later.

S5 read the focus questions and instructions for functional modelling and understood that he needed to identify what the car needs power for. He watched the videos in the first tab of the simulator and reported that the force diagrams and graphs in the videos helped him understand that drag opposes the car as it accelerates, which he was not aware of before. Together his prior knowledge and this understanding helped him reason about the actions of the car which require power, as seen in his functional model,

Figure 8.9: Sample Workflow of S5 in MEttLE2.0



> *"car needs to move with acceleration more than the drag force, to overcome the position of rest and start moving. to increase the acceleration velocity should be increased and time should be decreased, which is caused by the increase in RPM of the wheels"*

After this he continued to explore the simulator by varying parameters and observing the graphs in tabs 2, 3 and 4 in order to build an understanding of the factors that affect power. He reported that this helped him verify his prior knowledge and assumptions regarding power and served as an effective substitute to experimentation in order to understand the car and its power requirements.

Within the functional modelling sub-goal, S5 went back and forth between the tasks. He reported being confused as to what he was required to do and hence was trying to understand the tasks of model evaluation and contextualization by exploring. Model evaluation required examining whether all actions requiring power had been included and contextualization required calculating the exact acceleration and maximum velocity attained by the car and then using these to decide which actions will dominate. S5 did the model evaluation but did not calculate acceleration and maximum velocity. However when he came to the task of identifying dominant actions in the functional model, he reasoned that acceleration would be the dominating action in order to overcome drag and increase the velocity of the car. He used his prior knowledge to reason, without incorporating the exact acceleration and maximum velocity. Thus S5 primarily relied on his prior incomplete conceptual understanding to do model evaluation and contextualization and not on the simulator which had several graphs to support this reasoning. He articulated that this sub-goal fits into the estimation process by *"torque of the wheel"* and next he would *"... find the torque of the wheels required to cover the distance of the given track in minimum amount of time"* to estimate power.

Next S5 chose to do evaluation, even though he had not obtained a value. He used the hints and the values in the "Info Centre" to answer both the evaluation questions by comparing the power given in the evaluation questions to the requirements of the car described in the problem (mass, torque, etc). He reported that he had used "basic logic" to make the comparison and there could be other factors affecting the car which he had not considered. After this, he realized that there were other sub-goals that he had not done and chose qualitative modelling. Here he did not create a causal map in MEttLE2.0 but identified the parameters that affect power using his prior knowledge of power as work/time and drew a rudimentary causal map on paper 8.10. He used the simulator to verify his knowledge. Further he did not identify the nature of the relationships between power and other parameters as required during the model evaluation task, nor did he do model contextualization or planning. As he reported, he was "blank" or not reflective as he was doing this activity, focusing on completion only. As a result, he did not identify all the parameters affecting power that were described in the Simulator.

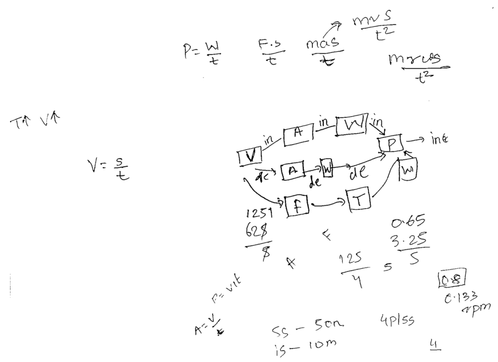


Figure 8.10: Causal map and equations of S5

S5 created an equation using his prior knowledge of power and manipulating the equations (see Figure 8.10). In this step, he built upon his functional model and continued with the plan he wrote in the functional model stage. He answered the model evaluation and contextualization questions, but his responses were incorrect and he went forward without realizing it or making changes. He re-did evaluation, but even after this he was unsure whether he had obtained a reasonable estimate. He went to calculation, but he did not know what data to enter. So he went back and forth between all the sub-goals, editing all his models and re-doing their evaluation and contextualization, ensuring that he had answered all the questions that were incomplete.

Finally in the calculation stage he entered values some of which were "random" and obtained an estimate. He acknowledged that he did not know how to use the data given in the problem and rushed through all the steps for the sake of completing the problem. In the reflection activity, he only answered the first question related to the steps taken to solve the problem as, *"I generated the equation to find the power required"* and reported that he did not see much value to answering these questions. Thus, while S5 adopted an iterative process, the self-reported lack of reflective activity and not completing the model evaluation and contextualization tasks at each stage was the reason he was not able to obtain a good estimate.

8.3.4 Results

Answering RQ5a: "What is the novice process of doing estimation in MEttLE2.0?"

Ten out of the twelve students (S1-S12) turned in the post-test. The remaining two students (S11, S12) did not attempt the post-test. Of the ten students, two students (S1, S2) scored a high grade, five students (S3-S7) scored a medium grade and three students (S8-S10) scored a low grade. The high performers also satisfied all the criteria for good estimates for the problem solved in MEttLE2.0, while the medium and low performers did not.

We elaborate the MEttLE2.0 estimation process of each category of novices, namely, high, medium and low performers on the post-test, separately. We started by grouping the students by post test performance. Then we examined their interaction path to examine if we can identify patterns during their interaction that may be responsible for the post test performance (high, medium or low). However as explained previously, we could not conclude from their written solutions if they actually followed a model-building process in the post-test. However, we examined their reported intention to use a model-building process during their reflection activity and interview.

In the figures below, the top series of rectangles (tasks) indicates the flow of the process. The grey rectangles are modelling tasks, while the yellow rectangles are metacognitive tasks. The rectangles at the bottom indicate the cognitive/physical resource(s) that was used to do the task. The thickness of the arrow connecting two rectangles is representative of the number of times this connection was observed. The thicker the line more often this path was observed in the data. The forward paths are shown in black while the backward paths are shown in color, with the color of the line signifying the "correctness" of the action taken (i.e. model evaluation or revision); green implies a correct action, while yellow or orange implies incomplete or partially correct actions.

1. **MEttLE2.0 process of high performers**

While solving the problem in MEttLE2.0, this group of novices did functional, qualitative and quantitative modelling followed by calculation and evaluation and obtained estimates which satisfied all the criteria of good estimates. As they satisfied the evaluation criteria, they did not iterate after evaluation. However, we found several action patterns of type 1 and 2 during their work in the functional and qualitative modelling sub-goals; they concentrated most of their efforts in obtaining good functional and qualitative models, as seen from the green links in Figure 8.11. They created models, did the model evaluation and contextualization tasks and based on their responses, read the feedback and guidance and revised and contextualized their models. They reported that the questions

> *"forced them to think about why they had (for example) chosen a particular set of parameters."*

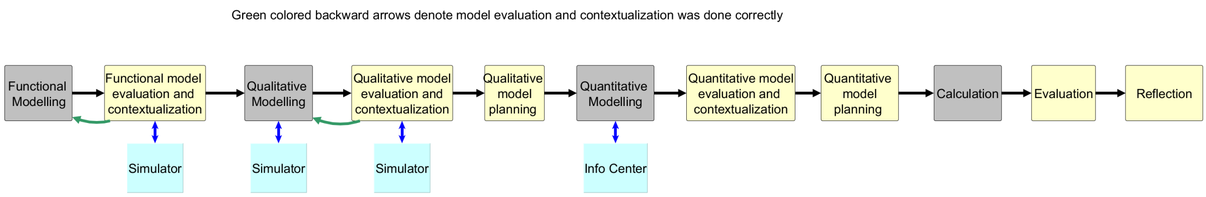


Figure 8.11: Process of high performers in MEttLE2.0

They used the simulator continuously at this stage, both for understanding the actions of the car and for taking decisions regarding dominating actions and parameters as described by S1,

> *"It just gave me the data. Like data and uh I must say an idea, like what you should actually focus on."*

Specifically, they used different tabs of the simulator at different times in the modelling to extract the relevant information. For instance, they understood the actions of the car using the videos in tab 1 and reasoned about dominating parameters using the graphs in tab 2 and 3 as elaborated by S1,

> *"I selected mass and I increased the parameters and velocity and then I compared where it is varying and then the maximum change that I got to know, I put that in one category and the smaller changes were in one category, from there I got to know that which will dominate the power requirements of the simulator."*

When they were unsure of what to do, they used the "guide me" prompts and proceeded as suggested. Finally, the high performers applied their conceptual knowledge correctly to create an equation incorporating all the dominating parameters by starting from the basic equation of power and manipulating it. While their responses to the planning questions show that they were unable to abstract the purpose of the functional modelling sub-goal, we found that after the qualitative modelling they examined all their activities and were able to understand the purpose of qualitative modelling. However they were still unable to plan their next steps. By the time they had completed quantitative modelling, they were able to abstract out the purpose of the sub-goal and in addition, plan their next steps. When these novices went to the calculation sub-goal they were able to substitute suitable values for the parameters and obtain an order of magnitude estimate of power because they had determined the operating conditions and contextualized all their models. Finally they used the hints in the evaluation sub-goal and assessed that their estimate was reasonable by both standards.

At the end, they reflected on their entire estimation process in MEttLE2.0, thinking about the purpose of each step and reported that identifying the parameters and their relationships, and then connecting the electrical and mechanical powers were the most important steps. These novices reported that they began by being unsure of which path to take but by the end recognized a logic to the steps they took as elucidated by S2,

> *"In the starting I assumed that it was sequential, so, let's go by this way and as soon as I entered, I got to know that okay, we can go this way and I think that was the good way. I didn't find so much difficulty for solving it, first of all we have to examine what we need to find, then okay, now I'll have to find power, then what is the problem with power, we have to, then we came into two types of power, electrical and mechanical power, then we find the solution for how to manage the mechanical power, how to manage loss, so it was step by step. So, I felt that okay, now we are going the right way, so I continued in that way."*

We found in the post test that they satisfied all three criteria of estimation (correct parameters and equation and OoM estimate), but we do not know if they actually followed a model-building process. However, as seen from their self-reports above, we found that they were able to abstract out a model-building process to solve estimation problems.

To summarize, we see that high performers on the post-test used the model-build affordances, simulator, info center, evaluation and contextualization questions and guidance of expert reasoning to build, evaluate and revise models while estimating in MEttLE2.0. Thus they were able to do all the component processes involved in obtaining good estimates, namely, building contextualized models by simulation, comparison and decision-making, along with applying conceptual knowledge. Finally they were also able to integrate the three models in order to obtain a good estimate in MEttLE2.0. Further, we find that high performing novices were able to abstract out a broadly applicable process and its components needed for solving problems of power estimation.

2. **MEttLE2.0 process of medium performers**

Overall the medium performers (S3-S7) on the post-test solved the problem in MEttLE2.0 by identifying the parameters involved and then creating the equation, but did not obtain order of magnitude estimates. However their models were not contextualized; thus they were unable to substitute the correct parameters and calculate the estimate. They began by doing functional modelling. However, while they attempted the model evaluation and contextualization tasks, they were unable to do these tasks well. This was confirmed from the quality of their answers to these questions and depicted using orange links in Figure 8.12. They did not apply conceptual knowledge to determine the operating conditions and did not use the guidance and the simulator appropriately to compare and make decisions regarding which powers will dominate. Some novices reported that they had ignored certain model evaluation and contextualization questions because they could not see what use they were in solving the problem.

After functional modelling, there was variation in the process with the group. All students except S6 showed jumps in the process as seen in Figure 8.12, such as from functional modelling to calculation (because it is the most familiar sub-goal)/evaluation (because it is the last sub-goal), because they reported being confused and stuck, and so used exploration

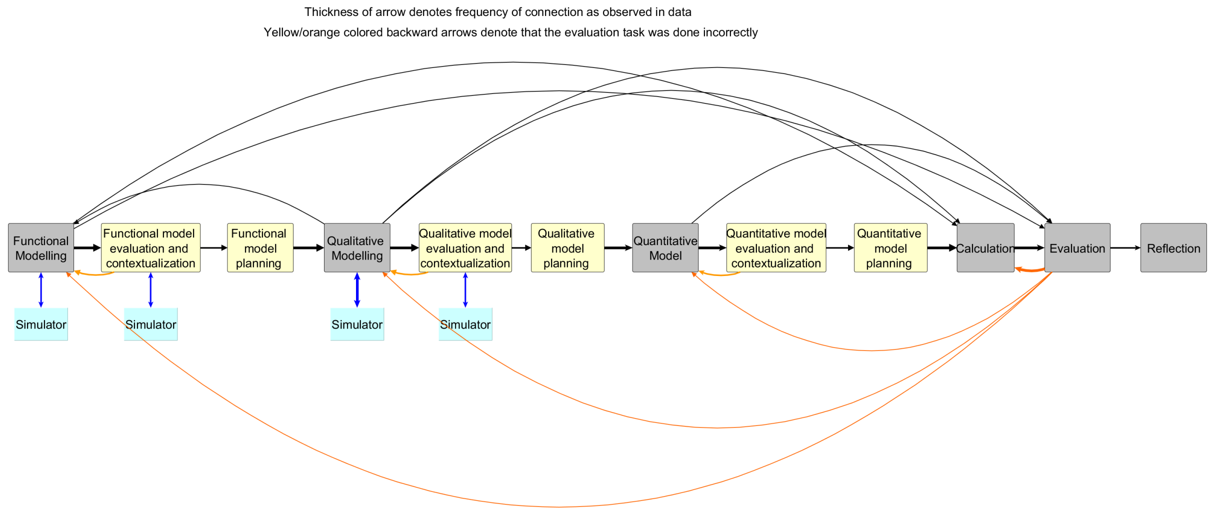


Figure 8.12: Process of medium performers in MEttLE2.0

as a technique to come unstuck. When they were unable to do calculation or evaluation, they returned to qualitative or quantitative modelling and continued. S6 continued with qualitative and then quantitative modelling after functional modelling.

As before, their responses show that these novices did not do model evaluation and contextualization well, and this was for two reasons. Firstly, they were unable to do the reasoning required, such as, identifying which parameters dominate even though the simulator was available for comparison. They used their intuitive reasoning rather than systematically exploring the graphs in the simulator to experiment, compare and reason. Secondly, they did not answer the questions or act upon the feedback/expert guidance regarding what to do, because they did not perceive it useful to solving the problem.

When medium performers did not satisfy the evaluation criteria, they iterated back to calculation first and then to each modelling sub-goal, often multiple times to identify the changes needed. Most often though, they only read but made no changes in the model because they were unable to self-assess their models and make changes. However, they persisted in their attempts to refine their models and estimate, going back and forth between the sub-goals. These students used the simulator to bridge the conceptual knowledge gap. But they did not use the simulator throughout the process, specifically not when it could have supported their model evaluation and contextualization reasoning.

Medium performers did not build on their models, effectively treating each sub-goal as an independent entity that needed to be completed without realizing its purpose. This was evident from their answers to the planning questions, which show that they were thinking in terms of the parameters associated with the car, rather than in terms of the purpose of each model in estimation. The fact that they did not understand the value in doing evaluation and contextualization was also the reason for their not doing the tasks well.

Finally, only two out of these five students completed the reflection activity and their responses during the interview show that they did not see much value to planning and reflection. They abstracted out a two-phased modelling-based process for solving such power estimation problems, as described by S4,

> *"...actually there was a table, in that table there were different things differentiated such as the first part. That included the identification of those parameters which would affect the power actually. Such as velocity, mass, acceleration. So first I properly identified those parameters and then further I went to the next step. My next step was to draw a general diagram which would relate all these parameters together. Then my third step was to provide a formula which could properly implement this using the previous knowledge that I have studied. Such as the linear equations of motion and all. My fifth step was to implement that formula using numerical values, in order to get a proper output. But actually, I wasn't successful in obtaining the proper result..."*

In summary, these novices did not use the simulator, model evaluation and contextualization questions and guidance of expert reasoning effectively and so did model building, but not model contextualization and evaluation in MEttLE2.0. As a result, they were unable to integrate all the three models and obtain a good estimate. Further, their reflection shows that they abstracted out a two-phased modelling-based process because they did not understand the role of functional modelling. Thus, they did not understand the components of the estimation process i.e. building contextualized models by using simulation, comparison and decision-making, because they were not systematic and reflective while solving. These novices reported that they would need to practice a few times to understand all the components of estimation problem solving.

3. **MEttLE2.0 process of low performers**

In MEttLE2.0, the low performers on the post-test (S8-S10) broadly followed the process of doing functional, qualitative and quantitative modelling, followed by calculation and evaluation; however they did not obtain order of magnitude estimates. They reported that they did not see the value of doing functional modelling and so they concentrated their efforts on creating contextualized qualitative and quantitative models. This is shown using thick links in qualitative and quantitative modelling in Figure 8.13. However similar to the medium performers they were unable to do model evaluation and contextualization appropriately and did not use the feedback or the expert guidance to revise their models, as shown using orange backward links in Figure 8.13. This was because, as their models at each stage show, these students had very low conceptual knowledge, and so they were unable to interpret and follow the guidance. Even though they used the simulator often, and read the hints and guidance, their retrospective reports show that the inferences that they drew were incorrect or incomplete. Thus, weak conceptual structures was a limiting factor for their incomplete and non-contextualized models.

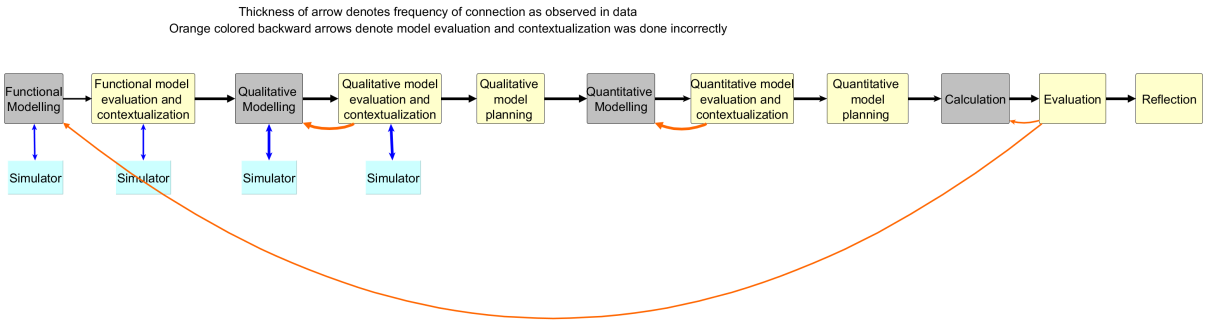


Figure 8.13: Process of low performers in MEttLE2.0

These novices went back to previously completed sub-goals when they were unable to satisfy the evaluation criteria. However unlike the medium performers they did not persist on revising their models and iterating, choosing instead to end the problem solving. They reported that this was because they were unfamiliar with the required conceptual knowledge (for instance, drag) which, as they reported, constrained their reasoning and led to frustration. Similar to medium performers, low performers did not build on their models in the sense that the functional model did not lead to the qualitative model, and the latter did not lead to the quantitative model. Their answers to the planning and reflection questions show that while they were able to identify "what" they needed to do, as described by S8, *"Later when I read carefully, I noticed what I needed to do. So the hints that were there were useful. After that, I understood that I was going by a wrong sequence, and if I follow the right sequence I would be able to get an answer. So I understood the right sequence and started proceeding like that."*

However, the lack of conceptual knowledge made it difficult for them to understand and implement the components of the "right sequence" and so, they obtained poor estimates in MEttLE2.0 because of their poor models. This was also the reason for their being unable to understand the three-phased model-based reasoning process for estimation. While they recognized the sequence, they did not understand its components and how to integrate them.

To summarize, low conceptual knowledge was the cause of the poor performance of low performers, both while solving the problem in MEttLE2.0 and during the post-test. These novices reported that they would need a better grasp over the conceptual knowledge and practice to learn all the components of estimation problem solving.

Answering RQ5b: "How did the features of MEttLE2.0 support novices in doing good estimation?"

In this section we only focus on the features which we changed from MEttLE1.0, ie, the simulator and the additional scaffolds for model evaluation and contextualization.

1. **Role of Simulator**
   The simulator was designed with four tabs, the first two tabs supported model building and contextualization of the functional model, tab 3 supported model building and contextualization of the qualitative model and tab 4 supported model building and contextualization of the quantitative model. We found that the simulator served these and several other purposes for novices. Primarily, the simulator bridged the conceptual understanding gap, by showing the variation of parameters affecting power in various graphs, the relationship between power and velocity as the car moves and the relationship between electric and mechanical power as explained by S1 and S3,

   S1: *"that simulator helped me to know what is the exact data, so I can figure it out and build up the relation, so, without that, I don't think it was possible for* *me to make that, because I didn't have the proper data for it and the table of variations of voltages and currents it was helpful."*

S3: *"the graph can be simulated and mass can be decreased and acceleration, what happens and, in such way, I was drawing my conclusions depending on this."*

In addition to filling the conceptual knowledge gap, the simulator also helped in verifying their answers, knowledge or assumptions. It served as an implicit guidance regarding what factors to focus on during estimation. As S9 mentioned she used the simulator to *"cross-check her own knowledge"* and S4 reported that

> *"...so using that idea I was confirmed that the answer that I wrote was correct or else whatever I have done the mistake I need to correct that thing."*

Secondly, the simulator supported the imagination in understanding the problem and specifically the working of the car as described by S6,

> *"So the question said the car is going 50m and its a 5kg car. So when I was imagining, I was thinking of the linear motion of the car. I was not imagining the rotational motion of the wheel. But then when I saw the simulator, I also understood the rotational specifications. So it was helpful."*

Specifically, it supported learners because it focussed their attention the problem requirements as elaborated by S4,

> *"before I was not using the simulator, I was thinking about the general cases that could actually happen. But when I saw the simulator, I got a correct idea actually. What the question wants, how it should be proceeded and what should be done according to the question. So, I started moving in the right path rather than providing a general answer."*

In some cases, the simulator became a tool for coming unstuck when the task was difficult or confusing as S2 reported,

> *"if something some question is there, then I was not getting the exact idea like what's the approach, but after watching the simulator, I got like what to do.*

If there was something like you can watch the simulator only once, then also it will be useful. Even though it was not like that. But, without seeing that it was very difficult because the approach wasn't so clear that by reading just the question, I can attempt to answer each and every question correctly, it would be very difficult."

Finally, the simulator was an alternative to prototyping and experimentation and thus supported the trial-and-error process inherent in engineering problem solving such as estimation and as S5 described

"It was a shortcut. Because what I said [experimenting and prototyping] is time-consuming, so this is like a shortcut."

2. **Role of additional scaffolds for model evaluation and contextualization**
The additional question prompts and expert guidance were designed for model evaluation and contextualization supported some novices in the designed purpose of verifying or checking their models and then revising them if necessary as elaborated by S9,

"there was this one question in which I had to write that particular equation, so I did that, I didn't know whether it is right or wrong, but later on moving to the next step, it actually at one point, when I wrote some particular answer, it just had that hint or something that check if the units on both, LHS and RHS are right or not. So, it was obvious that if it's not correct, it means there is something wrong with my formula, So, I'll have to go back and check it, so, yeah those things actually helped me, (like okay, I have to go back, like I've done this particular thing wrong there)"

These novices reported that they used the prompts and guidance along with conceptual knowledge, imagination and the simulator to do model evaluation and contextualization. However we found that several novices continued to struggle with model evaluation and contextualization, specifically identifying the operating conditions and reasoning about dominant parameters. They were unable to do these tasks because of (1) their low conceptual knowledge, (2) they did not effectively use the graphs in the simulator to make comparisons and decisions and (3) they did not read and follow the guidance of expert practices embedded in the system. Some novices also did not recognize the need for model contextualization at every stage, recognizing only at the end when they were unable to calculate and unable to trace the reason why. This is exemplified in the following snippet between the researcher and S5:

> *R: Hmm. So why didn't you do it [calculating acceleration and maximum velocity] at that time? S5: I just ignored it. R: Okay. So if you had those values what would you have done? S5: It would have been easy to solve the equation. R: So you didn't recognize this at that time? S5: No.*

As a result of this, these novices reported that they would need more practice to understand and learn all the components of estimation reasoning.

8.4 Reflection

At the end of study 5 which is also the end of iteration 2, we reflect on our findings to explicate theories of estimation problem solving (RQ5a) and extract design principles (RQ5b). The goal of this study was to investigate the effect of the redesigned features on the novice process of solving estimation problems. We had two research questions related to this. The first (RQ5a) examined the estimation process of novices in MEttLE2.0. The second (RQ5b) focussed on examining the role of the the modified features, namely, the simulator, the expert guidance and the metacognitive prompts and their associated feedback on the estimation process of novices. A summary of our findings for RQ5a are shown in Table 8.3 below and elaborated afterwards.

We identified that high performers on the post-test built contextualized functional, qualitative and quantitative models in MEttLE2.0. They expanded the problem space during functional modelling and then systematically narrowed the space and obtained a good estimate for the problem in MEttLE2.0. We found that they used the model evaluation and contextualization prompts and acted on the expert guidance and feedback to appropriately evaluate and revised their models if necessary. Through this process of evaluation and revision, they build on and integrated their models to obtain a reasonable estimate in MEttLE2.0.

Medium performers on the post-test built functional, qualitative and quantitative models in MEttLE2.0, but did not expand and narrow the problem space. They did not systematically use the model evaluation and contextualization prompts or act on the expert guidance and feedback to evaluate and revise their models. As a result their models were not contextualized and they

Post-test performance	MEttLE2.0 performance	MEttLE2.0 interaction
High	Order of magnitude estimate. Correct causal model and equation.	Used model-building affordances, simulator, model evaluation and contextualization questions, guidance of expert reasoning. Created contextualized models for estimation and integrated them. Reflected on and abstracted out a three-phased model-based reasoning estimation problem solving process.
Medium	Estimate off by an order of magnitude. Causal model incomplete. Correct equation.	Used model-building affordances to create models. Did not use simulator, model evaluation and contextualization questions, guidance of expert reasoning to evaluate and contextualize models. Did not create contextualized models and integrate them to obtain an estimate. Did not reflect on their process and abstracted out a two-phased model-based reasoning process for estimation.
Low	No estimate obtained. Causal map incomplete. Incorrect equation.	Used model-building affordances to create models. Unable to use simulator, model evaluation and contextualization questions, guidance of expert reasoning to evaluate and contextualize models because of low conceptual knowledge. Did not create contextualized models and integrate them to obtain an estimate. Reflected on their process, but were unable to abstract out the three-phased model-based reasoning process for estimation.

Table 8.3: Summary of performance in Study 5

did not integrate them to obtain an reasonable estimate in MEttLE2.0. Finally, low performers on the post-test built functional, qualitative and quantitaive models in MEttLE2.0, but again did not expand and narrow the problem space. They did not have the conceptual knowledge needed to use the model evaluation and contextualization prompts or the expert guidance and feedback to evaluate and revise their models. So, their models were incorrect and they did not obtain a reasonable estimate in MEttLE2.0.

Together, these results indicate that the MEttLE2.0 interaction path of building, contextualizing, evaluating and revising functional, qualitative and quantitative models, followed by reflectively integrating all three models together leads to obtaining good estimates and understanding that the three-phased model-based reasoning process is good for solving estimation problems. This may have led to the good performance on the post-test. On the other hand, not contextualizing, evaluating and revising the models accurately, and not reflectively integrating all three models together, is the reason for obtaining poor estimates in MEttLE2.0. Conceptual knowledge is required to do model contextualization, evaluation and revision and integrate all three models together. Further, lack of reflection while creating and integrating models leads to poor understanding of the three-phased model-based reasoning process for solving estimation problems, and may have been the reason for the poor performance on the post-test.

In study 4, we had investigated whether the features of MEttLE1.0, specifically the question prompts, were able to trigger the desired reasoning processes among novices. We found that while the prompts did trigger the model evaluation, contextualization and planning processes, novices did not know how to evaluate, contextualize and plan. So we incorporated several features in MEttLE2.0 to scaffold novices in their evaluation, contextualization and reflection. The results of study 5 show that when novices use the scaffolds effectively, they are able to evaluate, contextualize and reflect, and obtain good estimates (high performers). On the other hand, when novices do not use the scaffolds effectively they are unable to obtain good estimates (medium performers) because they do not go through the thinking process which would get them to the criteria for good estimates. These results highlight the importance of evaluation, contextualization and reflection on the estimation process, which we had obtained some evidence for in Study 1 (experts). Literature has also discussed the important role of evaluation and reflection processes in the solving of ill-structured problems (Ge & Land, 2004; Jonassen, 2000; Mayer, 1998).

In RQ5b, we investigated the role of these redesigned features on the estimation problem solving. We found that the redesigned simulator supported model-building, contextualization and evaluation among high and medium performing novices. The simulator was able to bridge the conceptual understanding gap for these novices, but not for low performers who had low conceptual understanding. This is because the simulator was not designed following the principles for designing simulations for conceptual understanding. Instead the simulator was designed to model for novices (1) the use of conceptual understanding in mental simulation to do functional modelling (2) how to compare the power (quantity to be estimated) required for various actions of the car (the problem system) (3) how to focus on the parameters which dominate power requirements and (4) how to visualize and relate the entire problem system. Thus the simulator supported various aspects of model contextualization and evaluation and when used for these purposes, along with the question prompts, hints, feedback and expert guidance, enabled novices to obtain good estimates. The simulator enabled novices to connect to and expand their imagination/mental simulation, compare and take decisions for estimation.

Study 5 also reaffirmed a result intuitively known to every domain instructor - poor conceptual knowledge is a limiting condition for obtaining good estimates. Estimation requires a specific type of conceptual knowledge constrained mental simulation which was supported by MEttLE, but accessible only to novices with good conceptual understanding. As the process of low performers showed, poor conceptual understanding makes it difficult for novices to understand and act upon the scaffolds (question prompts, hints, expert guidance, feedback) for evaluation, contextualization and reflection. The results of study 5 show that conceptual knowledge, evaluation, contextualization and reflection are all necessary components for estimation. Thus the process of solving estimation problems and obtaining good estimates is an intertwining of model-building, evaluation, contextualization and reflection processes, all of which use knowledge (informal and conceptual) and the problem context as inputs.

The role of motivation and interest in learning and problem-solving is widely acknowledged (Linnenbrink-Garcia et al., 2016; O'Keefe & Linnenbrink-Garcia, 2014). While we identified that MEttLE2.0 supported interested novices who were reflective about their estimation process, we found that MEttLE2.0 was lacking in aspects of creating interest among novices. It is known that more interested students are more metacognitively aware (McWhaw & Abrami, 2001). Therefore it is worth considering how to trigger the interest of novices in MEttLE2.0, so that they are reflective as they perform the various activities in MEttLE2.0 and are able to solve the estimation problem better.

8.5 Summary

The results of study 5 supported our theoretical conjectures 1 and 2 (Section 8.1.3). We found that when novices build contextualized models by using the simulator and guidance on reasoning practices at various points to make comparisons, evaluate their estimate by comparison, plan, monitor and reflect on their process they are able to obtain good estimates in MEttLE2.0, abstract an estimation problem solving process and obtain good estimates on the post-test. On the other hand, we found that when novices do not use the simulator or guidance of reasoning practices to build contextualized models, plan, monitor and reflect on their process they obtain poor estimates in MEttLE2.0, do not understand the estimation problem solving process and obtain poor estimates on the post-test. We identified the reasons for the poor performance in MEttLE2.0 which include lack of metacognition and weak conceptual knowledge. In the next chapter, we integrate the findings from all our studies to propose a model for estimation problem solving which leads to good estimates.

Chapter 9

Discussion

9.1 Summary of findings from DBR Studies

In this thesis, we reported on two iterations of a design-based research project to characterize the estimation processes of experts and novices. In the first iteration, we characterized the expert and novices processes of estimation, which highlighted the gap between expert and novices in estimation problem solving. Next, using a simple technology-tool as a intervention we re-characterized the novices processes and identified supports they need to obtain good estimates. In the next iteration, we designed a technology-enhanced learning environment with features to support novices in estimation problem solving. We studied how novices solve estimation problems in the designed environment and how the features support them in obtaining good estimates. We did two studies to characterize novice estimation processes, revising the design between the two studies. Together both the iterations led to characterizing the expert and novice process of doing estimation, identifying the supports that are productive in an estimation solving environment and how these supports influence novice estimation problem solving. Next we summarize our findings and then present the model for solving estimation problems which emerges from our findings, with extensions to learning estimation problem solving.

9.1.1 Expert-novice differences in estimation problem solving

Study 1 showed us that experts follow a three-phased progressively higher order modelling process at the end of which they have a simplified equation that can be used for estimation. During this three-phased process, experts use the cognitive processes of mental simulation, manipulating external representations and connecting to prior knowledge, experience and intuition, intertwined with the metacognitive processes for evaluating their models and monitoring their process. This is consistent with the multilevel model of metacognition proposed in literature (Efklides, 2008; T. O. Nelson & Narens, 1994) according to which there is a splitting of cognitive processes into two levels, namely, the object level and the meta level. Further, their is a flow of information between these two levels which lead to monitoring and control of the object level by the meta level.

The three phases of modelling are functional, qualitative and quantitative modelling. In the first two phases, experts enact the problem system in order to expand the problem space and then apply the problem requirements and conceptual knowledge to constrain the model and narrow the problem space. In the final stage, the qualitative model is frozen to an equation or a judgment regarding feasibility based on the conceptual knowledge of the underlying domains. Experts identify and use the appropriate cognitive processes for modelling and employ suitable physical resources from the environment as needed. They periodically evaluate whether the model is accurate, yet simplified and useful for estimation or whether it needs to be modified. Expanding the problem space to fully explore it to ensure that no aspects of the solution has been ignored is known to be an important aspect of solving ill-structured problems (Dennis et al., 1999; Tang et al., 2010). While the importance of metacognition in ill-structured problem solving is known (Jonassen, 2000; Mayer, 1998), in this work we have fleshed out the nature of the metacognitive processes undertaken by experts in the model-based estimation process.

The roles played by mental simulation and various external representations, such as diagrams and equations, employed in each phase of the modelling process are diverse. We identified that mental simulation of the given problem system in order to understand its structure and physical working supports the problem space expansion. Further, the problem requirements and conceptual knowledge are effectively integrated to constrain the mental simulation and thus the problem space. We found that experts extensively interact with external representations such as diagrams, flowcharts, animations and videos while doing the mental simulation process in order to create functional and qualitative models. Further we found that formal representations such as equations came only later in the expert processes, specifically at the quantitative modelling stage. The role of mental simulation and non-equation based external representations, in expanding the problem space and obtaining good estimates has not been mentioned in literature thus far.

In study 2, we studied novices and identified that when novices satisfied the criteria for good estimation products, their process was similar to experts. The remaining novices process focussed on identifying the right equation for the quantity to be estimated. In order to do so, they either recalled all the equations they had learned and selected one which was relevant in the context or searched on the Internet for an appropriate equation. We identified that novices did not focus on understanding how the problem system works and their diagrams were few and rudimentary (not descriptive of the situation). Novices did not expand and explore the problem space completely before freezing upon an equation as a result of which they obtained poor estimates. Novices often revised their equations if they did not know the numerical value of all the parameters in the chosen equation. Thus novices followed a model-searching process rather than the model-building process of good estimation which has also been mentioned in literature (Adams et al., 2008). Novices applied a means-end analysis (Simon & Newell, 1971) which is a result of the training that is prevelant in engineering education and the emphasis given to equation search and manipulation or plug-and-chug (Taylor et al., 1961).

Study 3 confirmed the results of study 2 that novices do not do problem space expansion for estimation, without additional scaffolds directing their attention to mentally simulate and build functional models. Novices create a causal map for the quantity to be estimated based on the equation that they knew for the quantity, for eg, power is work done/time, rather than enacting the problem system and then integrating conceptual knowledge to do qualitative reasoning. We identified that novices' familiarity with the problem system and ability to visualize and mentally simulate limited their model building, as confirmed by their descriptions and drawings. However, there was a shift in the process when the researcher intervened with scaffolds triggering model building and mental simulation. We found that scaffolds in the form of diagrams and gestures supported the visualization and mental simulation process. Further, we found that students need to be scaffolded in applying conceptual knowledge to the given problem and for making approximations, assumptions, selecting and reasoning about numerical values.

The results of studies 1, 2 and 3 show that when solvers obtain good estimates, they follow the estimation process shown in the Figure 9.1. Thus our studies show that contrary to what is stated in literature (Dunn-rankin, 2001; Linder, 1999; Shakerin, 2006), conceptual understanding is not the reason for the difference between expert and novice estimation performance; lack of problem space expansion via mental simulation is the reason for the difference in expert and novice estimation performance. In the next section, we summarize the results of studies 4 and 5.

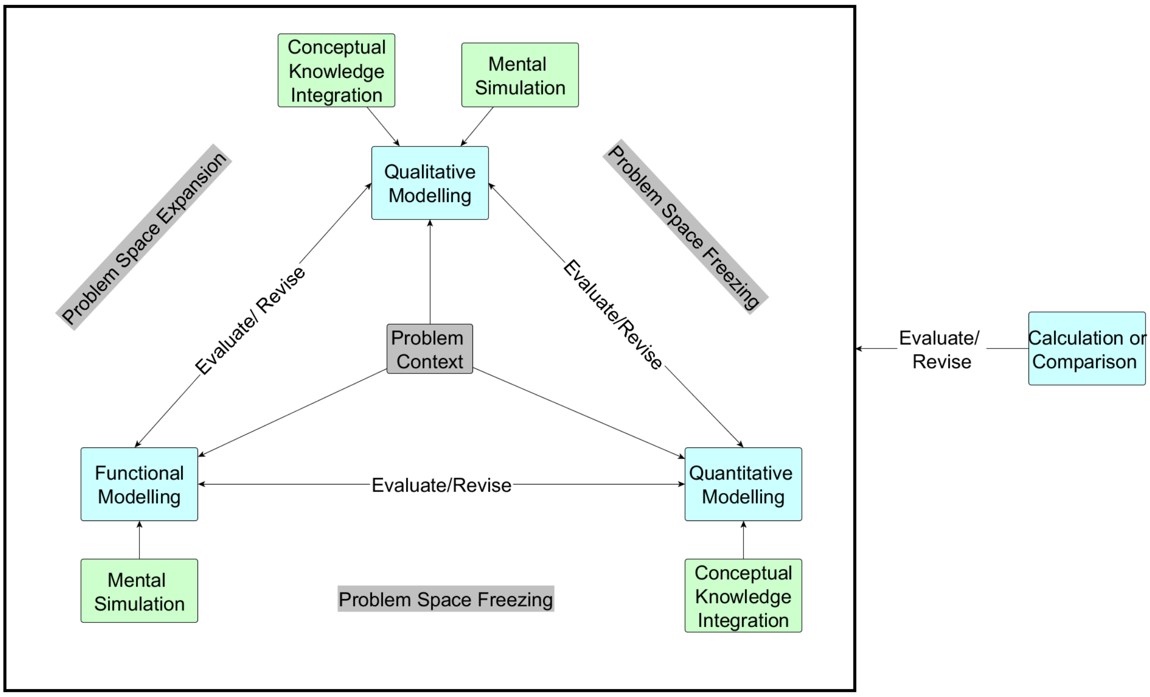


Figure 9.1: The enaction-freezing process underlying good estimates

9.1.2 Novice estimation problem solving process in MEttLE

In study 4, we studied how novices did estimation in MEttLE1.0, a TELE designed to trigger novices model-building, mental simulation and metacognitive processes. Broadly, novices solved the estimation problem in MEttLE1.0 by building functional, qualitative and quantitative models, and then calculating and evaluating their estimates. However they practically did a two-phased model-building process consisting of qualitative and quantitative modelling, without building on their functional models, but using the functional model to understand the system working. We elaborate on their process next.

Within each modelling phase, novices used the resources given in MEttLE to create the models. To create functional models, novices used their prior knowledge and experience of cars, read, watched a video, imagined, interacted with the simulator and used the words as triggers to build an understanding of the working of the car. To build the qualitative model, novices either used conceptual knowledge or the simulator. Finally, they used this qualitative model, the simulator and conceptual knowledge to create a quantitative model or equation connecting power with other parameters. Novices often did the qualitative and quantitative modelling simultaneously through the simulator. However none of these models were contextualized, so the model-based estimation process reduced to a model-based reasoning process of building knowledge (an equation) and plugging in values to solve the equation. This is different from the expert process where the problem requirements are always kept in mind, thus creating models which are contextualized at each stage. This is important because the problem requirements will dictate what parameters dominate the power required. Novices did not consider this aspect despite question prompts to trigger this reasoning. Thus novices did not do an important aspect of estimation reasoning, which focuses on identifying the dominating parameters for power.

Another aspect that was missing in the novice estimation process in MEttLE1.0 was metacognition. Even though we had designed evaluation, planning and monitoring tasks to trigger novices' metacognition, novices did not go through the evaluation and revision process or the monitoring and planning processes that define metacognition. In other words, they did not think about their models and revise them for estimation, or think about what they were doing or needed to do, instead answering the questions as if they were assessment. Thus, study 4 showed that while novices went through the enaction and freezing process, that was not enough to obtain good estimates. Their enaction did not include problem requirements and did not involve the reflective integration of all three aspects (functional, qualitative and quantitative modelling) which are crucial to estimation. This was because novices did not recognize the importance of model contextualization and did not know how to do the evaluation, planning and monitoring metacognitive processes. So in the next version of MEttLE, MEttLE2.0 we built additional scaffolds to support these processes.

In study 5, we identified how novices solved an estimation problem in MEttLE2.0, a TELE designed to trigger and additionally scaffold novices model-building, evaluation and contextualization, mental simulation and planning and monitoring processes. Broadly, novices obtained good estimates by going through a process of building, revising and integrating contextualized functional, qualitative and quantitative models, followed by calculating and evaluating their estimate. Novices used the scaffolds in MEttLE to create contextualized models and reflected on their models and process at each stage, which enabled them to revise and integrate their models to build on them.

While building functional models, novices used the words as triggers, in addition to the animations and graphs in the simulator to create the model and identify which actions would dominate the power for given problem requirements. Next they focussed on these actions and used the simulator to identify which parameters would dominate the power requriements of these actions. They then created an equation connecting power to these parameters using their conceptual knowledge and the simulator. Finally they subsituted the problem requirements into this equation and calculated and evaluated their estimate. Thus, when novices obtained good estimates in MEttLE2.0, they followed an expert-like iterative model-based estimation process, which integrated all three aspects of estimation, namely, functional, qualitative and quantitative.

This study reiterated results from the study 4 that doing model contextualization, evaluation and revision inadequately, and not reflecting on the estimation process led to novices obtaining poor estimates. Even though there were several resources and scaffolds in the form of feedback, hints/prompts, expert guidance and the simulator available for novices to do these processes, novices often under-utilized these resources and were not reflective in their actions, ie, they did not reflect on what they were doing, why they needed to do it and how to do it well. This may have been due to lack of interest or motivation to solve the problem (Linnenbrink-Garcia et al., 2016; O'Keefe & Linnenbrink-Garcia, 2014). In the solving of ill-structured problems (such as estimation) especially, affective and motivational states of learners play a crucial role in their metacognition and self-regulation (McWhaw & Abrami, 2001).

Finally, this study reiterated a result which most domain instructors intuitively know. In novices of low conceptual knowledge, the lack of conceptual knowledge was the limiting factor in obtaining good estimates. Even though they used all the resources in MEttLE2.0, did the evaluation and planning tasks, they were unable to obtain good estimates. This was because they were unable use conceptual knowledge to make sense of the problem system, compare and make decisions. While the simulator scaffolded learners regarding which aspects of conceptual knowledge to focus on, it was not intended as a replacement for conceptual knowledge. As a result, when novices did not have the conceptual knowledge they were unable to interpret the feedback, expert guidance, hints/prompts and the graphs in the simulator.

Summary and Synthesis

Results of studies 4 and 5 show that it is necessary to support model-building of the context via (mental) simulation and other external representations such as animations, graphs and causal maps. It is also necessary to support model evaluation and contextualization by providing guidance of expert reasoning and implicit guidance using graphs and tables. Finally, it is important to support monitoring and planning for effective integration of all the models to obtain an estimate.

The five studies in this thesis build on one another and each one contributes to our understanding of estimation problem solving and how it is done and supported, as shown in Figure 9.2. Study 1 highlighted a model-based reasoning process of solving estimation problems and obtaining good estimates, along with the cognitive mechanisms underlying this process. Study 2 showed why not following the model-based reasoning process and its underlying cognitive mechanisms leads to not obtaining good estimates, thus establishing the necessity of this process. Study 3 showed that it is possible to trigger and support the model-based estimation process and its underlying cognitive mechanisms among novices, and indicated a set of scaffolds that might be useful for doing so. On the basis of the findings of these three studies we designed MEttLE. Studies 4 and 5 with MEttLE fleshed out the nuances of the model-based estimation process, specifically the roles of model-contextualization and evaluation, the nature of mental simulation, specific estimation reasoning and practices and metacognition, which are necessary to estimation problem solving and obtaining good estimates. Next, we integrate all our findings and present a model for estimation problem solving that emerges from this thesis.

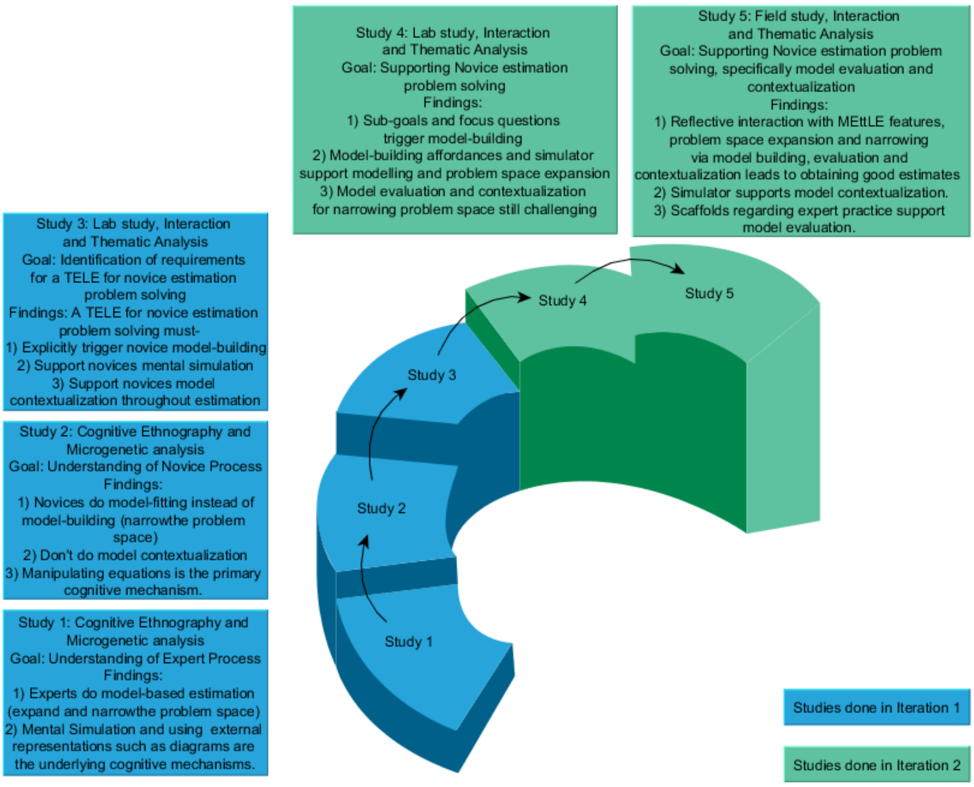


Figure 9.2: An overview of the studies done and results of this thesis

9.2 SENECA: A model for estimation problem solving

The results of our studies can be summarized in the SENECA model (shown in Figure 9.3) for solving estimation problems that leads to good estimates. SENECA stands for "**S**imulate to **E**xpand, **N**arrow using **E**ngineering concepts and problem **C**ontext, evaluate and reflect". Taken together our studies 1-5 show that the process of solving estimation problems well, i.e. obtaining good estimates, involves the metacognitive integration of three contextualized models of the problem system, namely, functional, qualitative and quantitative models (Figure 9.3). The underlying cognitive processes are mental simulation and manipulating multiple external representations which lead to problem space expansion and conceptual knowledge integration which serves to narrow the problem space and freeze upon a numerical estimate or a judgment. Below we detail out each phase of the estimation process.

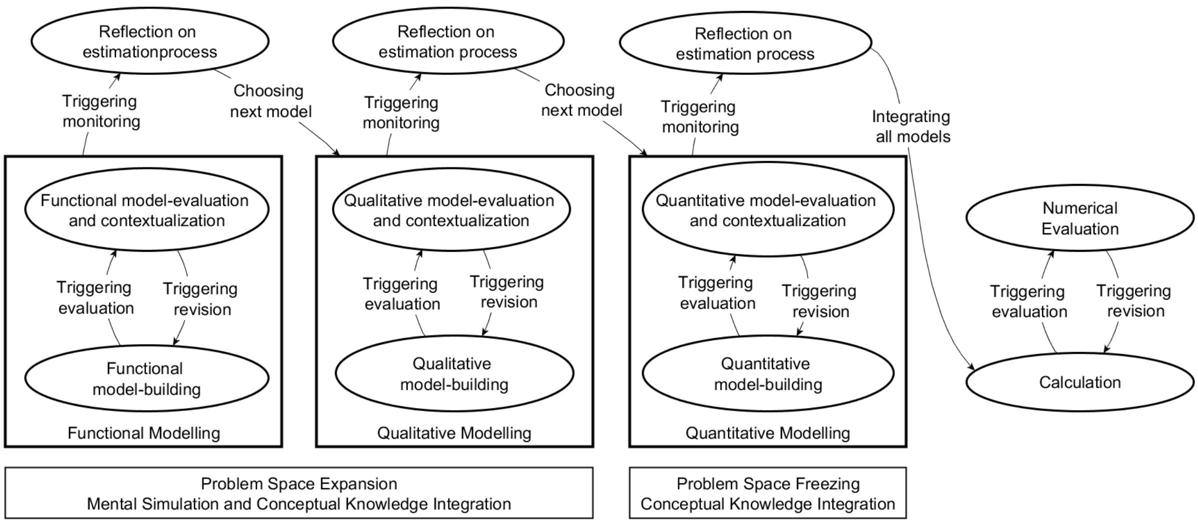


Figure 9.3: The SENECA model for estimation problem solving

9.2.1 Functional Modelling

Estimation begins with mentally simulating the problem system in order to connect to prior knowledge or experience regarding a similar system. The mental simulation is triggered and supported by reading descriptions of the problem system (fictive motion words), figures, animations and videos. This model includes an understanding of which components or functions of the system have or require the quantity to be estimated. For instance, if the quantity to be estimated is "weight", then understanding which components in the system have weight, and so on. Thus the goal of functional modelling is expansion of the problem space, by which we mean generating all possible variations of the problem system, to ensure that all components or functions have been included.

Next, the functional model needs to be contextualized which means identifying which of these components or functions will dominate the quantity to be estimated in the given problem context. For instance, in the case of estimating power, this includes identifying which functions of the system will dominate power requirements in the problem context. This comparison is also done by mental simulation and can be supported by graphs showing variation of the quantity to be estimated with each of the components/functions, such that the solver can compare and choose components/functions. Model-building, evaluation and contextualization is an iterative process and solvers will need to go back and forth based on their evaluation to ensure that at the end of this phase they have identified the dominating aspects of the context for the quantity to be estimated.

9.2.2 Qualitative Modelling

The problem system is detailed out by mental simulation; the components of the system are interconnected to generate the functions of the system such that they align with the problem context and requirements. Next, conceptual knowledge is used to constrain the mental simulation and identify the causal relationships underlying the physical interconnections. For instance, if component A is connected to component B, then how does parameter A vary when parameter B varies. This is the qualitative model of the system, which is contextualized by identifying which of these relationships dominate in the problem context. Thus the narrowing of the problem space begins at this stage.

The underlying cognitive mechanism of this phase is conceptual knowledge constrained mental simulation, ie, applying conceptual knowledge to the mental simulation so that it satisfies the laws of causality of the underlying domain and is not an unrealistic simulation. It can be supported using end-to-end or piecemeal variable manipulation simulations of the problem system, with affordances to vary parameters and observe the effect on other parameters in the corresponding graphs or visible changes to the behaviour of the system. The comparison to identify the dominating relationships is also done by mental simulation and the graphs in the simulator can support this comparison. Again model-building, evaluation and contextualization is an iterative process, and aspects of building the qualitative model may require building or re-examining the functional model.

9.2.3 Quantitative Modelling and Calculation or Comparison

The quantitative model is obtained by writing an equation for the quantity to be estimated (or based on which a judgment has to be made) in terms of the parameters that have dominant relationships with it. The equations are written based on the conceptual knowledge of the underlying domains, in terms of the parameters of the problem context. The underlying cognitive mechanism supporting this is symbol manipulation, beginning with familiar equations and then incorporating the parameters important in the context. This can be supported by providing a set of important parameters in the context and relationships from the underlying conceptual domain, and facilitating symbol manipulation.

It is at this stage that the problem space is frozen to an equation on the basis of which the quantity to be estimated is calculated or comparisons are done to make a judgment. At this stage familiarity and experience with numerical values is required in order to do the calculations and comparisons and make a judgment. Thus this stage requires extensive practice of reasoning with and about common numerical values, which can be supported by providing data sheets and lists of values to begin from.

9.2.4 Metacognition

As already mentioned, evaluation is necessary to examine that each of these models is accurate, yet simplified and useful, for the practical purpose of estimating a quantity in the given problem context. These models logically build on each other, however iteration is a natural part of this process; as solvers expand and narrow the problem space using mental simulation and conceptual knowledge, the models are evaluated and revised to increase their accuracy, simplicity and usability. Further, monitoring the evolving models and deciding next steps based on that allows solvers to integrate all the three models of estimation meaningfully. Depending on familiarity with the system, a solver may begin with any phase of modelling; however monitoring their process by comparing the generated model to the problem context and requirements can highlight gaps and suggest the next model to be built or revised. Thus this synthesis or integration of models, based on monitoring and control, is important to obtain a good estimate or make a good judgment.

9.3 From Solving to Learning: The emergence of a pathway for learning estimation problem solving

MEttLE has features such as sub-goals with focus questions, modelling affordances, expert guidance and the simulator to support building and evaluating contextualized functional, qualitative and quantitative models. Each of the three models serves a particular purpose in the estimation and integrated together lead to the final estimate. Thus, building and evaluating contextualized models is a component process of estimation. This was not made explicit in MEttLE and it was left open to novices to make their own understanding of the estimation process. However, MEttLE has planning/monitoring tasks, feedback and expert guidance to scaffold the novice in integrating the models while solving a problem.

In order to solve the estimation problem and obtain a good estimate, novices need to do each of these component processes of estimation and synthesize them. The design of MEttLE supports the tight interplay between cognitive and metacognitive processes necessary to successfully do this, by intermittently providing novices "metacognitive triggers" to move between one level and the next and synthesize the component processes. Generalizing the component processes of estimation we obtain the following representation of the SENECA model (Figure 9.4), which shows the component processes, namely model-building, contextualization and evaluation, and how they come together in estimation problem solving.

Studies 4 and 5 showed that when novices obtained good estimates, they used the designed features of MEttLE in different ways to build and evaluate contextualized functional, qualitative and quantitative models. Thus when novices obtained good estimates in MEttLE, they attained the lower two levels of *model-building* and *model contextualization and evaluation* shown in Figure 9.4. Further we found in study 4 that novices recognized that qualitative and quantitative modelling involved identifying a set of parameters that affect the quantity to be estimated in the context and then creating an equation for it. They also recognized that these two models were interlinked and important for estimation; however they did not synthesize the role of functional modelling into the estimation process, even though they did it. However, study 5 showed that when novices obtain good estimates, they use the additional feedback and expert guidance to recognize and synthesize the role of functional modelling (identifying which actions of the problem system require power in the context) into the estimation process.

Next we focus on what is there in MEttLE to help students learn estimation. By learning

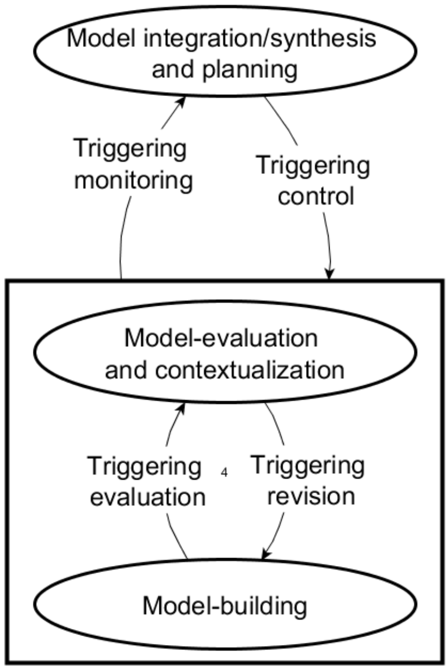


Figure 9.4: The SENECA model of estimation problem solving

estimation we mean that novices are able to apply the synthesized process effectively to solve other estimation problems. Long-term reflection, planning and practice (Litzinger et al., 2011) are known to be necessary for novices to learn complex tasks such as inquiry and problem solving (Kim & Hanna, 2011; Quintana et al., 2004). MEttLE had the Estimap and a reflection activity to support novice understanding of the overall estimation process. Thus MEttLE was designed to support *Model-building*, *Model contextualization and evaluation*, *Integration/Synthesis* and *Abstraction* of the model-based reasoning process (Efklides, 2008; T. O. Nelson & Narens, 1994). Studies 4 and 5 showed that novices understood the three-phased modelling-based process as a systematic way to solve estimation problems and that model evaluation and contextualization is necessary for estimation. The structuring of the estimation process into five sub-goals in MEttLE, each with focus questions and the design of the Estimap served as a productive constraint which led to novices adopting a modelling-based estimation process while solving the problem. Further, even though we did not find evidence of using this process on the post-test of study 5, novices perceived this process to be useful to solve power, and other, estimation problems. Novices reported that being able to practice this process systematically on other similar problems will make them proficient in the applicaton of this process on a variety of problems as seen in this exchange between S10 and the researcher, *S10: That after practising I think that it will be more convenient to make it.*

R: Okay, so how many times do you think you should practice?

S10: Three to four times.

On the basis of these results, we conjecture that when novices interact with MEttLE to execute the model-building processes, take action based on the prompts and expert guidance to evaluate and revise their models, reflect on the role of each model and synthesize them, abstract the model-based reasoning process and deliberately practice (Litzinger et al., 2011) it until it becomes a natural action, they will go through a learning pathway consisting of the four levels of *model-building*, *model evaluation and contextualization*, *integration/synthesis* and *abstraction* as shown in Figure 9.5. These levels are intertwined with metacognitive processes at appropriate times and support novices in learning estimation problem solving by *progressive abstraction* of the model-based reasoning process. Further we propose that such a learning pathway can be used for the teaching-learning of other ill-structured problem solving, with model-building replaced by the component processes of solving the particular ill-structured problem under consideration.

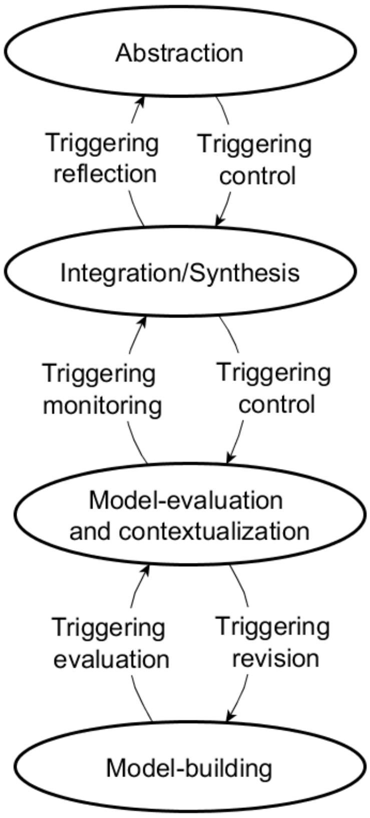


Figure 9.5: Learning through progressive abstraction: A pathway for learning estimation

9.4 Claims

9.4.1 Towards Process of Estimation

Estimation requires making models; the underlying cognitive mechanism is mental simulation.

In study 1, two experts solved three problems each while we video recorded and interviewed them later to identify their underlying cognitive mechanisms. From their gestures, diagrams and verbal descriptions we inferred that experts used mental simulation to model the dynamics of the system, to flesh out its structure and behaviour and to evaluate their built models. Further, we identified that the problem requirements and conceptual knowledge are used to constrain and fine tune this mental simulation and obtain an estimate. Thus making models via mental simulation is necessary to expand the problem space of estimation and focus on aspects that will dominate the estimate.

Model contextualization is necessary for good estimates; models need to be contextualized differently and appropriately at all stages of the estimation process.

In study 1, two experts solved three problems each while we video recorded and interviewed them later to identify their estimation process. From their explanations we identified that experts always began by considering the working of the system. Further, the problem context were throughout a part of the experts' estimation process, even when they did not obtain good estimates. In Study 2, ten novices solved one estimation each while we video recorded and later interviewed them to identify their estimation process. From their explanations, we identified that novices imposed pre-defined conceptual models on the problem, without considering the problem context, which led to poor estimates. However incorporating the problem context, even partially, improved their estimates. These results were confirmed in Studies 3, 4 and 5, when novices worked with a causal mapping tool and researcher scaffolds, and when they worked in MEttLE.

9.4.2 Towards Learning Design

Modelling and mental simulation does not happen naturally in novices; needs to be triggered.

In Study 2, ten novices solved one estimation while we video recorded and later interviewed them to identify their estimation process. From their explanations, we identified that novices were unable to do obtain good estimates because they fit pre-defined conceptual models to the problem rather than expanding the problem space and creating a model for the given problem. In study 3, six novices solved three estimation problems each using a causal mapping tool while we scaffolded them. From an interaction analysis of their causal mapping actions and our scaffolds, we identified that novices must be explicitly required to create models by incorporating the system structure, working and requirements. Further we identified that they must be scaffolded to mentally simulate the structure and behaviour of the problem system and requirements while model-building.

These scaffolds are necessary in any environment that supports extimation - a) Simulations, model-building and model-contextualization affordances b) Metacognitive scaffolds for model evaluation and revision

We designed MEttLE1.0 with explicit modelling sub-goals, focus questions and affordances for modelling. There was also a simulator to support novices mental simulation. In Study 4, ten novices solved one estimation problem each in MEttLE1.0 while we recorded their screen and interviewed them afterwards to identify their estimation process. From their interactions and explanations we identified that the features of MEttLE1.0 triggered model-building of the system working, which was supported by the focus questions and simulator and enabled them to obtain equations for power. We found that metacognitive prompting supporting evaluation and revision of models. However they faced difficulties substituting reasonable values and calculating, owing to the complexity of the models they had created. We modified the design of the TELE and in MEttLE2.0 we incorporated additional prompts and expert guidance for incorporating the system working and requirements, along with animations, graphs, variable manipulation simulations and prompts for productively constraining mental simulation. We found that novices were able to use these resources to obtain good estimates.

9.4.3 Towards MEttLE

MEttLE provides rich affordances for novices to successfully do estimation. With practice, MEttLE would enable novices to learn estimation problem-solving.

We designed MEttLE1.0 and MEttLE2.0 as instantiations of our design principles of supporting modelling via mental simulation with scaffolds for triggering modelling and productively constrained mental simulation of the system working and requirements. We provided affordances such as problem simulators, expert guidance and modelling tools. Studies 4 and 5 showed that novices were able to use these affordances and obtain good estimates. Further novices also reported that practicing on such an environment with three or four problems would enable them to learn how to solve estimation problems.

9.5 Generalizability

9.5.1 Generalizability of Estimation Process

As explained in section 1.5, our scope in this thesis was limited to studying experts and novices as they solved estimation problems dealing with estimation of length, power, mass and weight for the purposes of

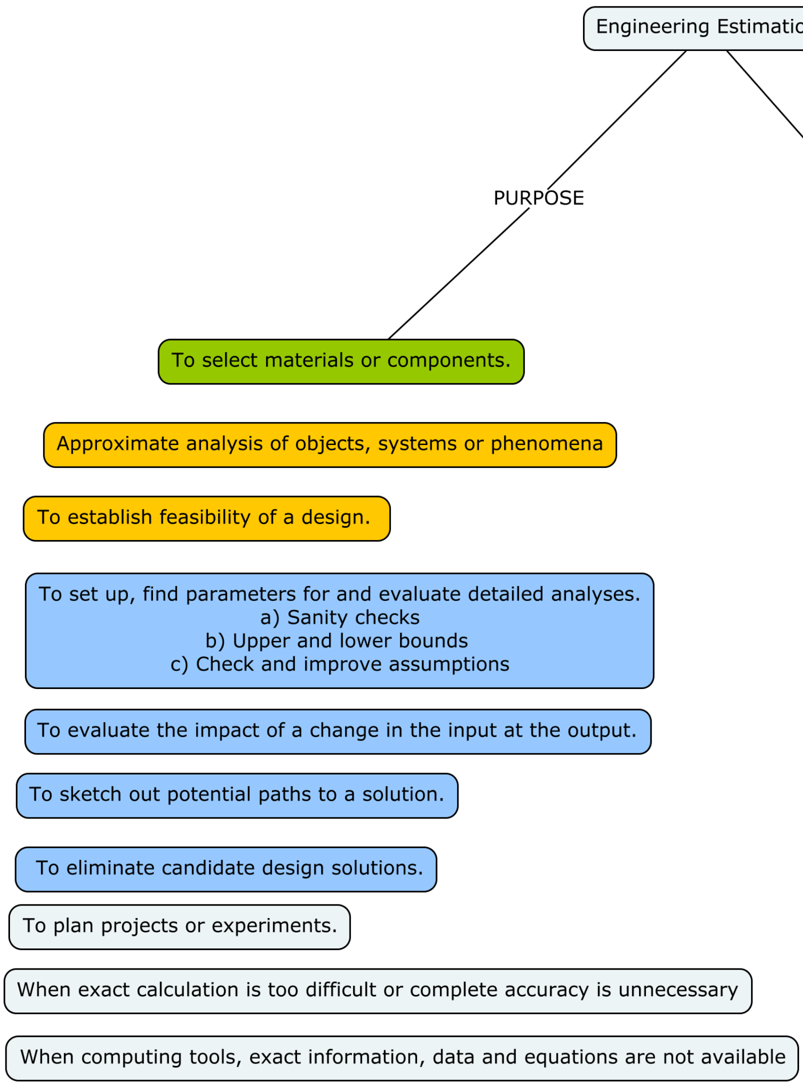
1. Select a material or component
2. Establish feasibility of a design
3. Approximate analysis of objects, systems or phenomena.

We identified a modelling-based estimation process based on mental simulation and manipulating external representations that can be applied to solve problems of estimating the above quantities, for the above purposes. We identified the critical role of model contextualization and metacognitive processes such as evaluation and monitoring throughout the estimation process. Next we consider whether this process is generalizable for other problems and purposes.

Generalizability to other types of estimation problems

All the purposes for which estimation is done are shown in Figure 9.6.The process of estimation proposed in this thesis can be applied to other purposes of doing estimation that require creating simplified models of an existing object, system or phenomenon or an object or system to be designed as shown in Figure 9.6 (nodes in blue) and elaborated below.

Figure 9.6: Estimation purposes and quantities



1. Set up, find parameters for and evaluate detailed analysis: In this type of problem, either before beginning or after completing a detailed analysis of an existing system, solvers need to develop a sense of the critical parameters that affect the behaviour of the system and hence which parameters they must focus on in the detailed analysis. The process of creating simplified models using mental simulation and manipulating external representations such as diagrams, graphs and equations that we have proposed in this thesis, can be applied for this purpose.

2. Evaluate the impact of change in input at the output: Similar to the above case, this type

of problem requires developing an approximate understanding of the behaviour of the system in order to relate changes in the input to the output. Therefore, a modelling-based process similar to the one we propose, consisting of functional and qualitative modelling alone, can be applied to such problems.

3. Sketch out potential paths to the solution; Eliminate candiate design solutions: Before beginning a design, designers often estimate in order to identify a way to approach the problem (for instance, the solution may vary depending on the power requirement) or to decide if a candidate solution is reasonable or not. Such problems require estimating a quantity and then making a decision based on it. Thus the estimation process we have identified in this thesis can be applied to solve such problems, except that the evaluation criteria after obtaining an estimate will vary depending on the purpose of the solver.

Generalizability to other quantities to be estimated

The value of any quantity such as, energy/ weight/ length/ area/ volume/ speed/ force/ bandwidth/ error rates, is estimated with respect to a physical system or object. Thus estimation of any of these quantities would also require modelling of the system or object, either existing or desired, that they are associated with. So, the modelling-based estimation process identified in this thesis can be applied for the estimation of any of the quantities listed above and marked in blue in Figure 9.6.

9.5.2 Generalizability of MEttLE Design

The design of MEttLE and the scaffolds for estimation are based on supporting a progressively higher order modelling-based process which includes model-building, contextualization, evaluation and revision. The supports are identified based on inputs from literature, expert-novice processes and instructor recommendations. MEttLE has been currently been instantiated and evaluated for a power estimation problem for the purpose of selecting a material or component. Here we examine whether the design are generalizable for other types of estimation purposes other than selecting a material or component and other quantities apart from power.

Generalizability to other types of estimation problems

The theoretical basis of MEttLE is model-order progression with supports for mental simulation, model-building and contextualization, in addition to metacognitive prompts for model evaluation, revision and monitoring. Thus design and scaffolds in MEttLE can be used to support novices in estimation for other purposes which require modelling. As we described in section 9.5.1, these include, (yellow and blue nodes in Figure 9.6)

- Approximate analysis of objects, systems or phenomena
- To establish feasibility of a design
- Set up, find parameters for and evaluate detailed analysis
- Evaluate the impact of change in input at the output
- Sketch out potential paths to the solution
- Eliminate candiate design solutions

Generalizability to other quantities to be estimated

The design and scaffolds in MEttLE can be used for the estimation of quantities which require modelling the systems or objects, either existing or desired, that they are associated with. These include quantities required from a system or object to be designed, or the characteristic of an existing system or object, such as (but not limited to) energy/ weight/ length/ area/ volume/ speed/ force/ bandwidth/ error rates. Thus the design of MEttLE and the scaffolds in it are generalizable to these quantities (marked in yellow and blue in Figure 9.6).

Generalizability to other domains

The design and scaffolds in MEttLE depend on the underlying estimation process and the causal structures underlying the system. The problem chosen in MEttLE derives its causal structures from Mechanical and Electrical engineering, which are heavily based on the physical sciences. Thus the pedagogy would be applicable for estimation in systems with similar causal structures, arising in related domains of engineering such as chemical engineering (for eg, energy of a chemical process), aerospace engineering (for eg, power of aircrafts) and networking (for eg, download time). However the applicability of this pedagogy for probabilistic causal structures such as software engineering (for eg, cost, effort and time of software projects), communications engineering (for eg, estimating the information from noisy signals) and aerospace engineering (probability of failure of structures) remains to be examined.

Generalizability to other contexts

We instantiated our design and scaffolds into MEttLE, an open-ended self-learning TELE; novices can work in MEttLE, use the scaffolds in any manner they choose and solve estimation problems. However MEttLE2.0 can also be used as is in a classroom to help students learn estimation problem solving. As an example, one instructor at our institute chose to use MEttLE2.0 in his classroom early in the semester to introduce estimation to his students, as he expected them to solve estimation type problems later in the semester. The instructor perceived that the system can be used to develop students' engineering intution because of the emphasis on modelling and simulation. We introduced the MEttLE2.0 system to the instructor and the TAs in a 2 hour session one day prior to the MEttLE classroom session. The goal was to familiarize them with the system and its functionality so that they may be able to guide novices in the classroom in case of technical difficulties with MEttLE. There were no additional requirements to use MEttLE2.0 in the classroom. An instructor may also use the identified scaffolds to create an instructional strategy for estimation problem solving to be used in a classroom or lab as described in section 9.7.2.

Generalizability to other technology

In MEttLE, the support for mental simulation was provided via variable manipulation computer simulations. However the same support can be provided via physical simulations as well. By physical simulations we mean a lab kit, where a novice can manipulate the various parameters of the system and examine the effect on the quantity to be estimated. For the car case, this would include a toy car, changeable motors, batteries, controllers, along with meters for measuring quanitities directly or derived quantities such as speed, acceleration, torque and power. In such a case, students can begin by seeing a sample car prepared for their understanding and then change its components to examine what happens. Indeed this was recommended by EI also as a way of providing real-world experience and seriousness to the problem of estimation. In addition, informal conversations with students also showed that this would increase their engagement and motivation.

9.6 Limitations

In this section, we elaborate on the limitations of this thesis owing to the conditions of the research.

9.6.1 Limitations related to learner characteristics

This work was scoped to novices of first and second year mechanical, electrical and allied branches, who were from urban colleges, whose medium of instruction was English and who were proficient in the use of computers. However there are several other characteristics of novices that are relevant to ill-structured problem solving such as estimation. These include prior experience, motivation, interest, persistence and beliefs. In our studies 2,3 and 4 we ensured that novices had high motivation and interest in solving estimation problems and thus were metacognitively aware while doing estimation (McWhaw & Abrami, 2001). However in Study 5 we did not purposively sample novices on the basis of motivation and interest and found that lack of interest might have been the reason for some novices lack of metacognition while doing estimation. However, we have not systematically incorporated novice motivation and interest in our analysis of their estimation process and so we do not understand how exactly these characteristics affect their estimation problem solving and subsequent learning from MEttLE. This is a problem worthy of further investigation, to tease apart the role of affective factors in estimation problem solving.

While we considered learners whose medium of instruction is English, we did not test their proficiency in English before they interacted with MEttLE. Given the open-endedness of MEttLE and the complexity of the estimation problem, it is likely that their fluency in reading and writing English may have impacted novices' interaction with MEttLE, and thus their estimation problem solving. We did not consider this aspect in our analysis.

While we ensured that we chose one male and one female expert, in studies 2, 3, 4 and 5 we had respectively 1, 0, 1 and 4 female participants. As we selected participants by convenience in studies 3 and 5, we had no control over the gender ratio. Even when we purposively selected participants in studies 2 and 4, we were unable to find suitable female participants. This is an aspect of the domains of engineering we chose, because in India the gender ratio is heavily skewed towards males in mechanical and allied branches. So it remains to be investigated further whether gender has any effect on the estimation processes.

9.6.2 Limitations related to the estimation problem

As explained in section 9.5, broadly the design and scaffolds of MEttLE are applicable to a set of purposes of estimation and quantities to be estimated. However certain context specific scaffolds such as the expert guidance and feedback on the model evaluation and contextualization questions, depend on the context of power estimation of a car that has to be designed. They will need to be adapted suitably for other contexts and quantities. For instance, model contextualization in the functional modelling stage involves focussing on the important action required from the problem system. In the case of a car, it is accelerating or overcoming drag and not playing music. However, in the case of designing a two-way paging system, the important action is transmitting the signal reliably and not the torch. These aspects of the problem context have to be brought to the novices' attention as they are solving the estimation problem. Therefore the expert guidance has to be changed according to the problem context and faded as the novice gains expertise so that they may develop the ability to focus on important actions. We have not considered how to fade these context-specific scaffolds in this work, and it is worth investigating this in future work.

The simulator is designed for the power estimation in the context of a car to select an appropriate motor. Broadly the simulator consists of four tabs, each focussing on different aspects of estimation. The first two support novices in mental simulation of the system, and then focussing on the important actions of the system. The third and fourth tabs support learners to identify and focus on important parameters for the quantity to be estimated. The nature of the simulator for other problem contexts would broadly remain the same. However the exact animations, graphs and variable manipulation would change depending on the quantities and purposes of estimation. We have not examined the effect of the change in the problem context on the design of the simulator.

9.6.3 Limitations related to research method

Every research method has its limitations; here we articulate the limitations of this work that result from our chosen research methods. In this thesis, we have employed several methods appropriate to answering our multiple research questions. However, broadly our research adopts an interpretivist approach (Thanh & Thanh, 2015) and thus our results depend on the theoretical lens through which we view the estimation problem solving process. First and foremost, our work is based on a distributed view of cognition (Hollan et al., 2000). We believe that cognition emerges as a solver interacts with the resources in his/her environment and therefore we study these interactions to understand how it led to solving the problem. Another theoretical lens might lead to other results. For example, another researcher might adopt a socio-cultural perspective and study how cultural artefacts, social interaction and language play a role in the estimation process. It is important to understand that neither of these approaches is incorrect, but together offer a more holistic view of estimation. In this thesis we have provided a view of the cognitive processes of estimation that we believe are important to support novices in doing and learning estimation, which was our larger goal.

In our endeavour to design supports for novices we adopted DBR, a pragmatic research methodology, which studies the effect of the design of MEttLE on novice problem solving and seeks to iteratively redesign the supports in order to improve novice performance. Thus, investigating the effect of each feature on novice performance is not within the scope of this work; our goal was to "optimize" the design in its entirety. However now that the design has been refined and evaluated, it is worth investigating the individual features of MEttLE and examining which of these has major effects and which has minor effects on the estimation performance.

When we undertake research in ecologically valid settings, we must be mindful of the conditions in the field in our experiments. In the last study, which we conducted in a college outside our institute, we had to adapt to the conditions in the college. So to keep with the college timings, we allowed participants a fixed time, between 1.5 and 2 hours, which led to some participants rushing through their solutions in MEttLE in the end. We considered this aspect in our analysis and tried to mitigate this effect by having them elaborate their steps in more detail during the interview.

Our analysis focusses on how solvers interact with MEttLE to solve the problem. Specifically, we investigated the cognitive and metacognitive processes that emerged from novices interaction with MEttLE and how that led to solving the problem. We have, however, not evaluated how interaction with MEttLE helps novices learn how to solve new estimation problems. We conjecture regarding the learning pathway in section 9.3 that learning how to solve estimation problems requires multiple interactions with MEttLE. The number and nature of such interactions is a question for future work.

9.7 Implications

9.7.1 For Theory

In this work, we analyse the cognitive processes of estimation guided by the distributed cognition framework; we examine how cognitive processing is distributed across internal operations and manipulations of external representations such as diagrams and symbols. We found that the cognitive processes underlying estimation are model-building using mental simulations and manipulations of external representations such as diagrams and videos. We identified that it is this model-building process that leads to good estimates, rather than symbol manipulation. Thus our work shows that estimation is an instance of model-based reasoning; however, model-based reasoning in engineering differs from model-based reasoning in science, where conceptual knowledge is generated by model building. We identified that, in estimation conceptual knowledge-constrained mental simulation is used to build simplified models of the context that can be used in estimation. While model-eliciting activities (Hamilton et al., 2008) have been used in engineering to assess and develop engineering students higher order thinking skills, our work has found that model-based reasoning is the underlying process for approaching open-ended engineering problems.

Engineering design has been extensively studied, albeit from an information processing perspective of cognition, except for recent work such as (Aurigemma et al., 2013; Chandrasekharan & Nersessian, 2015; Date & Chandrasekharan, 2018) studying design cognition from a distributed perspective. Other types of engineering problem solving have not been studied at the cognitive mechanism level and models of engineering problem solving are very broad and from an information processing perspective (Adams et al., 2008; Elger et al., 2003; Jonassen, 2000). While the role of different types of knowledge and visualization in engineering has been discussed (Ferguson, 1977; Vincenti et al., 1990), our work is the first to offer insights into the interplay between mental simulation, manipulation of external representations, conceptual knowledge and metacognition in engineering problem solving. Adopting a distributed cognition perspective allows us to examine problem solving at such a micro-level. The SENECA model of estimation proposed in this work can be applied to understand other engineering problem solving such as troubleshooting and design audit.

In this work, we used a novel approach to probe novices estimation processes by using a open-ended TELE with several features for solving an estimation problem. By examining novices' interaction with such a designed environment, we were able to develop fine-grained characterizations of different aspects of solving estimation problems, such as, model-building, contextualization, evaluation, revision and monitoring. We were able to investigate the different kinds of simulations and representations, and the solvers' interaction with them, that lead to breakthroughs in model-building and solving the problem. We were able to examine the role of prior knowledge (both formal and informal) in estimation. Allowing novices to continue working with MEttLE and evaluating their interactions, can lead to a model for the development of estimation problem solving.

9.7.2 For the Teaching-Learning of Estimation: Guidelines for Teachers

This thesis identified a process for solving estimation problems and a set of scaffolds that are necessary for doing estimation. Specifically, we identified that modelling via mental simulation and incorporating the problem context at all stages is necessary for estimation. This requires a shift in current engineering problem-solving pedagogies wherein problem-solving is taught by getting students to fit available conceptual models to the given system and its requirements. As we observed, this leads to novices inability to obtain good estimates.

We propose that novices be scaffolded in creating models of the system working via mental simulation and then to systematically incorporate the problem requirements and conceptual knowledge into their solution. We presented one approach to do so, which uses explicit modelling sub-goals, scaffolds for mental simulation and guidance for incorporation of problem requirements and conceptual knowledge. Below we present guidelines for teachers and instructional designers to recreate the MEttLE pedagogy in the classroom or in other technology-enhanced learning environments.

1. **Make modelling explicit for learners.**
   Begin by requiring learners to make a model of the structure and/or working of the system depending on the problem. This can be triggered using questions such as "What does this object look like?", "How does this object work?" or "What does this system need to do?". To facilitate this process, ask students to draw diagrams of their understanding of the structure and/or working. Depending on their familiarity with the system, learners may also need to be provided animations, videos, physical models or descriptions of similar systems to trigger their mental simulation.

2. **Scaffold learners to flesh out the structure & working (physical + causal) of the system.**
   Use prompts such as “Think about how this component is connected to this other component.” and “What would affect the size of this solar panel?”. Provide variable manipulation simulations of the type used in this thesis or other tools for experimentation, along with scaffolds regarding how to use the simulations and what to observe. Encourage novices to create a mind map or causal map of the structure, working and causality of the system. Specifically, require them to explicate how all the components are connected together and the causal relationships between the various parameters.

3. **Scaffold learners to evaluate and contextualize their models**
   Prompt learners to check whether the structure & working that they have identified focuses on the dominant aspects of the system and can meet the problem requirements with questions such as, “If a constant power is supplied will the car keep on accelerating?” or “What would the major source of weight in this radio?” or “If this component is connected to this component will I get the required motion?” or “What supplies energy and where is it used?” Encourage students to mentally simulate or use the variable manipulation simulations to answer these questions.

   An instructor or instructional designer must also incorporate problem context specific guidance of typical engineering practices at this stage. For instance, how is “major” in “major source of weight” quantified? Is it 70% or 80% of the weight?

4. **Scaffold learners to use the causal structure of the system, incorporate conceptual knowledge and make equations for the quantity to be estimated.**
   This part is critical for low conceptual knowledge learners who don’t know which equation to apply in the context. Provide the generic equations for the quantity to be estimated and asked them to adapt it to the given problem using the identified parameters in step 3. Additionally, encourage learners to break down the composite causal structure identified earlier into parts to facilitate identification of the right equatons for each part. For example, a separate equation for input part and the output part.

   Prompt learners to check for dimensions and ensure that all the parameters on the right hand side are known quantities. Prompt learners to ensure that they have not ignored any dominant aspects of the system that they had identified in step 3.

5. **Scaffold learners to choose reasonable numerical values and calculate the estimate.**

   Provide guidance for novices to identify the numerical values for parameters in the equation based on the system working and requirements. This maybe the performance expected from the design, such as, a power output of 2W or the size of some part of the system, such as, the area of a component or a quantity derived from the performance requirement, such as, cost should be less than 1000. Provide guidance regarding how to choose values for standard values, such as losses and inefficiences in systems, by providing data sheets or including these values in the simulator. Also provide guidance of typical engineering practice as values that experts typically choose or related case studies. Prompt them to justify their chosen values.

6. **Scaffold learners to evaluate the estimate by comparison to at least two other standards. Provide values for comparison**
   Provide learners the criteria by which to evaluate their estimate, such as, order-of-magnitude and comparison with a standard value. Provide lists of standard values for the parameter in other contexts, such as, masses of other objects, power required by other objects, etc. Prompt students to compare their obtained values with the standard values and justify their comparisons.

9.7.3 For research and methodology

In this work, we demonstrate an approach (Figure 9.7) for systematically designing a learning environment for estimation problem solving, which can be applied to designing learning environments for other kinds of engineering problem solving and practices (Jonassen et al., 2006; Sheppard et al., 2007). This approach is based on DBR and a distributed view of cognition. The design process begins with the problem analysis phase of DBR in which cognitive ethnographies help to understand expert and novice cognitive and metacognitive processes while problem solving and the differences between them that lead to novices' poor performance. These differences are translated into a set of requirements that any learning environment must have to support novices' problem solving. Applying the appropriate learning design principles, the set of requirements must be instantiated into a learning environment which allows novices to do the expert cognitive processes. Further, the learning environment must foster progressive abstraction of the problem solving process by including metacognitive tasks at appropriate points in the problem solving.

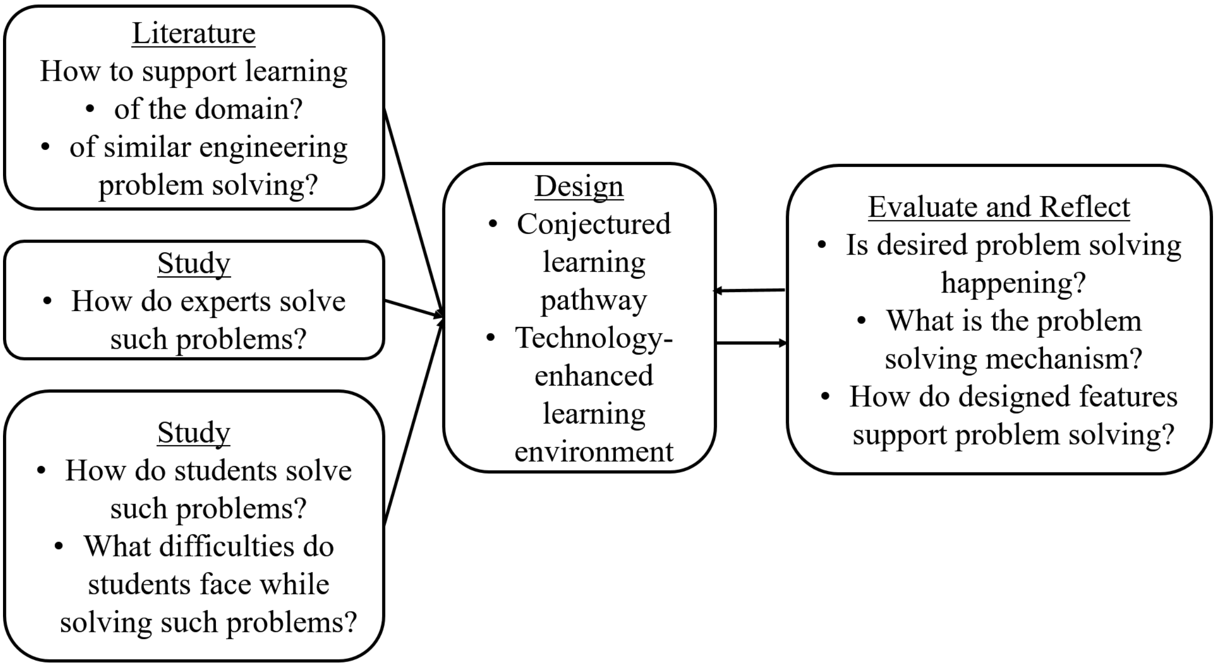


Figure 9.7: A research approach for designing learning environments for problem solving

This learning environment must then iteratively evaluated and redesigned to refine novice processes towards expert performance. The combination of interaction analysis and thematic analysis with stimulated recall interviews in order to understand novice problem solving processes as they work in the environment, and to identify the roles played by the learning environment features in these problem solving processes, is a promising approach to simultaneously study fine-grained problem solving processes and novices' development of problem solving.

Chapter 10

Conclusions

10.1 Contributions of the thesis

10.1.1 Theoretical understanding of estimation

1. This thesis is the first to provide a detailed characterization of expertise in engineering estimation and its cognitive mechanisms. These results have implications for researchers in the learning sciences, cognitive science and engineering education who wish to examine the nature of expertise in different kinds of engineering work.

2. This thesis provides a rich characterization of novice estimation processes, both without scaffolds and in a learning environment designed for scaffolding estimation problem solving. We also identified the role of various scaffolds in novice estimation problem solving. This has implications for researchers in the learning sciences and engineering education, who wish to understand the role of various scaffolds in novice solving of complex ill-structured engineering problems, that they can adapt to other such problems.

3. Based on expert and novice processes, we proposed a model for solving estimation problems that leads to good estimates. This has implications for researchers in engineering education who wish to understand estimation and train engineering students to solve estimation problems.

10.1.2 Pedagogy

1. This thesis describes a pedagogical design of a learning environment for supporting estimation problem solving. This design can be adopted directly by instructional designers and developers to develop technology-enhanced learning environments and engineering educators to teach estimation.

2. This thesis identifies a set of scaffolds necessary in a learning environment supporting estimation problem solving. These results can be used by instructional designers and engineering educators to design teaching-learning environments for estimation, and by researchers in engineering education and learning sciences to scaffold other types of complex ill-structured problem solving

3. This thesis proposes an approach for the teaching-learning of different kinds of problem solving via *progressive abstraction*. This pedagogical approach emerges from our pedagogical design of MEttLE, which has explicit focus on both the cognitive and metacognitive aspects of estimation and is based on our expert studies and the metacognitive model of (Efklides, 2008; T. O. Nelson & Narens, 1994). This can be adapted by educators and researchers in problem solving to design learning environments for their specific type of problem solving.

10.1.3 Learning environment development

MEttLE is an instantiation of a learning environment with the pedagogical design that enables novices to solve estimation problems and obtain good estimates. It can be easily re-developed for multiple problems and used by novices to learn estimation by repeating the problem solving activity at least three times. This has direct implications for students who can use MEttLE for self-learning of estimation and engineering educators who can deploy MEttLE in their classrooms or labs.

10.2 Future Work

In this work, we have opened the door on the investigation of estimation problem solving, its underlying cognitive mechanisms and design for supporting novices' estimation problem solving. Our work can be taken forward in many directions as we describe below. Some of this work is related to the limitations of the work carried out in this thesis, while others are extensions.

10.2.1 A deeper characterization of estimation

In this work, we studied the process of estimation, identified its cognitive and metacognitive mechanisms and how they come together to solve an estimation problem. An interesting question that arises is regarding the relative significance of each of these mechanisms on the quality of the final estimate obtained. For instance, the role of mental simulation vs conceptual knowledge vs metacognition is not clear from our work. While we found that all are important, and all are intricately linked in the estimation process, the question of which is more important remains. The answer is relevant to engineering education where the emphasis is still on conceptual knowledge, and understanding the relative importance of mental simulation and metacognition can re-distribute the emphasis and change the focus of engineering education.

Mining for productive action patterns in estimation

MEttLE is a useful platform to investigate the above question. It is an open-ended learning environment and has several features for estimation which solvers use as they solve the problem. These features trigger certain cognitive and metacognitive mechanisms. The goal then is to investigate which of the features contribute to the quality of the final estimate and through which *"productive action patterns"*. This goal can be investigated by having experts and novices solve problems in MEttLE and logging their interactions (mouse clicks, eye movements, artefacts). Then by integrating the data, we can identify the action patterns (for eg, viewing the animation and writing a model statement) that correlate with obtaining good and bad estimates. These are the productive and unproductive action patterns respectively, and these will help us tease apart the relative importance of each of these actions (eg, viewing the animation) and thus the underlying cognitive/metacognitive mechanisms (eg, mental simulation).

Once the productive and unproductive action patterns have been identified, this research can be taken forward to build additional adaptive scaffolds in MEttLE. The first step is to identify when learners are doing unproductive action patterns and provide feedback regarding the productive actions to be done at that point. This method of adpative scaffolding (Azevedo et al., 2011) is already heavily researched in several intelligent tutoring systems (Azevedo &

Hadwin, 2005) and is now being attempted in open-ended learning environments (Basu et al., 2017). Therefore it is worth investigating the role of such adaptive scaffolds on estimation problem solving as well.

10.2.2 Development of MEttLE for other problems and topics

As described in Section 9.6.2, the scaffolds for estimation reasoning and practices, and the design of the simulator depend on specific aspects of the estimation problem context. For example, while power estimation of a car requires comparing the power required for various actions of the car, energy of a chemical reaction will require comparing the energy required in breaking and forming chemical bonds. This will require different visualizations and scaffolds than the animations and graphs in the car simulator. We will gain a complete understanding of the types of scaffolds and simulator designs that are useful for estimation reasoning and practices in different contexts by studying the effect of various scaffolds and simulator designs on novice solving of different estimation problems. Towards this goal, the first steps will be to select a diverse set of topics and estimation problems, and redesign and redevelop MEttLE for these problems.

10.2.3 Learning of estimation problem solving

A pathway for learning estimation problem solving emerged from our work (section 9.3), which suggests that novices progress towards expertise when they apply the cognitive mechanisms of estimation, evaluate, synthesize and abstract, interspersed with metacognitive processes at the appropriate times. However, acquiring all the four levels requires novices to practice in a specific way, which is not clear. There are at least three aspects which will affect novice progression. The first is the quantum of practice that a novice gets, measured in terms of the number of problems solved in MEttLE. The second is the nature of the problems chosen for the practice, specifically, the impact of similar problems vs different problems in the practice set. For instance, a set of similar problems would be vehicle power estimation problems. A set of different problems would be power estimation of various systems such as a car, a radio and a solar panel. Another option would a set of widely different problems such as power estimation of car, cost estimation of a building and energy of a chemical process. The third factor that will affect the development of estimation problem solving is the fading or availability of scaffolds during the practice. The goal is to make novices gradually proficient in solving estimation problems independently.

We propose that this investigation will have to proceed in a phased manner. In the first phase, investigate the role of doing similar problems multiple times, with and without fading scaffolds, on the development of estimation problem solving proficiency. The specific research question is, **"What is the effect of practice (in terms of number of problems solved in MEttLE) and fading scaffolds on novices' estimation problem solving performance?"** The study design would consist of two groups (fading and non-fading group), each of which solve four problems in MEttLE across four weeks. In the fading group, novices solve one problem with all scaffolds, one problem without model evaluation scaffolds, the next without planning and monitoring scaffolds and the last with no scaffolds (but simulator available). In the non-fading group novices always have all scaffolds available. The evaluation should consist of a pre-test and a post-test with two problems, one similar problem and one different problem (as defined above), conducted after the second, third and fourth session with MEttLE. A repeated measures analysis of the novices post-test scores in each group, will provide evidence for novices' development of estimation problem solving. The difference (if any) between the post-test scores of each group, will explain the effect of fading the scaffolds on novices estimation problem solving. We conjecture that novices in the fading group will perform worse than the non-fading group on the similar problem in the post-test, but better on the different problem.

The role of changing the nature of problems during practice in MEttLE will have to be investigated next. The study design can be similar to above, except that the problems will be different from one session to the next. Here the problems will have to be chosen carefully so that while the the quantity to be estimated remains the same, the problem system changes, but not so much that the novices do not have the necessary conceptual knowledge. It is difficult to conjecture the results of this study at this time, because of the interaction between fading of scaffolds (and the consequent difficulties that novices may face) and problem solving proficiency. It is known that failure or difficulties are desirable at certain times in problem solving (Kapur, 2008; VanLehn et al., 2003), and while they do not lead to benefits in similar problem solving, there are benefits in different problem solving. This study will add to the literature investigating the effects of failure on problem solving proficiency (Manalo & Kapur, 2018).

10.2.4 An alternate understanding of estimation

In this work, we have explored the estimation process of trained expert engineering practitioners as they solved problems which were new to them. Further we studied the estimation processes of in-training engineering novices as they worked with and without MEttLE. Together these studies gave us an in-depth understanding of the model-based reasoning process for estimation which is grounded in conceptual knowledge. However it is possible to make estimates without (explicit) conceptual knowledge, based entirely on tacit knowledge and comparison, as we see in the case of many grassroots innovators (Date & Chandrasekharan, 2018). It would be interesting to understand this alternate estimation process as it would give us an understanding of how to develop novices comparison skills, which are required even in the model-based estimation process in order to evaluate estimates.

As a first step towards developing this understanding, we conducted a cognitive ethnography with two fourth year engineering students of our institute who had been tinkerers since their first year and were involved in extra-curricular technical activities. They each solved three problems while we video recorded them and interviewed them later to identify their reasoning processes. The complete analysis is in progress, but a preliminary look at the data suggests that the tinkerers way of doing estimation is qualitatively different from the estimation process proposed in this thesis. We see that despite the fact that the tinkerers have had courses in the relevant conceptual knowledge, they proceed not by doing estimation using the SENECA model, but through a process of informed trial and error, which is based on refining a preliminary estimate (often based on prior knowledge) using systematic comparisons, based on mental simulations and gradually expanding the causal map. Detailed analysis would give us insight into how we can develop this comparison skill among novices.

10.2.5 Role of affect on estimation problem solving

We did not systematically investigate the role of affective factors in this thesis. For studies 1-4, we purposively sampled motivated and interested participants and so the lack of motivation and interest was not a factor in the estimation problem solving. In study 5 however, the participants were required to participate in the workshop by their instructor and so individual participant motivation and interest is not automatic, even though participation in the interview was voluntary. As reported in the Section 8.4, we perceived from the student interviews that lack of motivation and interest could have been a reason for the poor metacognition and hence poor estimation performance of some participants. So it is important to investigate the effect of these and other affective factors on estimation problem solving. The research questions for such an investigation would be

1. **RQ:** Which affective factors of a novice impact his/her estimation performance in MEttLE?

2. **RQ:** How do the affective factors of a novice impact her/his estimation performance in MEttLE?

These affective factors may include, but are not limited to, the following: (i) Intrinsic motivation of the novice towards doing and learning estimation; (ii) Novices' self efficacy about how well /she can solve estimation problems; (iii) Novices' interest in solving and learning to solve such problems as estimation. There may be other factors which will have to be identified from further literature search on the role of affective factors in ill-structured problem solving and engineering practices (Sheppard et al., 2007). One way to investigate these affective factors is to intermittently track novices' self-reported motivation, interest, self-efficacy, etc as they are solving the problem in MEttLE and correlate these affective factors with their productive and unproductive action patterns (as described in section 10.2.1). This will throw light on the how the affective factors impact performance, and how performance in turn influences these affective factors.

10.2.6 Effect of collaboration on estimation problem solving and learning

Collaboration is believed to be valuable in ill-structured problem solving and design (OECD, 2017) and is a common practice in engineering problem solving (Jonassen et al., 2006). It is known that collaboration with peers can also serve as a scaffold, because it can activate a set of learning processes that can be beneficial for problem solving and learning, and that are not available to individuals working alone (Barron, 2003). These include providing and receiving explanations about a phenomenon, providing critiques and observing the strategies of others (Barron, 2003). There is evidence suggesting that when individuals collaborate on problem solving, they generate strategies and abstract problem representations that are rarely observed when individuals work alone (Schwartz, 1995). Collaboration and conversational interaction during problem solving can lead to students gradually constructing deep understanding of scientific concepts (Roschelle, 1992). Research suggests that collaboration can be beneficial for conceptual understanding because it promotes elaboration, but is not as effective for learning procedures as it leads to task distribution (Mullins et al., 2011).

However, there is also evidence that collaboration does not always lead to improved learning (Olsen et al., 2014) and a combination of individual and collaborative learning may be more beneficial for learning (Olsen et al., 2017). This has also been found in classroom studies of the Think-Pair-Share learning activity wherein a combination of individual and collaborative learning in different phases of the activity has been found to improve conceptual understanding and classroom engagement (Kothiyal et al., 2013, 2014). Similarly, research on the role of collaboration on idea generation or brainstorming consistently shows that people working individually produce more ideas and more good ideas when working alone than when working in groups (Stroebe & Diehl, 1994). Studies have also shown that a hybrid condition, which involves alternation of alone and group idea generation, leads to best performance in terms of ideas generated (Korde & Paulus, 2017). Further, when an idea selection task is added after idea generation, studies showed that neither individual nor group idea selection is better than chance, and so there is scope for further research into the idea selection process (Rietzschel et al., 2006). This literature together shows that the benefits of collaboration depend on the nature of the task involved and the type of collaboration engaged in during the task. Thus, there is need for further research into how and why collaboration may be useful during estimation problem solving. Specifically, we would also like to understand the nature of collaboration that is beneficial to learning estimation, particularly, at which stages of MEttLE learners should collaborate, and how. The broad research questions of interest in this area are,

1. **RQ:** What is the effect of collaboration on estimation performance?

2. **RQ:** How should learners collaborate while learning estimation in MEttLE?

3. **RQ:** At what stages of MEttLE should learners collaborate while learning estimation?

One way to investigate the role of collaboration on estimation performance (first RQ above) is to examine the action patterns of solvers during estimation in MEttLE, when they do and do not collaborate. The differences in the numbers and quality of action patterns can be used to quantify the effect of collaboration. The second and third RQs above deal with designing and evaluating scripts for collaboration in MEttLE. For instance, should learners collaborate during functional or qualitative modelling? Should the nature of collaboration be peer assessment or collaborative co-construction of models? What is the nature of external represenations needed to support this co-construction? How can the action patterns of learners be used to decide the collaboration script? How can a teacher orchestrate this collaboration, on the fly in the classroom? There are many such outstanding questions in the broad area of orchestrating collaboration for estimation problem solving that can be systematically investigated using MEttLE and learning analytics for designing and evaluating collaboration scripts.

10.2.7 Alternate instantiations of MEttLE

In this work, we designed and developed one instantiation of MEttLE where we chose a certain set of modelling affordances and a particular type of simulator which we found to be effective for supporting the modelling-based estimation process. However, EI recommended that a LE in which learners actually build things would be very valuable for learning the practical aspects of estimation, and this was corroborated in our interviews with tinkerers as well. There is literature which describes the value of tinkering and making for improving engineering problem solving and design (Davis et al., 2017; Tan, 2016). Further, distributed, embodied and situated cognition (Brereton, 2004; Hollan et al., 2000; Johri & Olds, 2011) also suggests that cognition and action share a common neural mechanism and cognition emerges from the interaction between external objects and internal resources. Thus it is worth designing and investigating the effect of alternate instantiations of MEttLE which give students a physical LE rather than a software-based TELE for estimation.

Such a physically instantiated MEttLE could have a prototyping kit instead of the simulator and learners would be required to build and revise their estimation models using the components in the kit. Thus a functional model of a car would not just be imagined, but instantiated using the motor, wheels, chassis, etc provided in the prototyping kit. By testing and revising these models, the learner would generate the variations necessary to expand the problem space, understand the problem system, the dominant actions and parameters and be able to estimate the quantity in the problem context. We conjecture that building, testing and revising these models would support the mental simulation and modelling processes and thus the support estimation. Learners would also be supported in this process using the scaffolds, hints and prompts that we designed and validated in this thesis. Preliminary studies in this research area are best undertaken as cognitive ethnographies of few learners working in such a LE, in order to understand the effect of each feature in the LE on the estimation problem solving and learning.

10.3 Final Reflection

This thesis has been an attempt to tease apart estimation, a complex engineering practice and as (Guzdial, 2016) wonders it might be “one of those hard-to-transfer higher-order thinking skills OR it could be a rule-of-thumb procedure that could be taught.” This thesis is now able to offer some answers in this regard. Estimation is definitely not one a rule-of-thumb procedure; it is based on the reflective integration of three kinds of models. In that aspect, it is a higher-order thinking skill that is a necessary practice in engineering. Its transferability is up for debate; we identified a broadly applicable process and its component cognitive and metacognitive mechanisms. However we also understood that estimation requires a kind of knowledge unique to engineering called “practical considerations” (Vincenti et al., 1990) which include rules-of-thumb. These practical considerations are tacit and specific to particular domains, and therefore non-transferrable. What might be a reasonable practice in power estimation might not be reasonable in error estimation. Thus an engineer must always be cognizant of the practical considerations of his/her domain.

For someone who has been fascinated by the practice of estimation ever since watching a professor estimate the maximum possible bit rate achievable with a given set of communication system components, literally on the back of an envelope lying on his desk, this dissertation has been a rewarding journey to gain insight into what went on in his head while he obtained that “quick and dirty” estimate. It is a marvel that such an intricate set of reasoning processes lies behind those few calculations on a piece of paper, and it is a marvel that this is what engineers are capable of, with and without the tools of their trade.

Looking back on my PhD, I find that this thesis has spiralled to its final conclusions: starting from a broad problem space, the intertwining of exploratory studies, design and reflection led me to the model I propose in this work. This process is at the heart of educational design research, allowing the researcher the space and time to explore and refine. This journey has been immensely useful to me, allowing me to grow as a researcher, and to learn to be patient and sensitive, acknowledge the ground realities and keep an eye out for the unexpected - because that is where the knowledge lies.

Appendices

Appendix A

Consent for participation in the study

CONSENT FORM

STUDY TITLE: Study of student use of MEttLE technology-enhanced learning environment.

You have been asked to participate in a research study conducted by Aditi Kothiyal from the Inter-Disciplinary Program in Educational Technology at the Indian Institute of Technology Bombay (IITB). The purpose of the study is to understand how students learn using the MEttLE technology-enhanced learning environment. The results of this study will be included in the Ph.D. thesis of Aditi Kothiyal. You were selected as a possible participant in this study because you are a student at the Indian Institute of Technology Bombay.

You should read the information below, and ask questions about anything you do not understand, before deciding whether or not to participate.

- In this study you will be asked to solve real-life engineering problems using the MEttLE technology-enhanced learning environment.
- Your solutions will be used for research purposes only by the investigators of this study.
- Participating in this research study is voluntary. You have the right not to answer any question, and to stop your participation in the study at any time. We expect that the study will take 2 hours.
- You will not be compensated for the participation.
- We will not use your name in publications; however we may need to use your academic qualification details if you give us permission.
- We would like to record the audio of your interview so that we can use it for reference while proceeding with this study. If you grant permission for this interview to be recorded, you have the right to revoke recording permission and/or end your participation at any time. If we use your voice anywhere it will not be identified by name.
- We would like to video record you as you solve the problems so that we can use it for reference while proceeding with this study. If you grant permission for this video recording, you have the right to revoke recording permission and/or end your participation at any time. If we use this video anywhere, we will blank out your faces.
- We would like to capture your computer screen using CamStudio software as you solve the problems so that we can use it for reference while proceeding with this study. If you grant permission for this screen capture, you have the right to revoke recording permission and/or end your participation at any time. If we use this screen capture anywhere, we will not blank out your personal information.

I understand the procedures described above. My questions have been answered to my satisfaction, and I agree to participate in this study. I have been given a copy of this form.

(*Please check all that apply*)

[ ] I give permission for the following information to be included in publications resulting from this study:

[ ] my academic qualification details [ ] my videos [ ] direct quotes from my audio recordings
[ ] screenshots from my computer screen

Your name:

Your signature _______________________________ Date ____________

Signature of Investigator _________________________Date _________

Please contact Aditi Kothiyal (aditi.kothiyal@iitb.ac.in) or Prof. Sahana Murthy, IDP ET IITB (sahanamurthy@iitb.ac.in) with any questions or concerns.

Appendix B

Sample interview questions for studies 1 and 2

Broadly, questions of the following type were used by the interviewer during the cognitive ethnography to elicit participants authentic process. The number of questions depended on the participant and the exact questions depended on the events observed and marked by the researcher for elaboration.

1. Tell me a little bit about your background.
2. Broadly, what did you do today?
3. What do you know about estimation?
4. How did you solve the problem? (physical actions + mental strategy)
5. For each marked event,
   (a) What were you thinking of at that time?
   (b) What helped you make that connection?
   (c) Can you draw out what you were thinking?
   (d) How did you know this was the thing that would help you at this point?
   (e) What information were you looking for?
6. What was the role of data/information search?
7. What assumptions did you make? How do you know they are valid?

8. What was the most critical part of solving this problem?

9. What was the breakthrough moment?

10. What is the role of iteration in this process?

11. What was easy, what was difficult about solving this problem?

12. What more did you feel you need to solve this problem?

Appendix C

Sample interview questions for studies 4 and 5

The following set of questions were used as a guideline by the interviewer to ensure that all aspects of the interaction of the participant with MEttLE were covered. The goal is to elicit their authentic process and so the interviewer began with broad questions, digging deeper and asking more specific questions only when the participant was unresponsive or did not understand the question.

1. Tell me a little bit about your background.
2. Broadly, what did you do in Mettle?
3. What was the first (or next) task you solved?
   (a) Why did you choose this task at this time?
   (b) How did you solve this task/focus question? (phyical actions + mental strategy)
   (c) Why this physical action? If you had not done this, what would have happened? Why this strategy?
   (d) What was the role of the given info/tool/feature in MEttLE in solving the task? What would have happened if this info/tool/feature was not present? What would you have done?
      i. How did you use the info/tools/feature to solve the task?
      ii. How was the info/tool/feature of MEttLE useful/not useful in solving the task?

(e) What more did you need to solve the task?

(f) How would you recommend changing/adding/removing to the features of MEttLE to do the task?

4. Repeat above set of questions for every task.

5. What was the difference between solving the problem on paper and in MEttLE?

6. What did you learn today?

   (a) What did you understand about solving problems like this from MEttLE?

   (b) What according to you is the process of engineering estimation? How did you understand this?

   (c) What features in MEttLE helped you understand this?

   (d) What features are needed in Mettle to understand the process of engineering estimation? How would you recommend changing/adding/removing to the features of Mettle to do the task? Without which feature would you not have been able to learn this?

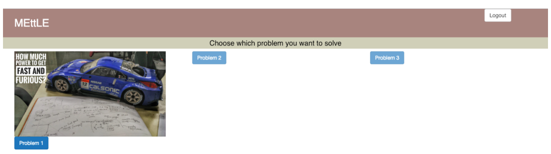
7. What is the role of this conversation on your learning today?

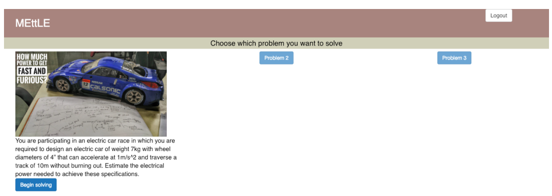
8. How would you redesign Mettle for a student such as yourself to better learn engineering estimation?

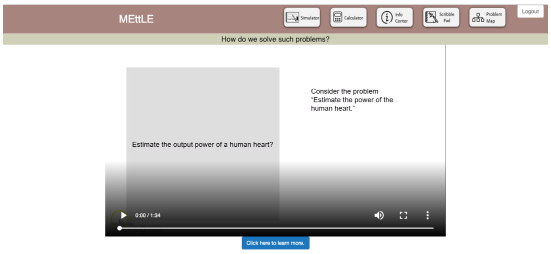
9. (if the participant has time and inclination, show another estimation problem) If I gave you this problem to solve how would you approach this problem?

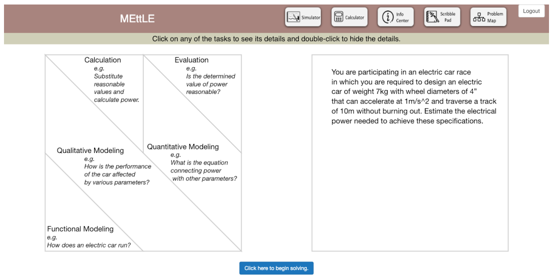
Appendix D

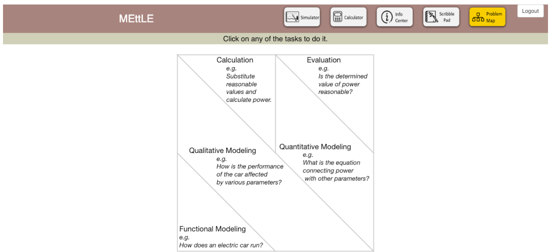
Screenshots of MEttLE1.0

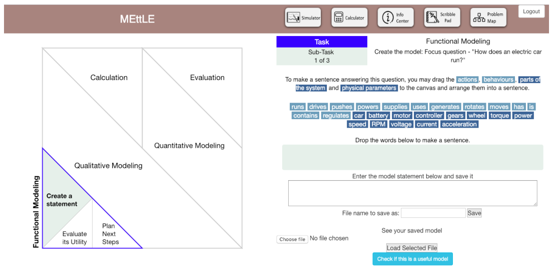




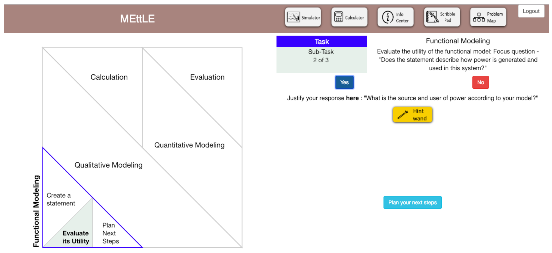

METtLE
Logout
How do we solve such problems?
Estimate the output power of a human heart?
Consider the problem "Estimate the power of the human heart."
0:00 / 1:34
Click here to learn more.

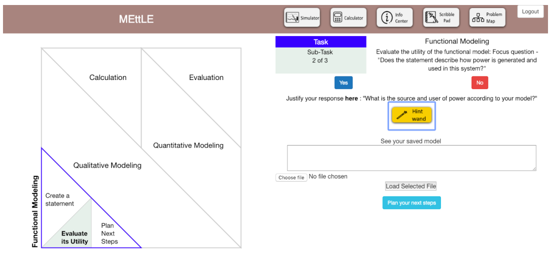

METtLE
Logout
Click on any of the tasks to see its details and double-click to hide the details.
Calculation
e.g.
Substitute reasonable values and calculate power.
Evaluation
e.g.
Is the determined value of power reasonable?
Qualitative Modeling
e.g.
How is the performance of the car affected by various parameters?
Quantitative Modeling
e.g.
What is the equation connecting power with other parameters?
Functional Modeling
e.g.
How does an electric car run?
You are participating in an electric car race in which you are required to design an electric car of weight 7kg with wheel diameters of 4" that can accelerate at 1m/s^2 and traverse a track of 10m without burning out. Estimate the electrical power needed to achieve these specifications.
Click here to begin solving.

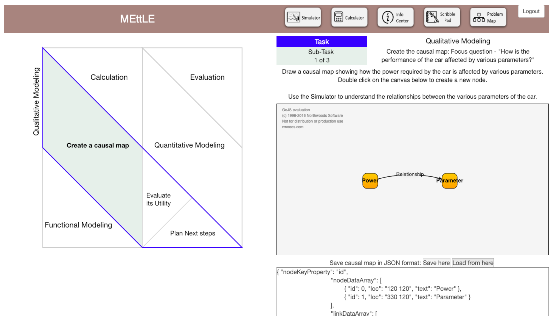

METtLE
Logout
Click on any of the tasks to do it.
Calculation
e.g.
Substitute reasonable values and calculate power.
Evaluation
e.g.
Is the determined value of power reasonable?
Qualitative Modeling
e.g.
How is the performance of the car affected by various parameters?
Quantitative Modeling
e.g.
What is the equation connecting power with other parameters?
Functional Modeling
e.g.
How does an electric car run?

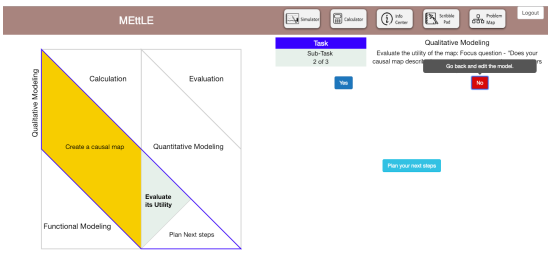

METtLE
Logout
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Create a statement
Evaluate its Utility
Plan Next Steps
Task
Sub-Task
1 of 3
Functional Modeling
Create the model: Focus question - "How does an electric car run?"
Drop the words below to make a sentence.
Enter the model statement below and save it
File name to save as:
Save
See your saved model
No file chosen
Load Selected File
Check if this is a useful model

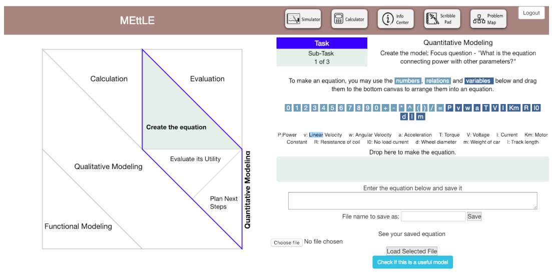

METtLE
Logout
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Create a statement
Evaluate its Utility
Plan Next Steps
Task
Sub-Task
2 of 3
Functional Modeling
Evaluate the utility of the functional model: Focus question - "Does the statement describe how power is generated and used in this system?"
Yes
No
Plan your next steps

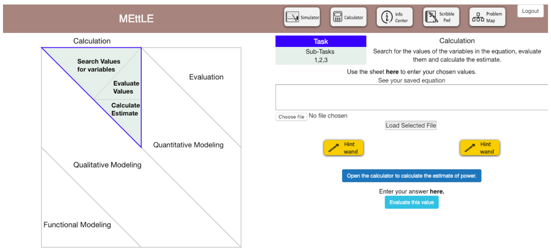

METtLE
Logout
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Create a statement
Evaluate its Utility
Plan Next Steps
Task
Sub-Task
2 of 3
Functional Modeling
Evaluate the utility of the functional model: Focus question - "Does the statement describe how power is generated and used in this system?"
Yes
No
Justify your response here : "What is the source and user of power according to your model?"
Hint wand
Plan your next steps

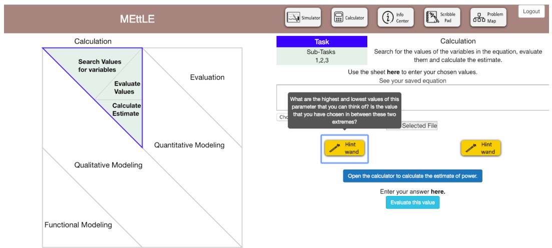

METtLE
Logout
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Create a statement
Evaluate its Utility
Plan Next Steps
Task
Sub-Task
2 of 3
Functional Modeling
Evaluate the utility of the functional model: Focus question - "Does the statement describe how power is generated and used in this system?"
Yes
No
Justify your response here : "What is the source and user of power according to your model?"
Hint wand
See your saved model
No file chosen
Load Selected File
Plan your next steps

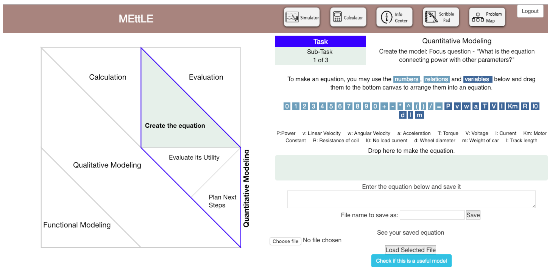

METtLE
Logout
Qualitative Modeling
Calculation
Evaluation
Create a causal map
Quantitative Modeling
Evaluate its Utility
Functional Modeling
Plan Next steps
Task
Sub-Task
1 of 3
Qualitative Modeling
Create the causal map: Focus question - "How is the performance of the car affected by various parameters?"
Draw a causal map showing how the power required by the car is affected by various parameters. Double click on the canvas below to create a new node.
Use the Simulator to understand the relationships between the various parameters of the car.
Power
Relationship
Parameter
Save causal map in JSON format: Save here
Load from here

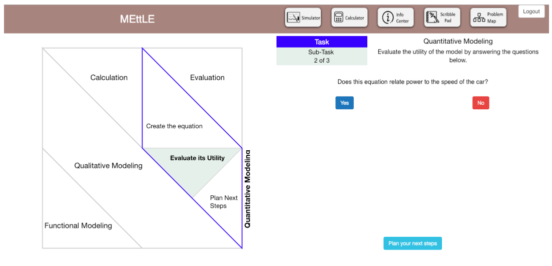

METtLE
Logout
Qualitative Modeling
Calculation
Evaluation
Create a causal map
Quantitative Modeling
Evaluate its Utility
Functional Modeling
Plan Next steps
Task
Sub-Task
2 of 3
Qualitative Modeling
Yes
No
Go back and edit the model.
Plan your next steps

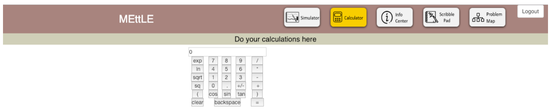

METtLE
Logout
Calculation
Evaluation
Create the equation
Evaluate its Utility
Plan Next Steps
Qualitative Modeling
Functional Modeling
Quantitative Modeling
Task
Sub-Task
1 of 3
Quantitative Modeling
Create the model: Focus question - "What is the equation connecting power with other parameters?"
Drop here to make the equation.
Enter the equation below and save it
File name to save as:
Save
See your saved equation
No file chosen
Load Selected File
Check if this is a useful model

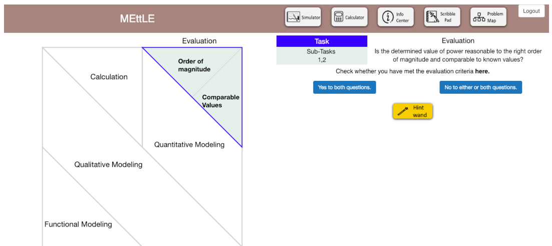

MEttLE
Calculation
Search Values for variables
Evaluate Values
Calculate Estimate
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Task
Search for the values of the variables in the equation, evaluate them and calculate the estimate.
Open the calculator to calculate the estimate of power.
Evaluate this value

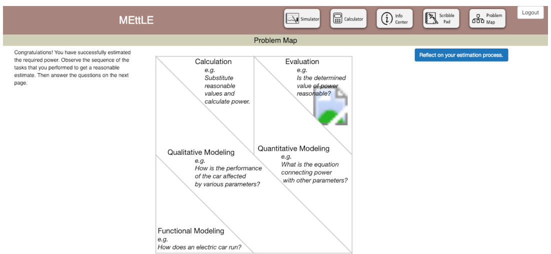

MEttLE
Calculation
Search Values for variables
Evaluate Values
Calculate Estimate
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Search for the values of the variables in the equation, evaluate them and calculate the estimate.
Open the calculator to calculate the estimate of power.
Evaluate this value

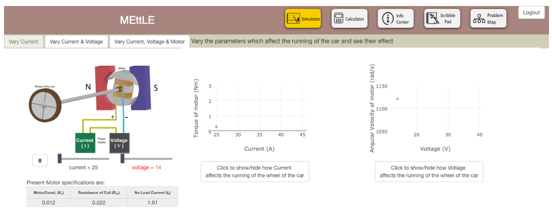

MEttLE
Calculation
Evaluation
Create the equation
Evaluate its Utility
Plan Next Steps
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Task
Quantitative Modeling
Create the model: Focus question - "What is the equation connecting power with other parameters?"
Drop here to make the equation.
Enter the equation below and save it
Check if this is a useful model

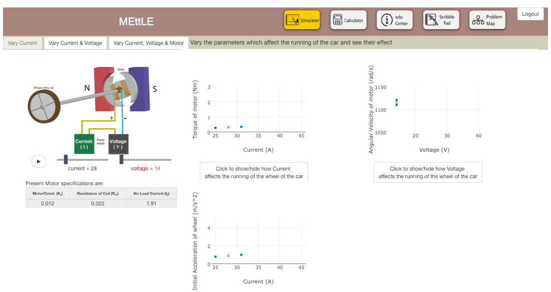

MEttLE
Calculation
Evaluation
Create the equation
Evaluate its Utility
Plan Next Steps
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Task
Quantitative Modeling
Does this equation relate power to the speed of the car?
Yes
No
Plan your next steps


MEttLE
Do your calculations here

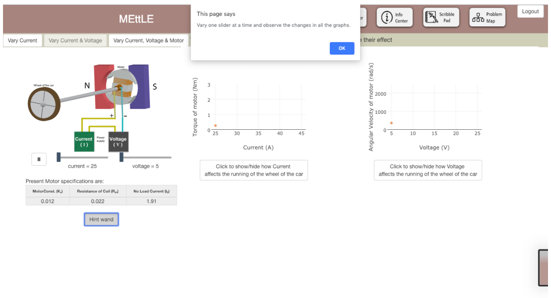

MEttLE
Evaluation
Order of magnitude
Comparable Values
Calculation
Quantitative Modeling
Qualitative Modeling
Functional Modeling
Task
Yes to both questions.
No to either or both questions.

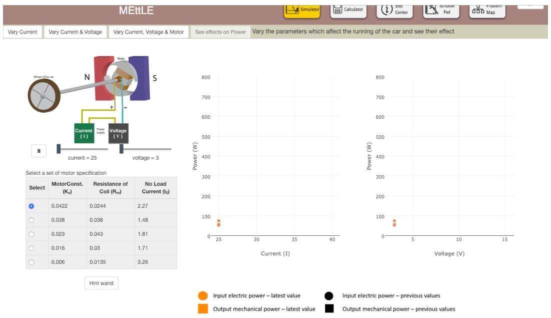

MEttLE
Problem Map
Reflect on your estimation process.
Calculation
Evaluation
Qualitative Modeling
Quantitative Modeling
Functional Modeling
How does an electric car run?

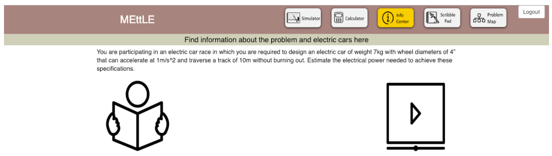

MEttLE
Vary the parameters which affect the running of the car and see their effect
Current (A)
Voltage (V)

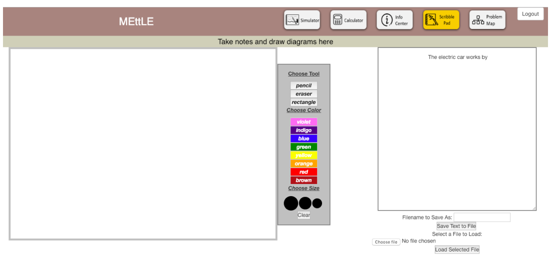

MEttLE
Vary the parameters which affect the running of the car and see their effect
Current (A)
Voltage (V)


MEttLE
Vary the parameters which affect the running of the car and see their effect
Current (A)
Voltage (V)



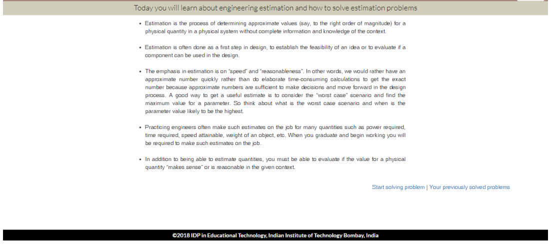


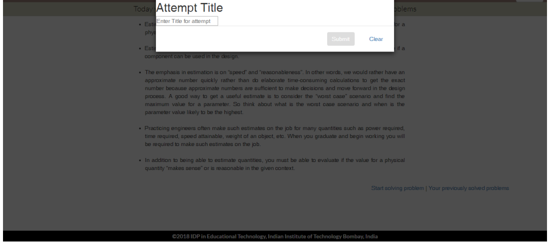


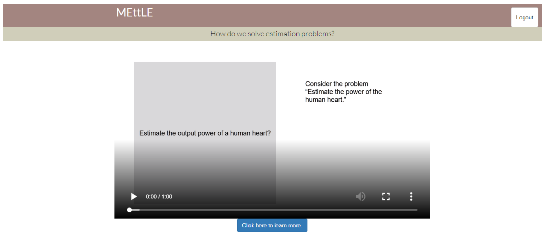


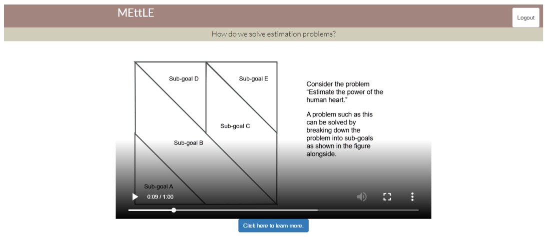
Appendix E

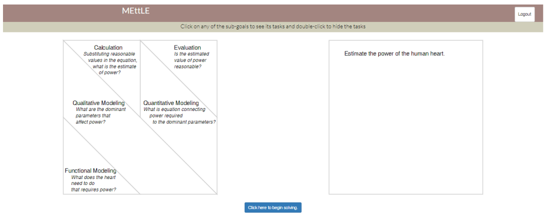
Screenshots of MEttLE2.0

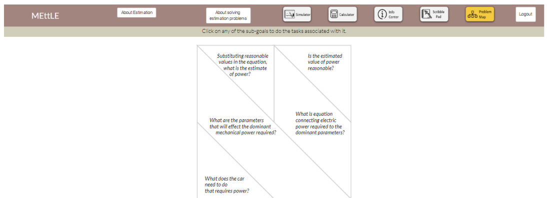


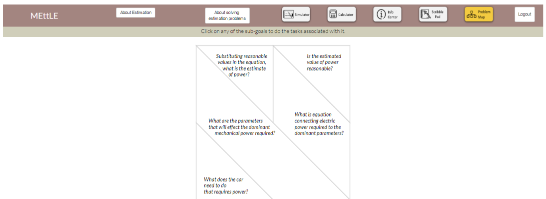


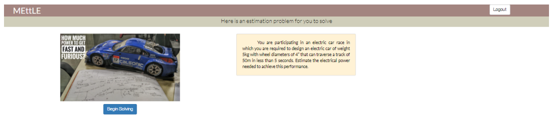

METtLE
Logout
How do we solve estimation problems?
Estimate the output power of a human heart?
Consider the problem "Estimate the power of the human heart."
Click here to learn more.

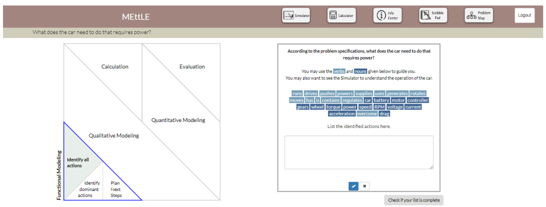

METtLE
Logout
How do we solve estimation problems?
Sub-goal D
Sub-goal E
Sub-goal C
Sub-goal B
Sub-goal A
Consider the problem "Estimate the power of the human heart."
A problem such as this can be solved by breaking down the problem into sub-goals as shown in the figure alongside.
Click here to learn more.

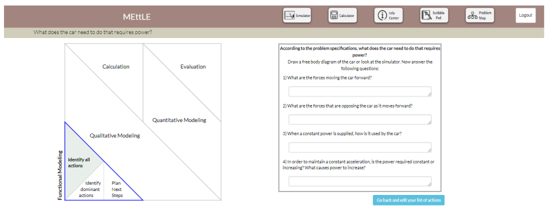

METtLE
Click on any of the sub-goals to see its tasks and double click to hide the tasks
Calculation
Evaluation
Qualitative Modeling
Quantitative Modeling
Functional Modeling
Estimate the power of the human heart

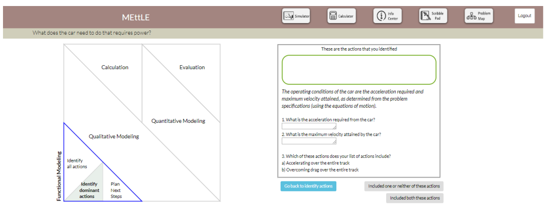

METtLE
Logout

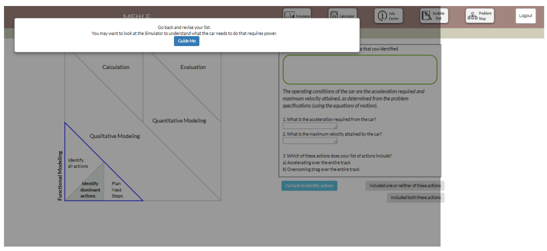

METtLE
Logout

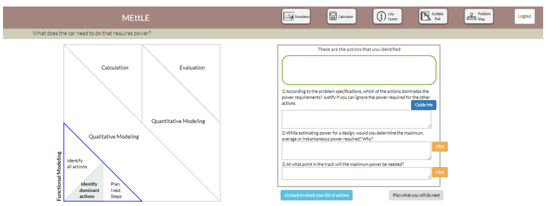

METtLE
Here is an estimation problem for you to solve

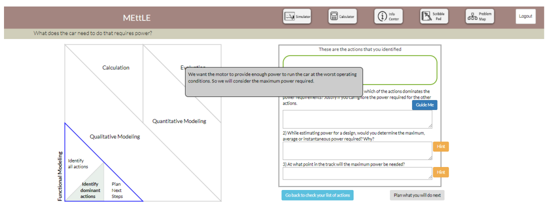

METtLE
What does the car need to do that requires power?
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling

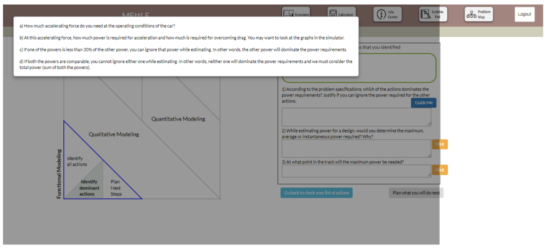
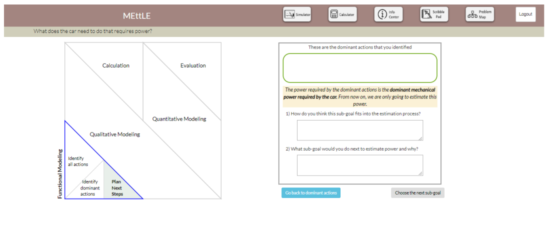
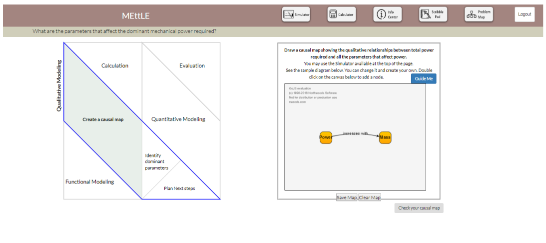
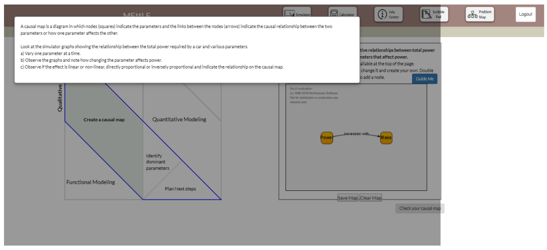
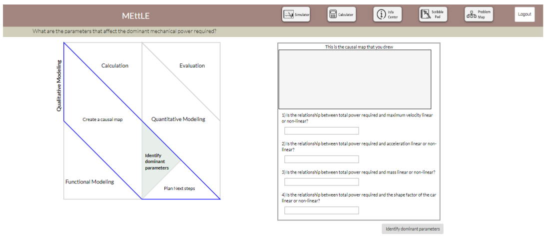
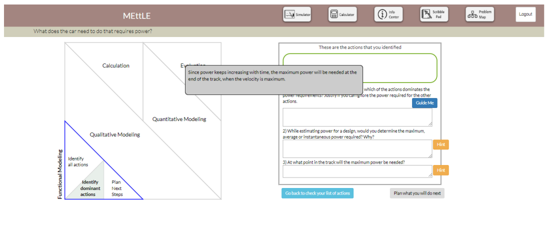
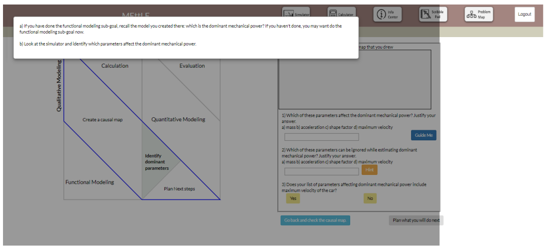
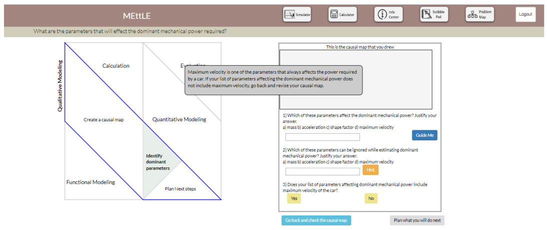
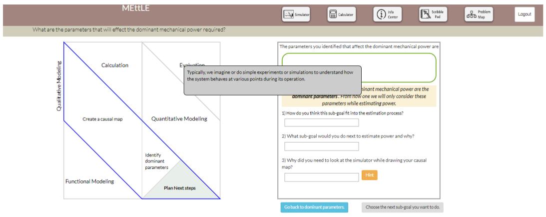
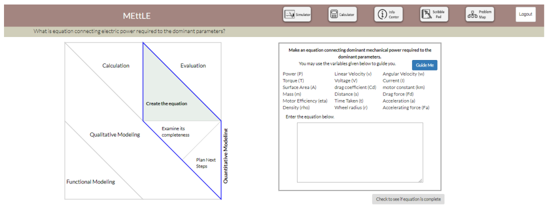
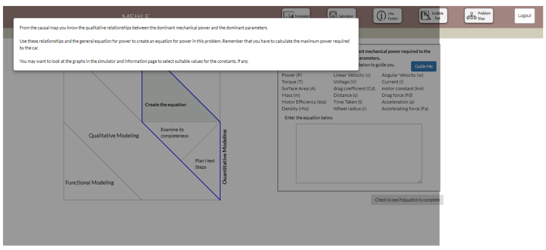
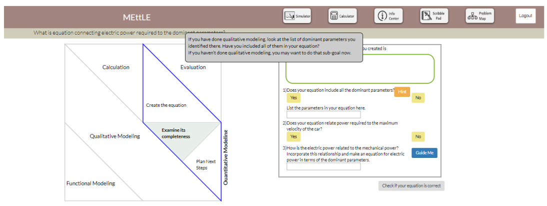
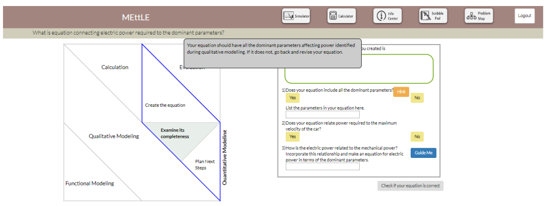
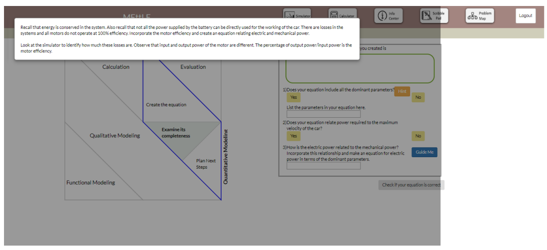

METtLE
What does the car need to do that requires power?
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling

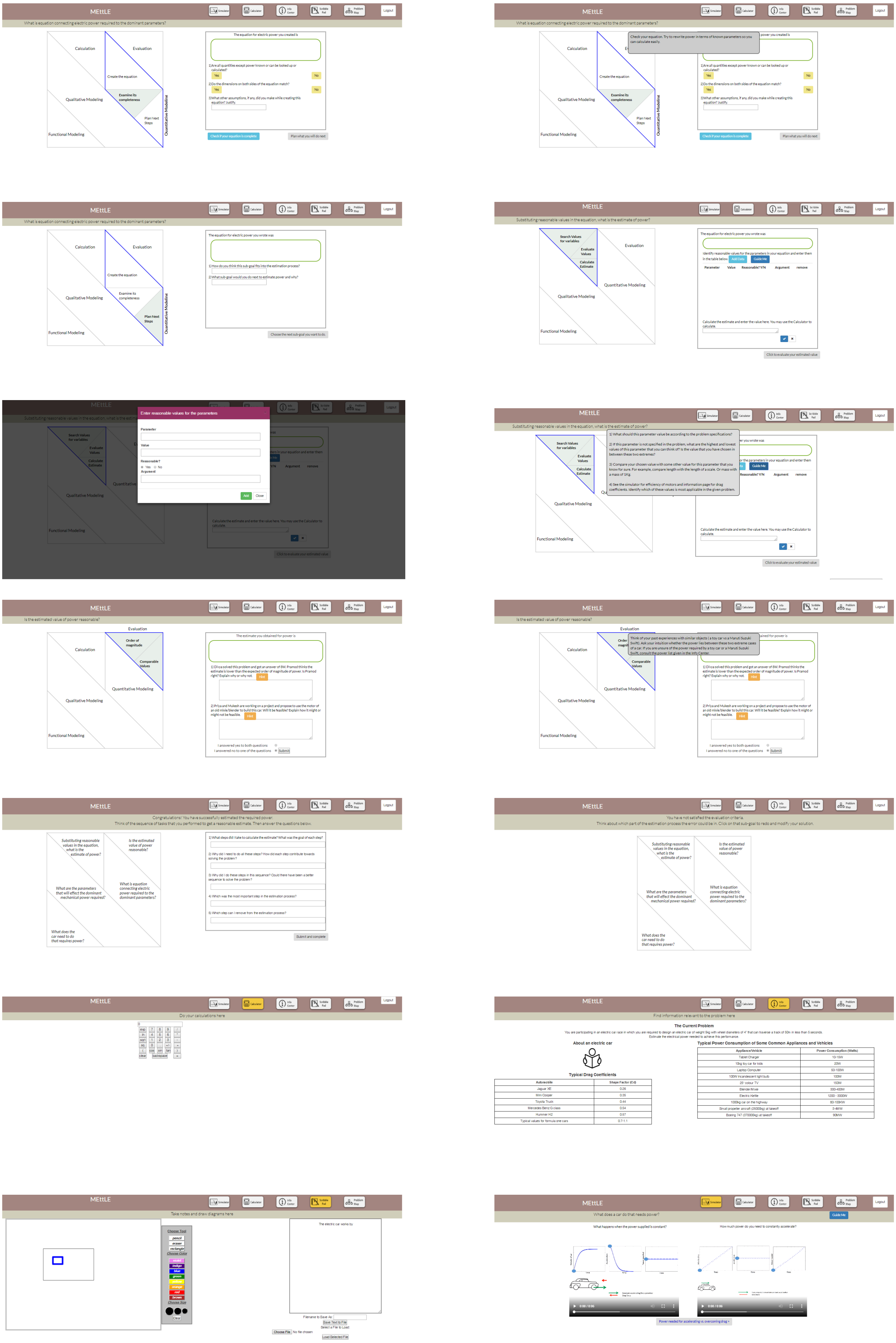

METtLE
What does the car need to do that requires power?
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling

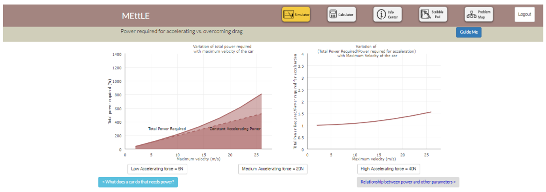

Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling

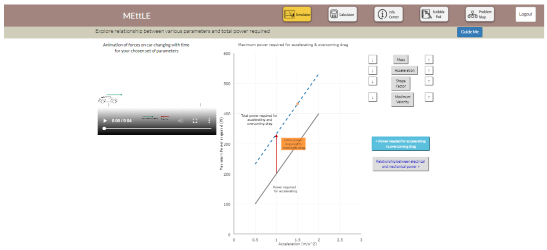

METtLE
What does the car need to do that requires power?
Calculation
Evaluation
Quantitative Modeling
Qualitative Modeling
Functional Modeling

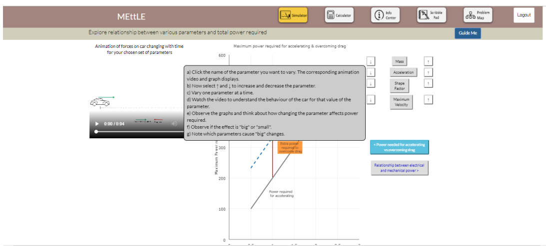

METtLE
What does the car need to do that requires power?
Calculation
Quantitative Modeling
Qualitative Modeling
Functional Modeling

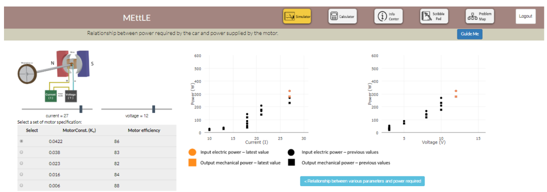


















MEttLE
Power required for accelerating vs. overcoming drag


MEttLE
Explore relationship between various parameters and total power required


MEttLE
Explore relationship between various parameters and total power required


MEttLE
Relationship between power required by the car and power supplied by the motor

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Kothiyal, A., & Murthy, S. (2018). MEttLE: a modelling-based learning environment for undergraduate engineering estimation problem solving. *Research and Practice in Technology Enhanced Learning*, 13 (1), 17.

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1. Kothiyal, A., & Murthy, S. (2018). Exploring how students learn estima-tion using a modelling-based learning environment. In *Proceedings of the 13th International Conference of the Learning Sciences* (pp. 1543-1545). London: International Society of the Learning Sciences.

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