A STUDY ON MEASURING DESIGNERS' COGNITIVE PROCESSES

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Abstract

Design cognition, human information processing in design, has been studied for decades in order to understand creative behavior and improve the creativity of design outcomes. Comparing designers' performance during different design tasks is challenging since data obtained from sketches and verbal protocols are unstructured. Furthermore, there is no established method to evaluate directly the effectiveness and efficiency of the transition from novice to expert designer. This study argued that designers' cognitive load had an effect on designers' performance, and therefore designers' cognitive demands during design tasks should be considered in the evaluation of design outcomes. The concept of cognitive efficiency, describing the relationship between design outcomes and designers' cognitive demands, was proposed and found to be related to expertise levels and design strategies. Designers' cognitive processes were described quantitatively using information-based approaches from three different perspectives: the process of problem structuring, the complexity of cognitive actions, and the connections between design ideas. The quantitative measures were found to relate to cognitive efficiency and designers' expertise levels. The quantitative measures make it possible to highlight where and when cognitive resources should be focused and which design behaviors should be encouraged to improve cognitive efficiency. Effective design strategies related to high cognitive efficiency were also identified. Explicit decomposition and the breadth-first control strategy were found to benefit problem structuring. Generating early design conjectures was related to high cognitive efficiency. The application of the systematic design method helped the designers to organize their design processes and effectively revisit and improve previous design ideas. These design strategies can be used for design education and design method comparison.

Preface

This study contributes to the design community and the human factors community. The majority of the outcomes of this study has been published in (or submitted to) peer-reviewed journals and conference proceedings. The main contributions of this study are listed as follows.

1. Investigating the relation between designer's cognitive load and the creativity of design outcomes, which is described as cognitive efficiency;

   Sun, G., & Yao, S. (2012). Investigating the relation between cognitive load and creativity in the conceptual design process. *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 308-312. doi:10.1177/1071181312561072.

2. Comparing cognitive efficiency between experienced and inexperienced designers;

   Sun, G., Yao, S., & Carretero, J. A. (2014). Comparing cognitive efficiency between experienced and inexperienced designers. *Journal of Cognitive Engineering and Decision Making*, 8(4), 330-351. doi: 10.1177/1555343414540172.

3. Evaluating problem structuring strategies by measuring the complexity of structuring process;

   Sun, G., Yao, S., & Carretero, J. A. (2015). An experimental approach to understanding design problem structuring strategies. *Journal of Design*

Research, in press,

http://www.inderscience.com/info/ingeneral/forthcoming.php?jcode=jdr

Sun, G., Yao, S., & Carretero, J. A. (2013). An investigation of the relation between the complexity of problem structure and mental effort in ill-structured problem solving. *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, vol.57, pp. 260-264. doi: 10.1177/1541931213571057.

4. Identifying factors that contribute to high cognitive efficiency by information-based measures;

   Sun, G., Yao, S., & Carretero, J. A. (submitted for review). An information based approach to studying designers' cognitive processes.

   Sun, G., Yao, S., & Carretero, J. A. (2013). Evaluating cognitive efficiency by measuring information contained in designers' cognitive processes. *Proceedings of ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2013)*, vol. 5: 25th International Conference on Design Theory and Methodology, p.V005T06A029; 10 pages. doi: 10.1115/DETC2013-13628.

5. Investigating factors that affect designer's cognitive load;

   Sun, G., Yao, S., & Carretero, J. A. (2015). A pilot study for investigating factors that affect cognitive load in the conceptual design process. *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, accepted.

6. Proposing new frameworks for studying the cognitive model of creative design and supporting concept generation;

   Sun, G., & Yao, S. (2012). A framework for an evolutionary computation approach to supporting concept generation. *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 1972-1976. doi:10.1177/1071181312561292.

   Sun, G., & Yao, S. (2011). A new framework of studying the cognitive model of creative design. DS68-7: *Proceedings of 18th International Conference on Engineering Design (ICED11)*, vol. 7: Human Behaviour in Design, pp. 501-510.

Dedication

This dissertation is dedicated to my parents, my sister and brother, and my family. My sons Andrew and Evan were born during this program. They are a source of inspiration and motivation for me.

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Words will never express adequately my gratitude for all the support that I have received during this program.

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I would like to thank my advisory committee, Dr. Edmund Biden, Dr. Andy Simoneau, and Dr. Michel Couturier, for taking the time to read through my dissertation and provide feedback. I would like thank Dr. Shi Cao for reviewing my dissertation. Their thought-provoking questions enlarged my perspective.

I would like to thank my husband William for his undying support in this long journey. I also thank my parents and parents-in-law for their understanding and selfless devotion to their children and grandchildren. And I thank my friends, who lift my spirits.

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I would like to thank the University of New Brunswick for the President Tuition Fee Awards and travel awards. Special thanks are due to the Human Factors and Ergonomics Society (HFES). Part of the work of this dissertation were submitted to the HFES annual meetings and obtained constructive comments from reviewers of the society. The society supported me twice to attend the annual meetings, giving me opportunities to present my research, meet society colleagues, and broaden my understanding of human factors research.

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C_A complexity of cognitive actions

C_T complexity of the functional tree structure

E_c cognitive efficiency

E_p effectiveness of problem structuring

G_M grand mean of scores for mental effort

G_P grand mean of scores for performance

H entropy of a random variable

H_b entropy of back-links in a design session

H_f entropy of fore-links in a design session

H_j joint entropy of a sequence of discrete random variables $(X_1, X_2, \ldots, X_\Lambda)$

H_l entropy of whole links in a design session

$K_\mu(x)$ Kolmogorov complexity of a string x with respect to a universal computer μ

L number of total cognitive transitions in a design segment

M normalized score for mental effort

M_o original score for mental effort

N number of total cognitive actions in a design segment

O_n overall novelty score for the design outcomes

O_v overall variety score for the design outcomes

O_q overall quality score for the design outcomes

O_u overall quantity score for the design outcomes

P normalized score for performance

P_o original score for performance

p probability of a sequence of discrete random variables ($X_1, X_2, \ldots, X_\Lambda$)

S number of design segments in a design process

X_i independent identically-distributed discrete random variables

Λ length of a design segment, that is, the sum number of total cognitive actions and total cognitive transitions ($\Lambda = N + L$)

λ size of basic elements in a design segment, that is, the sum number of unique cognitive actions and unique cognitive transitions ($\lambda = \rho + \upsilon$)

ρ number of unique cognitive actions in a design segment

σ_M grand standard deviation of scores for mental effort

σ_P grand standard deviation of scores for performance

υ number of unique cognitive transitions in a design segment

Chapter 1 Introduction

Design cognition, focusing on investigating cognitive mechanisms and thinking processes of human designers, has been studied to understand the design process and improve the creativity of design outcomes. Currently, most of the studies rely on empirical and qualitative descriptions obtained from protocol studies and process monitoring. The progress of design cognition studies is limited by a lack of quantitative measures because of the limited information available about the early stage of the design process. The current study is initiated as an exploratory attempt focusing on the integration of two domains: design cognition and information theory. This study attempts to address the question of how to elicit quantitative information from unstructured data, such as sketches and verbal protocols, from the perspective of human information processing. The quantitative measures developed in the study can deepen the understanding of the design process and designers' behaviors that qualitative description cannot reach. The relations between the quantitative measures and designers' performance are investigated to identify effective design strategies. These design strategies can be applied for design education and design methods comparison.

This chapter provides the context for background issues including the conceptual design process, designers' cognitive processes, and creativity in design. Afterwards, the research motivation, research questions, assumptions, and framework are specified.

1.1 Background

The present study crosses disciplinary lines between engineering design and cognitive science. This section is structured to introduce briefly distinct knowledge contributions from research in the conceptual design process, designers' cognitive processes, and creativity in design.

1.1.1 Conceptual design process

The design process varies from product to product and industry to industry. The engineering design process usually involves task clarification, conceptual design, embodiment design, and detail design (Pahl, Beitz, Feldhusen, & Grote, 2007). In the conceptual design process, the essential problems are identified and the principle solutions are specified (Pahl et al., 2007). The main goal of the conceptual design process is to generate and evaluate concepts for a product. When the concepts are generated, a functional model of the product is developed based on the customer's requirements; when the concepts are evaluated, the best alternatives with the least expenditure of time and other resources are chosen (Ullman, 2009).

It can be argued that conceptual design is the most critical phase in the engineering design process because this phase determines product quality, performance, and cost (Pahl et al., 2007). About 75% of the manufacturing cost of a typical product is committed by the end of the conceptual design process (Ullman, 2009). Conceptual design is a very significant factor when determining a company's competitiveness. Many decisions made during this phase can have far-ranging impacts on the rest of the development process. The selection of an unsuitable concept may lead to delays, budget overruns, and possibly project cancellation. Meanwhile, conceptual design is one of the most challenging phases because very little information is available to the designers at the early stages of the design process. The existing understanding of design concept generation and evaluation is limited, and this lack of quantitative information impedes the application of any existing design process model directly to computational design tools (Jin & Li, 2007).

Various methodologies and theories have been proposed to support the design process. Systematic Design Methodology (or specifically called the Pahl and Beitz Methodology) provides an effective way to rationalize the design process by breaking down the design process into phases and distinct steps, each with its own working methods (Pahl et al., 2007). Axiomatic Design Theory uses design axioms (that is, design principles given without proof) to analyze the transformation of customer needs into functional requirements, design parameters, and process variables (Suh, 1990). General Design Theory attempts to cast design in the framework of set theory and provide a prescription for the development of computer-aided-design (CAD) systems (Yoshikawa, 1981). The Hybrid Model, an extended form of axiomatic set theory, provides a standard logic notation of design information (Salustri & Venter, 1992). Formal Design Theory, a mathematical theory of design, aims to develop a domain-independent core model of the design process (Braha & Maimon,1998a). These models and theories prescribe how to accomplish the design process or how to formally represent the design process, but provide limited guidance for designers on how to generate design concepts, which is the most critical issue in the design process for product creativity.

Specific tools and techniques have been developed to support design problem solving. For example, TRIZ (Russian acronym for the Theory of Inventive Problem Solving) is a problem-solving method that relies on the study of patterns of invention from more than three million patents (Altshuller, 1984). This theory reveals that the vast majority of challenging problems can be solved by overcoming a dilemma or a trade-off between two contradictions. TRIZ identifies 40 principles that solve the trade-off contradictions and 4 separation principles that solve the inherent contradictions. Other most often used tools include the morphological method (exploring all the possible design solutions in a morphological chart; Ullman, 2009) and the decision-matrix method (ranking the design solutions by establishing a set of criteria options; Pugh, 1981).

Furthermore, some software packages were developed for simulating the process of concept generation and evaluation by human designers (Bentley & Wakefield, 1996; Jin & Li, 2007). The computational models can mimic part of the human cognitive process such as the discovery process (Langley, Simon, Bradshaw, & Zytkow, 1987) and the analogical process (Falkenhainer, Forbus, & Gentner, 1989). These packages are expected to provide novel design alternatives for human designers rather than replacing humans with computers. High-level perception, the process of making sense of complex data at an abstract and conceptual level, is fundamental to human cognition (Chalmers, French, & Hofstadter, 1992), and it is difficult to replace high-level perception with artificial intelligence. Therefore, the conceptual design process relies mostly on designers' mental work.

1.1.2 Designers' cognitive processes

Cognitive design research investigates cognitive mechanisms and design thinking (Finke, Ward, & Smith, 1992; Horvath, 2004) by connecting the cognitive process to the design process. The engineering design process is a knowledge-based problem-solving process. The problem-solving process has been described by researchers based on their unique understanding of the design process (Kurakawa, 2004). The general problem-solving process in design involves confrontation, information, definition, creation, evaluation, and decision (Pahl et al., 2007). A basic design cycle consists of the following five phases: analysis, synthesis, simulation, evaluation, and decision (Roosenburg & Eekels, 1995).

Studying a problem solver’s cognitive process by examining a designer’s cognitive activity can help researchers find effective ways to improve the conceptual design process. Studies that have compared the effective design strategies applied by experienced designers can be used for training novice designers (Atman, Cardella, Turns, & Adams, 2005; Cross, 2004; Kim, Kim, Lee, & Park, 2007). Studying designers’ cognitive processes can also help researchers to understand the generation of design creativity. The cognitive processes at the breakthrough stage of conceptual design can be studied empirically by analyzing some illustrative examples (Madanshetty, 1995). Explanatory cognitive models suggest the procedures by which creative design might occur, for example, combination, mutation, analogy, design from first principles, and emergence (Cross, 1997). The cognitive model of creative design has been developed to capture the relationship between the properties (that stimulate cognitive processes) and the design operations (that facilitate cognitive processes; Jin & Benami, 2010). A creative design process (model) has been proposed by linking the usual representations of the design process (that is, task analysis, conceptual design, and embodiment design) and the nature of the activities in creative process terms (that is, analysis, generation, and evaluation; Howard, Culley, & Dekoninck, 2008).

These empirical studies analyze designers' cognitive activities and are expected to improve design creativity. However, these models are either too general for guiding designers in the conceptual design process or too specific focusing only on one attribute of the cognitive process (Yilmaz, 2010). Furthermore, only design outcomes are evaluated to examine how these models work. It is not clear, however, whether the design process is efficiently improved or whether the design strategy applied is effective. At least, there is no existing systematic measurement to quantify the efficiency and effectiveness of the design process. Such types of measures as efficiency and effectiveness are necessary to evaluate design methods and strategies across different design tasks and expertise levels.

1.1.3 Creativity in design

Creativity is an integral and essential part of the engineering design process. Although there are many different definitions of creativity, the ultimate concern about creativity lies in the production of novel, socially-valued products (Mumford & Gustafson, 1988). Creativity in design produces not only something new but also a result that is unexpected and valuable (Gero, 1996). Mayer summarized various definitions of creativity as the "creation of new and useful products including ideas as well as concrete objects" (Mayer, 1999, p. 450). Creative design is normally regarded as a significant aspect of an overall "good" design (Dorst & Cross, 2001).

Although creativity is related to a personality trait, the generation of creative ideas can be stimulated. A series of important empirical findings support the hypothesis that a wide breadth of attention facilitates creative performance (Memmert, 2007); the more elements that a person can focus on simultaneously, the more likely it is that a creative idea will occur (Kasof, 1997). Studies have also shown that patterns exist in designers' creative thinking processes by which certain intermediate design concepts stimulate cognitive processes (Jin & Benami, 2010). More behavioral, ambiguous, and less mature concepts, as well as more meaningful and relevant stimulations, tend to be more effective in stimulating creative idea generation.

Boden summarized three types of creativity in design: combinational creativity, exploratory creativity, and transformational creativity (1990). Combinational creativity arises from the unusual combination or association of familiar ideas. Exploratory creativity consists of applying search procedures within a defined conceptual space in the human mind. Exploratory creativity is valuable because it can enable individuals to see possibilities they had not thought of before. Transformational creativity models are based on evolutionary techniques and include procedures for modifying parts of defined solutions.

Creativity can be improved by applying methods, software tools, and strategies which support the generation of creative ideas. The morphological method is developed for combining and exploring all the possible solutions to a multi-dimensional, non-quantified complex problem (Zwicky, 1969). TRIZ, as well as software based on this theory (for example, the Innovation WorkBench, Ideation International Inc.), can improve exploratory creativity by providing 40 inventive principles which can deal with engineering contradictions between physical parameters. Evolutionary algorithms, which have been widely applied to solve engineering problems (Kicinger, Arciszewski, & De Jong, 2005; Oduguwa, Tiwari, & Roy, 2005; Renner & Ekart, 2003), can improve exploratory creativity through their combination and mutation mechanisms (Hybs & Gero, 1992). Designers using a solution-driven strategy tend to have higher creativity scores than those using a problem-driven design strategy (Kruger & Cross, 2006). Some instructional strategies, such as design heuristics (Yilmaz, Seifert, & Gonzalez, 2010), have been found to increase creativity in idea generation. However, in these empirical studies, the enhancement of creativity was evaluated based on different criteria, and the effectiveness and efficiency of these methods, tools, and strategies were not directly assessed. Furthermore, it seems that the applications of these methods were quite individually dependent. Sometimes it is hard to identify which strategies are unique for expert designers or which are just personal differences since data are collected from the small samples of experts and novices.

Creativity in engineering design can also be improved by studying the design process. A design process that results in a creative product can be learned, provided designers have enough ability and experience to generate ideas and enough experience and training to evaluate them (Ullman, 2009). In addition, studies have shown that knowledge to structure the design process, not like domain-specific knowledge to generate and evaluate ideas, is largely independent of domain-specific knowledge. Therefore, it is possible for novice designers to learn the knowledge to improve the design process before they have accumulated experience in design and domain-specific knowledge.

1.2 Research Motivation

This study is motivated by designers' performance evaluation. Currently, designers' performance is often evaluated by the creativity of design outcomes. Designers' "human" performance is rarely considered. This study argues that designers' performance evaluation should include not only design outcomes but also designers' cognitive demands. Designers' cognitive demands, referring to their desired level of mental effort as they work on a design task, likely affect designers' performance. Studies have shown that processing too many cognitive tasks at one time may cause cognitive overload which has a negative impact on designers forming linkages between ideas and slows down the rate of idea generation (Bilda & Gero, 2007). Cognitive overload degrades human performance because human cognitive capacity is limited with respect to the amount of information the cognitive system can hold and the number of operations it can perform on that information (Van Gerven, Paas, van Merriënboer, Hendriks, & Schmidt, 2003). Cognitive underload can also be detrimental to performance in learning and operating tasks (Paas, Renkl, & Sweller, 2004; Young & Stanton, 2002), just as cognitive overload can. Therefore, it is necessary to consider designers' cognitive demands as part of the evaluation of designers' performance.

This study is also motivated by cognitive process quantification. Information in cognitive processes can be collected from sketches and verbal protocols generated by designers. But the information is not well structured. It is difficult to compare quantitatively designers' behaviors observed in different empirical studies because there is no standard measure to describe the observations. Results are sometimes task-dependent, model-dependent, and individual-dependent. Some studies have attempted to organize the unstructured data (Kavakli & Gero, 2002; Suwa & Tversky, 1997), but the measures of structured information have not been well connected to the measures of designers' performance.

In addition, this study is motivated by design education. Design education aims at teaching students design knowledge and skills which are required to accomplish design tasks. Designers' behaviors and cognition are studied to identify design strategies applied by expert designers. These strategies are expected to help novice designers to improve their design solutions. However, some strategies applied by experts seem to conflict with the principles recommended by design theorists (Cross, 2004). What are the key differences in behavior and cognition between experts and novices? How is the transition made from experts and novices? Can certain educational methods assist the transition more effectively or efficiently? These questions have been studied for decades in the design community (Cross, 2004), but the answers are still not clear. There is no established method to directly evaluate the effectiveness and efficiency of this transition.

In summary, designers' cognitive demands should be considered in the evaluation of designers' performance. It is also necessary to have a tool which can quantitatively describe cognitive processes. This tool can be used for identifying design strategies, comparing design methods, and benefit design education.

1.3 Research Objectives and Framework

Based on the research issues discussed in previous sections, the research questions raised are as follows:

- The first question is how to describe quantitatively designers' cognitive processes.
- The next question is whether the quantitative measures are related to designers' performance, including the creativity of design outcomes and designers' cognitive demands. The expectation is to identify design strategies that can improve design outcomes and at the same time accommodate designers' cognitive demands.
- The final question is whether the quantitative measures are related to designers' expertise levels. Investigating the factors that relate to the development of design expertise is expected to benefit design education.

The objective of the present study is to address the three questions. The present study is based on a framework for the evaluation of designers' performance considering designers' cognitive load (see Figure 1-1; Sun & Yao, 2011). In this framework, designers are involved in the physical/physiological process, the cognitive process, and the design process to deliver a creative design outcome. Designers' performance measures how successfully a designer accomplishes a design task. It consists of two parts: design outcomes and designers' behaviors. Design outcomes can be specifically quantified by four measures, namely, novelty, variety, quality, and quantity (Shah, Smith, & Vargas-Hernandez, 2003; the definitions of the four measures and examples will be introduced in Section 4.2.2).

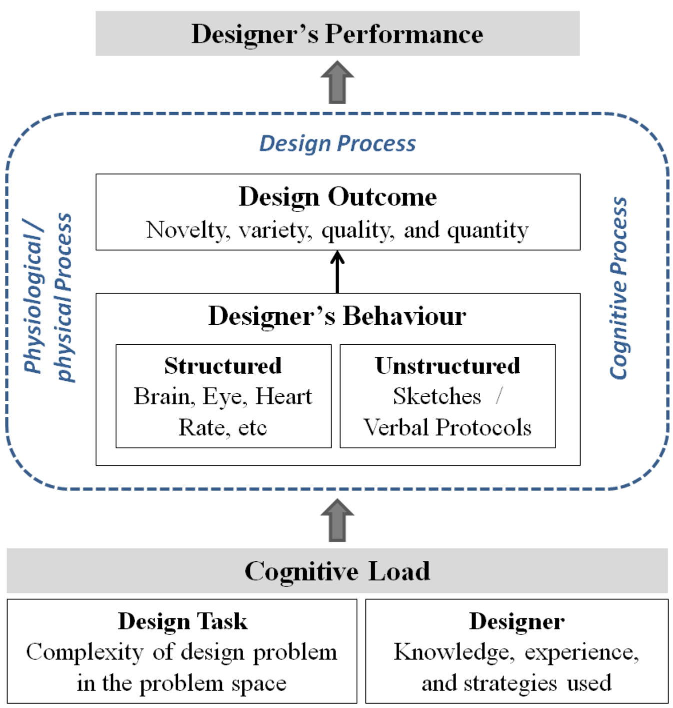

Figure 1-1 Framework for the evaluation of designers' performance
(Sun & Yao, 2011)

The general assumption of this research is that human cognition is information processing: a cognitive process can be seen as a sequence of internal states successively transformed by a series of information processes (Simon, 1978). In Figure 1-1, the structured information refers to the physical/physiological measures, such as designers' brain activity, eye movement, and heart rate (Lee, 2003; Sun, Xiang, Chai, Yang, & Zhang, 2014). The unstructured information refers to sketches and verbal protocols generated by designers. The physical/physiological measures have not been widely used in design behavior research because of some technical bottlenecks. The physical/physiological signals are likely influenced by designers' physical/psychological states, especially when a design session takes as long as several hours. Furthermore, it is challenging to connect the physical/physiological signals to thoughts in the human mind. Therefore, the unstructured sketches and verbal protocols are currently often used for studying designers' behaviors.

Cognitive load represents the load imposed on the cognitive system by a particular task (Paas & van Merriënboer, 1994). Cognitive load can affect designers' behaviors and then affect designers' performance. Both cognitive overload and underload can degrade human performance due to a mismatch between cognitive demands and human capabilities (Byrne & Parasuraman, 1996; Hancock, 1989). Therefore, it is necessary to avoid cognitive overload and underload in the design process. Cognitive load is not only task-specific but also individual-specific (Rouse, Edwards, & Hammer, 1993). Task complexity is determined by the objective properties of the design problem itself and what designers have perceived and constructed in the problem space. The capability of the cognitive system is affected by a designer's knowledge and experience in solving design problems. Skill and strategy usage can help maintain performance when a task's complexity or difficulty level is increased (Stevens, Galloway, & Berka 2007; Svensson, Angelborg-Thanderz, Sjoberg, & Olsson, 1997).

The relation between designers' cognitive load and design outcomes can be examined from the perspective of cognitive efficiency. Cognitive efficiency, also known as mental efficiency, describes how individuals optimize mental resources to achieve improvements in learning, problem-solving, or academic performance (Hoffman, 2012). Mental resources include characteristics such as working memory capacity and existing knowledge stored in long-term memory. Studies have shown that people differ in the efficiency with which they use their available cognitive capacity (Ahern & Beatty, 1979). In the present study, cognitive efficiency indicates how efficiently designers complete a design task given a limited amount of mental resources. The present study attempts to directly evaluate designers' cognitive efficiency and to investigate the factors that affect cognitive efficiency by examining the relation between cognitive efficiency and the quantitative measures of cognitive processes.

The quantification of cognitive processes will be represented by the concept of complexity. A complex process consists of many different parts that are all connected in different ways (Summers & Shah, 2010). The quantification of cognitive processes will be described from three different perspectives: the complexity of structuring a design process, the complexity of parts in a design process, and the complexity of connections between those parts.

Figure 1-2 explains the structure of the three complexity measures. Problem structuring is a process of using knowledge and external information to construct the problem space (Restrepo & Christiaans, 2004; Simon, 1973). Designers conduct design tasks on the basis of a personally perceived and constructed design problem space (Dorst & Cross, 2001). Problem structuring usually happens at the beginning of a design process and can reoccur in the design process. Studies have shown that structuring a design problem is highly related to the achievement of creativity (Christiaans, 1992), and the processes of structuring the problem are frequently identified as key features of design expertise (Cross, 2004). Therefore, studying design problem structuring can help researchers understand design strategy usage and improve design processes.

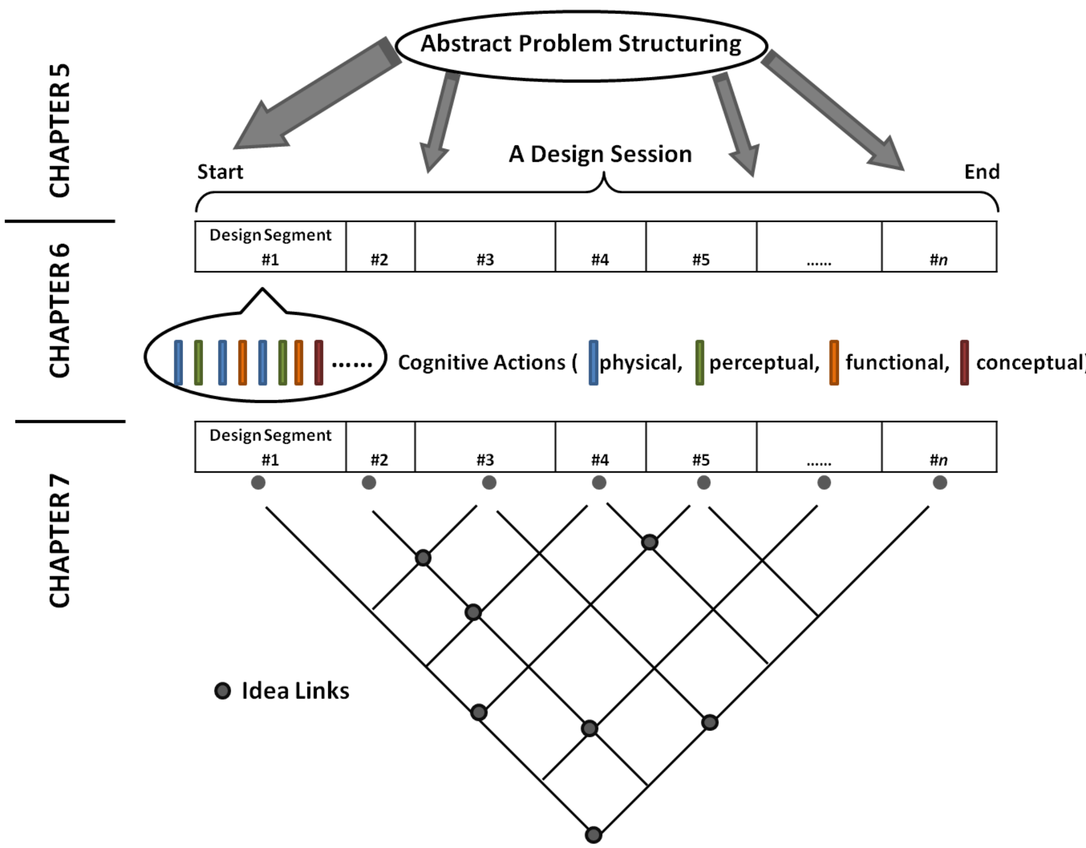

Figure 1-2 Structure of three complexity measures

A design session (process) comprises a sequence of design segments. Each design segment is an act of reasoning and consists of different cognitive actions. The cognitive actions represent how information is processed sensually, perceptually, and semantically. Cognitive actions can be defined in a systematic way by encoding verbal protocols with the vocabulary of the scheme (for example, physical, perceptual, functional, and conceptual actions corresponding to the sensory, perceptual, and semantic level of information processing in human cognition; Suwa, Purcell, & Gero, 1998). A designer's cognitive behavior in a design process can be represented as a structure composed of defined primitive actions. A previous study has found that the expert designer's cognitive actions were well organized and clearly structured, while the novice designer's cognitive process was divided into many groups of concurrent actions (Kavakli & Gero, 2003). Therefore, studying structures of cognitive actions can help researchers understand which structures of cognitive actions differ according to designers' expertise levels and design strategies used.

Cognitive segments in a design process are not independent. The patterns of their relations, such as chunks (a group of design segments that are almost exclusively linked among themselves) and webs (a large number of links among a relatively small number of design segments), have been identified and are related to the creativity of design outcomes (Cai, Do, & Zimring, 2010). Therefore, studying links between cognitive segments, also called idea links, can help researchers understand and improve the design process.

1.4 Thesis Organization

The literature on methods of studying designers, the assessment of designers' performance, expertise in design, and complexity in design will be reviewed in Chapter 2, and the research methods will be further introduced in Chapter 3. The evaluation of cognitive efficiency will be elaborated in Chapter 4. The quantification of cognitive processes will be described from three different perspectives of complexity (see Figure 1-2): the complexity of structuring a design process (that is, problem structuring in Chapter 5), the complexity of parts in a design process (that is, design actions in Chapter 6), and the complexity of connections between those parts (that is, idea links in Chapter 7). Each of the three chapters can be relatively independent and includes its methods and results. In Chapter 8, the conclusions of the study and its contributions will be summarized, and the limitations of the study and future work will also be discussed.

Chapter 2 Literature Review

This chapter reviews the literature on methods of studying designers, designers' performance assessment, expertise in design, and complexity measures in design. To understand the designers' role in design creativity, theoretical and experimental methods have been proposed to study design cognition and designers' behavior. Designers' performance can be assessed on the basis of design outcomes. Since designers' physical and physiological performance is related to cognitive performance, physical and physiological signals obtained in the design process can also present information on designers' performance. Designers' performance is highly related to expertise in design. Since design cognition studies human information processing, measuring information processed during the early design stage is important to understanding how designers generate creative ideas.

2.1 Methods of Studying Designers

Studying designing is unlike studying many other human activities because when different designers are given the same set of design requirements, their design outcomes are different. Designers play an active and important role in guiding the design process to achieve design breakthroughs and innovation. To understand the designers' role in design creativity, it is important to study designers. Theoretical and experimental methods have been proposed to study design cognition and designers' behavior (Yao, 2007). Design cognition research comprises cognitive mechanisms and design thinking (Horvath, 2004). The former focuses on knowing, perceiving, and conceiving design knowledge, intuitions, and hypotheses (Finke et al., 1992), and the latter investigates designers' thought processes, with special attention to logical, visual, spatial, and functional thinking (Dewey, 1933). Designers' behavior research observes what designers do during the design process (Whitefield & Warren, 1989) and identifies the features of expert designers' behavior such as the use of design strategies (Cross, 2004). Designers' behavior is thought to indicate design thinking. The behavior research also investigates designers' physical actions include sketching activities (Bilda & Demirkan, 2003) and eye movements (Sun, Xiang, Chai, Yang, et al., 2014). In this subsection, the methods of studying designers will be reviewed in two categories: empirical studies and theoretical analysis. Empirical studies include cognitive models and experimental approaches. Many cognitive models of engineering design are also studied using experimental approaches. Designers' behavior in team design is also reviewed.

2.1.1 Empirical studies

2.1.1.1 Cognitive models

<u>Cognitive process of creativity</u>

"Cognitive" pertains to thinking or conscious mental processes. Cognitive process of creativity has been studied by psychologists (Helmholtz, 1826). One of the earliest models of creativity was Dewey's model, which described the process of problem solving in five logical steps: feeling a difficulty, locating and defining the difficulty, considering possible solutions, weighing consequences of these solutions, and accepting one of the solutions (Dewey, 1910). Wallas (1926) went beyond Dewey's logical sequencing and generated a series of five steps that probably is the classic description of the creative process: preparation, incubation, intimation, illumination, and verification. Guilford (1957) first proposed the concept of "divergent thinking" and separated the creative process into convergent and divergent forms of thinking.

Torrance (1988) divided the creative process into four logical stages: sensing problems, making hypothesis, evaluating, and communicating. Taura and Nagai (2005) argued that cognitive process of creativity is a concept-synthesizing process including combining, blending, and integrating. Comprehensive creativity researches were collected in *Handbook of Creativity*, edited by R. J. Sternberg (1999).

Cognitive process of engineering design

Howard et al. (2008) argued that the creative process of engineering design should end with the evaluation stage, as the phase of communication and implementation should be deemed a design activity. Therefore, the generic creative process model of engineering design contains the three stages of analysis, generation, and evaluation. These three stages can be connected with the design process by relating the elements of the whole design process—analysis of task, conceptual design, and embodiment design—to function, behavior, and structure (the FBS model proposed by Gero & Kannengiesser, 2004), respectively. The function is related to the analysis of the task phase, the behavior of the design is formed in the conceptual design phase, and the structure is established during the embodiment phase.

The cognitive process of engineering design might be concisely expressed as a procedure of information processing and decision making. Literature on cognitive science considers human problem solving as an information processing activity (Simon, 1978). In the conceptual design process, information is required from diverse sources in order to define the functional requirements, operating constraints, and evaluation criteria pertinent to accomplishing a design task (Wood & Agogino, 1996). Unsuccessful information processing will lead to poor definition and uncertainty in conceptual design processes (Parmee, 2002). It has been found that the cognitive process for information processing is significantly different in expert and novice designers (Cross, 2004). For expert designers, information processing is based on breadth-first searching, which is much more effective than novices' depth-first searching (Ho, 2001). Liikkanen and Perttula (2009) investigated a cognitive process in the information processing stages and found that that novice designers tended to use the implicit decomposition method coupled with top-down control strategies, and explicit decomposition was seldom used and without obvious benefits.

Engineering design has also been regarded as an iterative decision-making procedure. Decisions make the product development process go forward. Akin and Lin first identified the occurrence of "novel design decisions," which are unlike routine design decisions and critical to the development of design concepts (Akin & Lin, 1995). The decision-making stage was found to correlate with the overall creativity (Hasirci & Demirkan, 2007). Experienced engineers were observed to make a preliminary evaluation of their tentative decisions before implementing them and making a final evaluation (Ahmed, Wallace, & Blessing, 2003), and student designers decided their main ideas earlier than expert designers (Kim et al., 2007).

In addition to viewing the design process as a procedure of information-processing and decision-making, some cognitive models focus on designers' mental iterations (Adams, 2001). Jin and Chusilp (2006) developed a cognitive model to study designers' mental iterations in response to different problem types and constraint conditions. This study observed that creative design involves more iterations than routine design. Co-evolutionary design is an approach to design problem solving in which the requirements and solutions of design evolve separately and affect each other (Maher & Poon, 1996). Maher and Tang (2003) argued that co-evolutionary design can be the basis for a cognitive model of design by characterizing the way in which designers iteratively search for a design solution, making revisions to the problem specification.

The cognitive models of creativity can help researchers understand how cognitive processes are stimulated to generate design ideas. Jin and Benami (2010) developed a cognitive model to capture the relationships among design entities, design operations, and cognitive processes. This empirical study showed that different design concepts have different effects on stimulating creative idea generation; more product-oriented and mature concepts lead to less effective stimulations. The more meaningful and relevant the stimuli are, the more effective the stimulation will be.

Cognitive studies have also been applied to some specific design methods, for example, biologically-inspired-design (BID). The goals were to understand BID innovation, to identify opportunities for enabling more effective learning, and to examine the implications for developing computational tools for enabling effective BID (Helms, Vattam, & Goel, 2009; Mak & Shu, 2004; Vattam, Helms, & Goel, 2007). These studies were initial trials to investigate the cognitive aspect of specific design methods and to attempt to develop BID into a systematic cognitive model. Sometimes, the cognitive model itself matches the design method, for example, co-evolution as a design process and a cognitive model of design (Maher & Tang, 2003).

To summarize the models introduced above, the existing cognitive models are proposed to explore cognitive mechanisms relating to human creativity, to investigate the features of design expertise, and to represent the characteristics of the design process or a design method. Although the effect of the design process on a designer's mental activity and the feedback of the latter on the former need further study, cognition research may contribute to the development of effective tools to satisfy designers' needs. A cognitive model of memory can help designers store and retrieve mechanical design plans using information found in the description of the design problem (Bardasz & Zeid, 1992). Learning designers' preferences (what is preferred or desirable about a design) and aiding designers in making decisions can reduce designers' cognitive burden (Wan & Krishnamurty, 2001). The way in which designers use their reasoning and data processing capacities to make decisions can be modeled, and a decision-making cognitive amplifier can be used for project risk management in new product design (Gidel, Gautier, & Duchamp, 2005). Furthermore, appropriate architecture of intelligent software was able to mimic human cognitive processes as the basic tool for providing decision-making support for planning and controlling a concurrent engineering design process (Reidsema & Szczerbicki, 2002).

2.1.1.2 Experimental approaches

Cross et al. (1992) first noted that the methods of studying design thinking included interviews with designers, observations and case studies, protocol studies, controlled tests, simulation trials, and reflection and theorizing. This set of methods ranges from the more abstract to the more concrete types of investigation on design thinking, and from the more close to the more distant study of actual design practice. Simulation trials attempt to simulate designers' thought processes through artificial intelligence techniques, and theoretical analysis and reflection focus on the nature of design thinking.

Interviews, observations, and case studies

Interviews with designers, observations, and case studies are less formal but more close to actual design practice than the other methods. Interviews with designers have usually been with those who are acknowledged as having well-developed design ability and have usually been unstructured interviews which attempt to obtain these designers' reflections on the processes and procedures they use. The methods of interviews and observations can be used in case studies (Candy & Edmonds, 1996; Cross & Cross, 1996), which usually focus on one particular design project (either real or artificially constructed) at a time, with observers recording the progress and development of the project (either contemporaneously or post-hoc).

In case studies, designers are interviewed, and/or design outcomes, including sketches, log books, prototypes, mock-ups, and final products, are reviewed. Case studies of particularly successful designers and innovators can provide much useful understanding and insight into how creative designers conceive ideas and develop them (Cross & Cross, 1996; Roy, 1993). Comparisons among case studies can reveal the common characteristics of creative designers, such as design ability, personal motivation, and practical skills, and identify other characteristics such as personal factors and working methods. Case studies of design outcomes can be used for demonstrating how to apply the procedures of measuring ideation effectiveness (Shah et al., 2003). Case studies with historical examples have been used to explain cognitive phenomena in the conceptual design process (Madanshetty, 1995) and to verify an existing design theory (Hatchuel & Weil, 2009). Case studies with protocol analysis can obtain more details of designers' cognitive activities, for example, different structures of concurrent cognitive actions in novice and experienced designers (Kavakli & Gero, 2002).

Protocol studies and controlled tests

Protocol studies are applied to artificial design projects because of the stringent requirements of recording the protocols. Participants are asked to perform a particular design task and think aloud, that is, verbally report their thought processes. The assumption of protocol analysis is that the verbal process is consistent with the cognitive process. Three criteria must be satisfied in order to use verbal protocols to explain underlying cognitive processes: relevance, consistency, and generating memories for the task just completed (Ericsson & Simon, 1993).

Two primary categories of protocol studies are concurrent reports (during the task) and retrospective reports (after the task). Both have defects. The former method may interfere with the design process and slow down its pace (Dorst & Cross, 2001; Gero & McNeill, 1998; Hasirci & Demirkan, 2007), while the latter may miss something important if the designer cannot remember the subtle order (Jin & Benami, 2010; Suwa, Gero, & Purcell, 2000). The collected protocol data are transcribed into written text documents, segmented into distinct verbalizations, and encoded into different activities according to the coding system, which is related to the cognitive activities in the cognitive model. Then the designers' cognitive activities during the design process could be further analyzed by the encoded verbalizations. The encoded verbalizations can be used for understanding designers' behavior protocols and/or for validating a cognitive model. The shortcoming of protocol studies is that they cannot capture all cognitive activities and some other non-verbal thought processes (Cross, 2004). Non-verbal thought processes may be captured by designers' physical and physiological signals, such as gestures and electroencephalography (EEG). The physical and physiological methods will be reviewed in the subsection on designers' performance.

Protocol studies are often applied with the help of sketching studies. Sketching plays an important role in conceptual design and could be used to investigate cognitive process during the design process (Purcell & Gero, 1998; Scrivener, Ball, & Tseng, 2000). Goel proposed that lateral and vertical transformations that occur between designers' sketches are respectively related to divergent and convergent thinking modes (Goel, 1995). These transformations can be used to track designers' thinking modes which might increase the efficiency of the sketching activity (Rodgers, Green, & McGown, 2000). On the one hand, the sketching process and final sketches could be used to evaluate ideation effectiveness, for example, the quantity of novel ideas, the difference between two ideas, and the degree of satisfying requirements (Shah et al., 2003). On the other hand, the sketching process indicates the interaction between designers and their sketches: how designers draw depictions, inspect depicted elements, perceive visuospatial features, and think of non-visual functional or conceptual information (Suwa, Gero, & Purcell, 1998). The findings suggest that design sketches serve not only as external memory or as a provider of visual cues for association of non-visual information, but also as a physical setting in which design thoughts are constructed on the fly (Suwa, Gero et al., 1998).

Controlled tests are conducted in controlled laboratory conditions, in which participants (novice or non-designers, inexperienced or student designers, and experienced and expert designers) are required to perform a specialized task (or different tasks), and data on participants' performance is recorded and analyzed. In controlled tests, experimental design methods (Montgomery, 2005), such as the factorial design method, are used to investigate research issues. The design of experiment should include a clear hypothesis testing (problem statement), identification of response variables, controlled and manipulated factors, levels, and ranges, subjects chosen, sample size, type of data collected, statistical analysis of the data, and hypothesis validation (Dinar et al., 2015). For example, in order to investigate whether different types of stimuli lead to different numbers of ideas generated, the designers were randomly divided into four treatment groups, and each group was provided with one type of stimulus, such as mechanical functions, component shapes, product behavior, and synthesis knowledge (Jin & Benami, 2010). In another controlled test to study the effect of different design problems and constraints on the behavior of mental iteration, two design problems with or without constraints were used, and there were four treatment groups in total (Jin & Chusilp, 2006). After the experiment, analysis of variance (ANOVA) was performed to assess the statistically significant effects of problem types and constraint conditions and their interactions on the number of iterations, frequency of iterations, and percentage of each type of iteration loops. Since more than one dependent variable existed, multivariate analysis of variance (MANOVA) was carried out to ensure the appropriateness of ANOVAs. The results of controlled tests are quantitative assessment.

In summary, findings from human-based experimental approaches are interpretations of designers within given scenarios and contexts. Summers and Eckert (2013) argued that the scenarios and contexts of interviews can influence the scope of research conclusions, and suggested that information about interviews should include research purposes, research methods, study contexts, materials recorded, questions, answers, and the duration of interviews in the reporting of research findings. The same suggestion may apply to other experimental approaches.

Computer simulation

Computer simulations refer to algorithms and programs that can simulate design activities such as planning, reasoning, and decision making. Newell and Simon (1972) suggested that computer simulations can provide sufficiently powerful approaches to investigate human thinking. Artificial intelligence techniques have been used to help understand human intelligence and support some aspects of the design process (Blessing, 1992), such as knowledge-based sketch support tool (Elsen, Demaret, Yang, & Leclercq, 2012). Computational models have been developed to describe some features of the conceptual design process, such as the situated cognition model (Gero, 2002) and the co-evolutionary model (Maher & Tang, 2003).

Only a few studies have addressed designers' thought processes. A recent study found that in the design process of a multi-input-multi-output-coupling parametric design problem, designers' search patterns exhibited some characteristics of a simulated annealing algorithm (Yu, 2015). The designers who were faster problem solvers had decreasing "cooling schedules" similar to simulated annealing, that is, the likelihood of accepting a worse design and the step size at each iteration decreased as the problem progressed. However, the designers who were slower used a pseudo random search strategy.

2.1.1.3 Studying designers in groups

One way to study team designing and achieve repeatable direct observations is to make a video record of a number of teams engaged in a team design activity. Video-based interaction analysis (Tang & Leifer, 1991) focuses on conversations, non-verbal behavior (such as hand gestures), and interactions between designers and technology (such as sketching tools) during collaborative design within a small team (rarely more than four members). The utility of interaction analysis is predicated on the assumption that all important activities within a team setting must lead to interactions (communications) between team members. One study compared student teams and professional engineer teams (Smith & Leong, 1998). This study found that the engineer teams engaged in more management activity, more exchange of information about functions, and less evaluation activities during early design than the student teams. Moreover, experts' design behavior in team designing was consistent with that in individual designing. For example, expert designers took a more abstract or overall view of the design problem, balanced more constraints, more carefully formulated the design problem and explored the solution space, and more frequently searched for underlying principles or heuristics to guide their design construction than student designers.

Studying designers in groups can improve team design practice. In individual designing, the designer creates his/her own private understanding of the design problem and the design solution. In team designing, the individual designers have to share knowledge, information, and their personal understandings of the design problem and the possible solutions and synchronize their thoughts and activities with those of other team members. Valkenburg (1998) argued that "shared understanding" is an important condition for team designing and team decision making; without this understanding, decisions will not be supported by all team members and later activities in the design process can be hampered by different views of the team members on relevant design topics.

Structuring the group process is an important issue in design teams (Stempfle & Badke-Schaub, 2002). Valkenburg and Dorst (1998) observed and compared two design teams who had similar educational background but applied different design strategies. One team determined a frame as the main aspect of the design task from the beginning, developed this single frame throughout the project, integrated new aspects of the design task in the early frame, and finally won the design competition. However, the other team represented all relevant aspects simultaneously through the whole design project and afterwards failed to integrate all the subparts in the prototype stage.

How the group affects idea generation has not been widely examined in the design community. Gero (2002) developed the individual model into the group model and social model based on situatedness, which means that the interaction between the designer and the environment strongly determines the course of designing. Most people believe that ideas suggested by others aid the activation of problem-relevant knowledge (Paulus & Yang, 2000). But studies out of the design research have found that group interaction can inhibit the ideation process (Mullen, Johnson, & Salas, 1991). Nijstad and Stroebe (2006) argued that idea generation is a cognitive task and that various effects of group interaction on performance can be interpreted as either cognitive stimulation or cognitive interference effects. Cognitive models extending the scope of an individual designer's thinking are applicable for industrial case studies (Badke-Schaub, Goldschmidt, & Meijer, 2010; Chiu, 2002; Lang, Dickinson, & Buchal, 2002).

2.1.2 Theoretical analysis and reflection

Theoretical approaches attempt to establish a formal model to capture the mechanism of design processes. Based on the logic of design (Zeng & Chen, 1991), Zeng and Gu (1999) speculated that a chaotic motion is implied in design creativity. Kryssanov et al. (2001) studied creative design using the notations of algebraic semiotics and clarified the nature of emergence in design: while emergent properties of a product may influence its creative value, emergence can simply be seen as a by-product of the creative process. Designing is also considered as balancing a situation, through which a new product, process, or artifact is generated (Salustri, Rogers, & Eng, 2009).

Schön's reflective practice theory argues that "a kind of knowing is inherent in intelligent action" (Schön, 1984, 1992). This implicit "knowing-in-action" is vital for action-oriented professions like design. In this paradigm, the basic elements of design activities are actions, and the kernel of the design ability is to make intelligent decisions about those actions. The results of the experimental actions are scrutinized by the designer, who reacts to this new state of his/her own making. The final design is a result of this interaction. In this "reflective conversation with the situation," designers work by naming the relevant factors in the situation, framing a problem in a certain way, making moves toward a solution, and reflecting on these moves (Valkenburg & Dorst, 1998).

When an empirical study is "theory-driven," the theory will determine what observations are made, and thus what data are analyzed. Most protocol studies on design engineering are mainly data driven because a strong design theory is still missing (Christiaans & Dorst, 1992). Most theorists have tried to offer prescriptive methods for structuring design processes (Pahl et al., 2007).

In summary, empirical studies are the main methods to study designers in the design process. These studies are case-dependent and very time consuming, both in collecting data and analysis. Design research based on empirical studies lacks standard methods to avoid inter-coder disagreement and need new methods to speed up the discovery process (Dinar et al., 2015). These concerns motivate design researchers to seek alternative methods of collecting data. Future studies may need to develop computer based data collection and automated analyses, which may include: voice-to-text transcription; computer vision techniques applied to sketch recognition; web based design tools to collect massive amounts of data; use of natural language processing and data mining to automate data analyses; and shared repositories of experimental data (Dinar et al., 2015).

In addition, outcome-based studies of design creativity cannot provide direct data on cognitive processes but can investigate factors that contribute to design creativity. Designers' physical and physiological performance can be related to cognitive performance. The physical and physiological signals are regarded as "hard" data compared with verbal protocols, which are viewed as "soft" data. Hard data can easily be processed using computers. Outcome-based studies and physiology-based methods will be reviewed in the next subsection on designers' performance.

2.2 Assessment of Designers' Performance

Designers' performance can be specified based on design outcomes and behavior during the design process. Design outcomes are mainly represented in sketches, and design behavior can be observed from physical movements (such as gestures and eye movement) and physiological signals (such as heart rate and EEG).

2.2.1 Design outcomes assessment

The assessment of design outcomes is the foundation for outcome-based studies of designers. Various approaches have been developed for the assessment of sketches generated by designers, for example, the complexity and size scales of sketches (McGown, Green, & Rodgers, 1998); the quantity, quality, novelty, and variety of design ideas in sketches (Shah et al., 2003); sketching ability to accomplish sketching tasks and drawing fluency (Yang & Cham, 2007); and coding sketch content regarding mechanical design issues (Westmoreland, Ruocco, & Schmidt, 2011).

Many studies employ expert judges by using predefined metrics so as to reduce the subjectivity of judges (Shah et al., 2003). A variety of metrics have been developed, for example, originality, fitness to requirements, fluency, variety, elaboration, problem sensitivity, and ratio of usefulness (Dinar et al., 2015; Kim et al., 2007; Shah et al., 2003). In addition, it is common to apply multiple judges and perform inter-rater reliability tests so as to reduce and examine bias (Dorst & Cross, 2001).

A recent study extended the outcome-based into process-based study by investigating 20 factors in the product design process (Yuan & Lee, 2014). This study identified six critical factors that significantly correlated to design creativity scores: time for generating design ideas, time for gathering information, the number of information requests, the number of categories of the information requested, and the transitions between the design stages and steps (Yuan & Lee, 2014). This study attempted to establish a standard for assessing creativity in the product design process rather than assessing design outcomes alone.

2.2.2 Physiological performance assessment

Besides designers' outcomes, their physiological performance can present cognitive information. Studies in neuroscience have shown that reliable and valid measures of creative thinking become possible by directly measuring human brain activities, for example, functional magnetic resonance imaging (fMRI), near infrared spectroscopy (NIRS), regional cerebral blood flow (rCBF), positron emission tomography (PET), and EEG (Fink, Benedek, Grabner, Staudt, & Neubauer, 2007). It has been quantified that the dimensional complexity of the EEG was greater during divergent thinking than during convergent thinking (Mölle, Marshall, Wolf, Fehm, & Born, 1999). Different thinking modes can be measured by brain activities probably because creativity requires a variety of classic cognitive abilities, for example, working memory, sustained attention, cognitive flexibility, and judgment of propriety, and all these factors are typically ascribed to the prefrontal cortex, a structure of brain (Dietrich, 2004).

The tasks in neuroscience studies used for measuring creative thinking, however, are relatively simple compared with a design task and not domain-specific, such as "thinking of unusual or original uses of conventional everyday objects" (Fink et al., 2009) or "thinking of things or situations in an incomplete picture" (Mölle et al., 1999). Accomplishing a design task involves understanding the design problem, generating and evaluating solutions to it, and deciding on the best solution (Ullman, 2009). Only when signals representing brain activities are linked to specific design activities, can the signals significantly indicate designers' behavior in the design process. An integration of the cognitive models from empirical studies and information from physiological signals can extend our understanding of how creative design ideas are generated in engineering design.

It has been pointed out that other physiological performances (such as respiration, blood pressure, pulse wave, and heart rate) are also highly related to mental performance (such as mental stress, vigilance, fatigue, and attention; Lin, Leng, Yang, & Cai, 2007). These physiological parameters used to quantitatively evaluate human performance might provide some supportive evidence concerning cognitive activities during creative design. For example, heart rate variety (HRV) and EEG energy have been used to assess designers' mental stress and mental effort respectively during the conceptual design process (Nguyen & Zeng, 2014). Nguyen and Zeng argued that at the highest level of mental stress, designers' mental effort is the lowest, which they believed to result in the lowest level of creativity. In summary, such studies that integrated physiological data with verbal reports and sketches might provide more quantitative and more objective information to help us further understand when and how creative solutions are generated during the design process.

2.3 Expertise in Design

Design creativity and expertise often exist simultaneously, and the preparedness for the occurrence of creativity is a matter of expertise (Akin, 1990). Two aspects of expertise are directly related to creative performance: the *recognition* of a creative design solution and the *restructuring* of a given design problem (Akin, 1990). The acquisition of expertise, or learning, is shown to consist of transforming a declarative knowledge base into a procedural one (Akin, 1990). It has been suggested that one of the key factors in the acquisition of expertise is to practice deliberately (Ericsson, Krampe, & Tesch-Römer, 1993).

Studies have found that expertise in design has some aspects that are significantly different from that in routine problem solving since design problems are often ill-defined. Problem solvers in routine problem solving attempt to define or understand a problem fully before looking for solutions; however, creative expert designers move rapidly to early solution conjectures and use these conjectures as a way of exploring and defining problem-and-solution together (Lloyd & Scott, 1994).

Creative experts treat design problems as harder problems than novices do (Cross & Cross, 1998). Creative experts are also reported as solving similar tasks from first principles each time, rather than recalling previous solutions (Cross & Cross, 1998).

The comparisons between experienced and inexperienced designers can reveal their different behaviors and ways of solving design problems. It has been found that experienced designers often put more effort into understanding design problems and design constraints, use more reasoning strategies, structure cognitive actions more efficiently, and demonstrate more efficient design behavior than inexperienced designers, as summarized in Table 2-1.

Table 2-1 Comparison of designers' behaviors

No.	Comparison	Differences
1	Understanding the problem (Casakin, 2004; Cross, 2004)	Experts dedicate a substantially greater effort than novices while elaborating on their understanding of a problem.
2	Use of analogy (Cai et al., 2010)	Experienced designers tend to draw analogies based on structural similarities while inexperienced designers tend to make a surface analogy, that is, mapping and linkage to their everyday knowledge.
3	Use of metaphor (Casakin, 2004)	Experts identify and retrieve analogies from between-domain displays. However, novices identify a large number of between-domain displays, but retrieve analogs from between-domain and within-domain displays at the same time.
4	Constraints (Casakin, 2004)	Experts add constraints to the design problem.
5	Transitions between design steps (Atman et al., 2005)	Senior designers spend more time, consider more alternatives, produce more transitions between design steps, and generate higher quality solutions.
6	Mental iterations (Adams, 2001)	Skilled designers do more mental iterations.
7	Organization and structure of cognitive actions (Kavakli & Gero, 2003)	Experts' cognitive actions are well organized and clearly structured (chunks), while novices' cognitive performance is divided into many groups of concurrent actions. Experts' strategic knowledge allows them to use a smaller number of processes and to form different groups of processes.
8	Design behavior: problem scoping and problem framing (Cross, 2004)	Expertise in design (creative domain) has some aspects that are significantly different from expertise in other fields (standard solution). Expert designers are solution-focused, not problem-focused.

Studying designers with different expertise levels can obtain information from different perspectives. Studying creative designers can provide an insight into the creative process and an understanding of innovative product development (Roy, 1993). Design strategies used by expert designers can be used for training novice designers

(Kim et al., 2007). A within-subject study by comparing senior and freshman engineering students provides an opportunity to observe design processes change over time on the individual level (Atman et al., 2005).

However, there is not an existing standard that can be used to identify designers' expertise levels. Researchers in the field of expertise agree that the acquisition of expertise requires a minimum period of practice and sustained involvement before performance reaches an international peer-level of achievement—at least 10 years from first involvement (Ericsson, Krampe et al., 1993). In empirical studies, participants are usually divided into different groups according to their demographics and professional experience in design. Participants in existing studies include outstanding designers who have actively engaged in design for many years and obtained extraordinary results such as patenting design and leading design teams, expert designers with many years of professional experience in one particular design field, experienced designers with several years of professional experience, non-experienced students studying in design-related programs, novice students at the beginning of studying design-related courses, and non-designers outside design fields. Participants defined at a high level of design expertise in one study may be at a relatively low level in another study. It is difficult to compare design behavior between cases. Therefore, it is important to describe designers' demographic information as precisely as possible.

2.4 Complexity in Design

Complexity refers to a system or process which consists of many different parts that are all connected in different ways. Measuring complexity in design has been applied in industry, such as estimating product development time (Griffin, 1993), evaluating properties of a given configuration of components in a device (Kannapan, 1995), simplifying the engineering design (El-Haik & Yang, 1999), and developing computer-aided design tools (Jin & Li, 2007). In engineering design, complexity measures the degree of interconnections, the size of the composite, and how difficult it is to solve or analyze a design problem (Summers & Shah, 2010). The measure of complexity is suggested to be extended from the processes of engineering design and product development to the processes of manufacturing and assembly, as well as to a global supply chain and business management, because increasing complexity continues to be one of the biggest challenges facing manufacturing (ElMaraghy, ElMaraghy, Tomiyama, & Monostori, 2012).

2.4.1 Categories of complexity

Complexity in design is usually divided into three categories: design problem complexity, design process complexity, and product complexity. To measure design problem complexity, information about design goals (for example, basic functions of a product), design constraints (for example, cost), design variables (for example, length), and expected physical properties of the product (for example, velocity) could be included (Summers & Shah, 2010). A general design problem is characterized by design components (which convey the physical constituents of a design) and design attributes (which describe the behavioral properties of a design). The dependence of m design attributes on n design components can be formulated via an $m \times n$ incidence matrix (Chen, Ding, & Li, 2005). The complexity of the incidence matrix can be formulated as $m \times \ln(2^n)$. The matrix-based complexity index of decomposition (which is the ratio of the complexity of the decomposed problem to the complexity of the original problem) has been proposed to validate quantitatively the decomposition solution to the design problem (Chen & Li, 2005).

Product complexity can be calculated as the sum product of the number of product functions and the level at which the functions appear in a decomposed function tree (Bashir & Thomson, 1999). Therefore, time for product development can be empirically predicted according to product complexity (Bashir & Thomson, 2001). Five main dimensions of product complexity impacting the product at different stages have been identified: variety, functional index, structural index, design index, and production index (Orfi, Terpenny, & Sahin-Sariisik, 2011). Studies indicate that coupling (between the performance parameters and the design variables) and size (the number of components, assemblies, and design variables) are two independent measures of product complexity (Ameri, Summers, Mocko, & Porter, 2008), and the two measures can be applied to different representations, for example, connective complexity in the assembly process (Mathieson, Wallace, & Summers, 2013).

A design process can be divided into several distinct phases (or tasks) such as problem structuring, preliminary design, refinement, and detail design (Goel, 1995). From a perspective of information processing, a design process consists of three basic tasks: analysis, synthesis, and evaluation (Maimon & Braha, 1996). Each design task is an element of the design process. Design process complexity might include the number, type, and repeatability of design tasks (Summers & Shah, 2010). Additionally, designers' cognitive processes as well as designers' sketching processes would be another indispensable part of information involving design processes. Complexity measures currently have focused on geometric or parametric problems at the embodiment level. Design process complexity has not been applied for studying designers' cognitive processes at the conceptual design level. Quantitative methods are required to assess information in cognitive processes.

2.4.2 Computational and information complexity

Various disciplines have studied the complexity measures with respect to computational complexity and information complexity in engineering design (Summers & Shah, 2010). Computational complexity theory concerns how much computational resources or operations (for example, time, storage, program, and communication) are required to solve a given problem (Arora & Barak, 2009). For example, computational complexity can be proportional to the time it takes for an implemented algorithm to solve the design problem given that the basic operations are roughly equivalent in time. The process of design, an abstract model of computability, is a Turing machine (Fitzhorn, 1994). A design process comprises a series of states that transition to a halted final solution. Kolmogorov complexity, the minimum length of a program to reconstruct a message, can be used for representing computational complexity. Kolmogorov complexity is based on the number of elements, components, or parts of a system/process.

The amount of information can also be used as a measure of complexity in design. Complexity is defined as the "quantity" of information required to describe a system (Ashby, 1973). Axiomatic Design utilizes entropy to measure complexity (based on the concept of information content) and defines entropy as a measure of uncertainty in achieving the set of functional requirements to be satisfied (Suh, 1999). In Axiomatic Design, the product and design problem are coupled through functional requirements and design parameters. Two axioms are proposed: independence and information. The independence axiom states that the functional requirements should be maintained independent of each other. The information axiom states that a good design is decoupled and has a minimal number of functional requirements and design parameters. Therefore, a simple design is preferred to a complex design when the problem and product are evaluated by the coupling and the size of the description.

It has been suggested that complexity is a measure relating what is the desired objective to what is known and unknown (Suh, 2001). This measure of complexity is based on the amount of information available and the probability that this information will yield a valid final product. Therefore, information complexity is composed of two orthogonal components: the real and imaginary components of design. The real complexity is a measure of the uncertainty in meeting the requirements, and the imaginary complexity is a measure of the probability of finding a solution.

Another viewpoint from the perspective of information suggests that complexity is fundamentally a characteristic of the information content within a design process (Braha & Maimon, 1998b). Two complexity measures are developed: structural complexity and functional complexity. Structural complexity is a function of the represented information. Defining information in the structural way states that the "quantity" of information may be measured directly based on a system's internal structure. Defining design process complexity in the structural way means that if two design processes successfully achieve the required specifications, the best design process is the one with the minimum total information content. Thus, the complexity of a design process may be said to be a function of its information content at each level of the design process hierarchy.

However, functional complexity is independent of representation. Representations exist at the symbol level and not at the information level. Defining design process complexity in the functional way means that if a designer has information that one of the decisions will lead to one goal, then the designer will select that decision. This means that information can be described in terms of its operation to satisfy the goals of the system. Alternatively, two design processes may be compared based on their output. The best design process is the one that yields an artifact in which its probability of successfully achieving the required specifications is maximized. Thus, a design complexity may be said to be a function of its probability of successfully achieving the required specifications.

An approach based on Shannon's information theory was proposed to measure the entropy of links in linkographs (Kan, Bilda, & Gero, 2007). Linkography is a technique used in protocol analysis to study a designer’s cognitive activity (Goldschmidt, 1995). The entropy of links is interpreted as a measure of idea development and design creativity (Kan et al., 2007; Kan & Gero, 2008). A creative design process is found to have a high linkograph entropy (Kan & Gero, 2009).

Some studies support that complexity should be nurtured to create novelty in manufacturing system design and development (van Eijnatten, Putnik, & Sluga, 2007). However, it is argued that complexity in design should be reduced, controlled, or if possible eliminated because the better a design, the lower the uncertainty and information complexity according to the axiomatic complexity theory (Suh, 1999). The conflict between observations from human cognitive processes and theories on design processes implies that the methods and criteria used for measuring complexity in design problems, design products, and design processes cannot be copied into the complexity measures of cognitive processes.

2.5 Summary

According to the literature reviewed, empirical studies are the main ways of studying designers in the design process. Outcome-based studies of design creativity cannot provide direct data on cognitive processes. Verbal protocols and sketches generated during the design process are still a main source of data. However, new methods are needed to measure information contained in these unstructured data.

Designers' performance is related to design creativity. Designers' performance including mental and physiological performance cannot be assessed by design outcomes alone. A measure of designers' cognitive processes should be integrated with the assessment of design outcomes.

Design expertise is also related to design creativity. But there is not a standard way to measure expertise in design. Some features of expertise in design are common in expert designers, while others are personal. Measuring information processed during the design process may provide insight on the transition from novice to expert designers.

The present study focuses on the measure of design process complexity, which will contribute to three aspects of design research. First, the evaluation of process complexity can help identify design strategies applied by designers. The effective design strategies can be used for training novice designers and developing computer-aided design tools. Meanwhile, process complexity measures can support product development, for example, by estimating how much effort should be invested in a design task. Furthermore, process complexity measures provide feedback on methodology research indicating, for example, which design method is beneficial for concept generation.

In the present study, computational and information complexity measures are used to analyze cognitive processes. Computational complexity measures the process of problem structuring based on function decomposition procedures (Chapter 5). Computational complexity also measures the amount of information about cognitive actions and transitions between those actions (Chapter 6). Information complexity measures the probability of a design segment connecting to other design segments (Chapter 7). The relationships between the complexity measures and other measures including cognitive efficiency, the creativity of design outcomes, and designers' cognitive demands and expertise levels are investigated to look into the research questions (Chapter 1: Section 1.3).

Chapter 3 Research Design and Experimental Setup

3.1 Research Design

This exploratory research uses a mixture of qualitative and quantitative methods to study designers' cognitive processes and cognitive efficiency. Participants were randomly recruited to attend individually an experiment, which was conducted in a design lab environment. Methods of studying designers included surveys, questions, case studies, and verbal protocols. Participants' cognitive demands were self-reported using a standard rating scale. Participants' expertise levels were quantified according to the engineering work experience requirements for licensure. The creativity of design outcomes were evaluated based on the sketches and verbal protocols generated by the participants. A rubric procedure and rating criteria were applied for the calculation of creativity scores. The four measures of creativity can help reduce inconsistency and bias by comparing a design concept to others within the same group. The inter-rater reliability was also examined quantitatively. The complexity measures were strictly defined by information-based approaches.

The results of the experiments were analyzed by comparison and correlation analysis. The participants were divided into two groups according to their experience in engineering design. The measures of cognitive demands, expertise levels, creativity, cognitive efficiency, and complexity were compared between the two groups, and the relations between these measures were investigated to identify factors that affect designers' performance including cognitive efficiency. The relations between complexity measures and cognitive efficiency were also translated into design practice recommendations, for example, by determining which design strategies were related to high cognitive efficiency. These design practices were compared with those of previous studies.

3.2 Participants and Expertise Levels

The research ethics were approved by the Research Ethic Board at the University of New Brunswick (UNBF REB File #2010-053) before the experiment. Twenty-three participants, 17 males and 6 females, 20 to 50 years of age, were randomly recruited from the students and staff of Engineering at the University of New Brunswick. The participant group included 9 mechanical engineering students and 14 others from civil, chemical, electrical, and geomatics engineering, and computer science and mechanics. Out of the 23 participants, 5 were undergraduate students, 9 were Master's students, 7 were PhD students, and 2 were staff members. Three graduate students worked in the field of engineering design before they returned to school for their graduate studies.

The expertise level of participants can be quantified according to the engineering work experience requirements for licensure (Professional Engineer Ontario, 2013). The detailed calculation is listed in Table 3-1. Work experience per year in the field of mechanical engineering can be counted as one score. One academic degree or diploma can be converted into one year work experience which counts as one score. For students who have no real work experience, the experience of attending an engineering project in summer work or senior design courses can be converted into 0.5 scores. Work experience outside the field of mechanical engineering design was not counted. The three graduate students who had work experience got the scores of 4, 7, and 11 respectively. Out of the 23 participants, 6 got their scores between 1 and 2, 5 got 0.5 scores, and 9 got 0.

Table 3-1 Expertise level evaluation

Score	Content
1	University/college education (a diploma or a bachelor degree) in the field of mechanical engineering
1	A master's degree in the field of mechanical engineering
1	A PhD degree in the field of mechanical engineering
1	One year work experience in the field of mechanical engineering
0.5	Having engineering project experience but no work experience

3.3 Experimental Procedure

The experiment was conducted in a quiet research lab. The participants were informed of the objective of the study and the experimental procedure. After signing the consent form (Appendix A), all the participants completed a survey form (Appendix B) to allow the researcher to obtain information about their educational background and work experience in design.

Each experiment was divided into a design session and an interview session. Both sessions were conducted according to the desired pace of each participant. Before the design session, each participant spent several minutes practicing sketching on the graphics tablet (Wacom® Cintiq® 21UX pen display) and using the sketch software (Corel® Painter™ sketch Pad). The standard user guide for tablet and sketch software was orally introduced to the participant. Figure 3-1 shows the experiment setup. Three webcams (Logitech® Pro 9000) separately recorded the side, top, and front views of the sketches and gestures. The researcher watched real-time videos from three monitors.

During the design session, the participants were asked to write down any ideas about the design problem, including sketches, textural descriptions, plans, notes, tables, signs, and so on. There was no interaction between the researcher and the participants in the design session. The design sketches were drawn on the graphics tablet screen and recorded by screen recorder software (My screen recorder, DeskShare®) throughout the entire design session. Each participant worked individually and independently. In the whole process of the experiment, the participants could ask any questions about the design problem, the usage of tablet and software, and the experiment procedure. The researcher would not provide any information about design solutions.

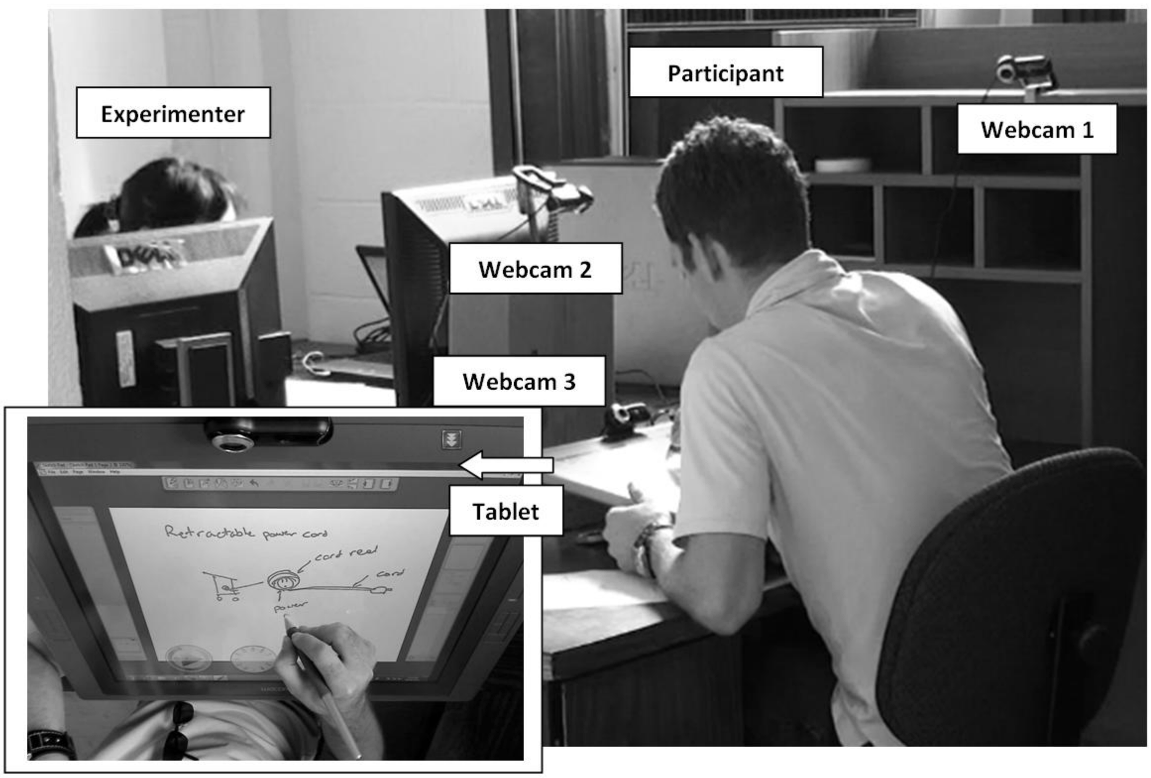

Figure 3-1 Experiment setup

The task was to design a teaching podium. The following standard description of the design task was provided to the participants with a picture of the classroom layout (Figure 3-2).

> "A teaching podium, also called a lectern, is a stand for instructors to set up a laptop and present their lecture notes and other teaching materials. Some of the classrooms at our university do not have a good teaching podium. The space between students' desks and the chalkboard is limited. Sometimes, the teaching podium needs to be moved or adjusted so that it doesn't block the students' view of the chalkboard.
>
> You are asked to design a teaching podium used in general-purpose classrooms, which can accommodate at least 100 students. It can be moved and installed easily. It is a useful multimedia teaching tool for the instructors. You need to show all the steps toward the final solution and draw sketches to represent your design concepts."

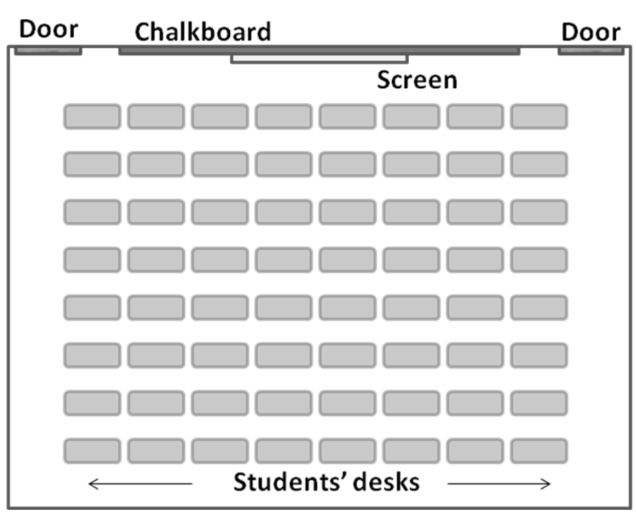

Figure 3-2 Classroom layout provided to the participants

Immediately after completing the design task, each participant was asked to report the level of mental effort using the Rating Scale Mental Effort (RSME; De Waard, 1996; Zijlstra & van Doorn, 1985, see Appendix C). The RSME scale is 150 millimeters long, representing 150 scores from 0 at the bottom to 150 at the top. The score is indicated by 16 increments on the left side of the scale from 0 to 150 with a step of 10, and on the right is the description of nine levels of effort ranging from *absolutely no effort* to *extreme effort*. This scale translates the perceived amount of mental effort into a numerical value between 0 and 150.

During the interview session, the participants were encouraged to report verbally the content and sequence of their thoughts while watching the video records of their sketches and hand gestures recorded during the design session. The video records were replayed as cues to help the participants recall their physical and cognitive actions. The interview session was also video- and audio- recorded for subsequent verbal protocol analysis.

After reporting their thoughts, participants were asked to answer three specific questions by the researcher: (a) How would you rate the difficulty of the design task on a scale of 1 (*not difficult at all*) to 5 (*very difficult*)? (b) How would you rate your level of interest in the design problem on a scale of 1 (*not interesting at all*) to 5 (*very interesting*)? and (c) How would you rate your degree of satisfaction with your own design solution on a scale of 1 (*not satisfied at all*) to 5 (*very satisfied*)?

After the experiment, the verbal reports were transcribed. The sketches and verbal protocols from all the participants were collected for the evaluation of design outcomes (see Chapter 4) and problem structuring (see Chapter 5). The sketching processes and verbal protocols were further segmented and encoded into a bottom-up hierarchy of information processing to investigate the cognitive actions (see Chapter 6) and idea links (see Chapter 7).

Chapter 4 Cognitive Efficiency Evaluation [1]

4.1 Introduction

The concept of cognitive efficiency is proposed to evaluate how effectively a design strategy/method is applied and how efficiently a design process is proceeding. Cognitive efficiency can be measured at two levels: neurological efficiency and performance efficiency. Neurological efficiency is substantiated by the location and the degree of brain activity, such as changes in regional cerebral blood flow and neural activation detected by brain-imaging technology (Neubauer & Fink, 2009). Individuals are considered cognitively efficient when they solve tasks correctly using less brain energy resources as evidenced by a lower cerebral glucose metabolic rate (Haier, Siegel, Tang, Abel, & Buchsbaum, 1992) or higher alpha power of electroencephalography signals (Jausovec, 2000). Studies in neuroscience also suggest that the efficiency of interactions between brain regions is a critical determinant of differences in individual performance (Rypma et al., 2006).

However, due to technological bottlenecks, the understanding and interpretation of physiological signals are still a long way from explaining the complex design cognition during design processes. For example, electroencephalogram (EEG) technology can only record the electrical voltage on the cortical surface rather than within the brain. Also, EEG signals are very sensitive to fluctuating mental and emotional states, so they should be re-calibrated as frequently as every few minutes. Hence, experimental tasks are always designed to be very specific, for example, well-

[1] Part of this chapter has been published (Sun, Yao, & Carretero, 2014).

and ill-defined problems (Jausovec, 1997), convergent and divergent thinking questions (Mölle et al., 1999), and free-associative and intelligence-related tasks (Fink et al., 2009), so that the tasks can be completed in a short period of time. In addition, designers' sketching activities, which are critical for visual thinking and concept development (Menezes & Lawson, 2006; Suwa, Gero et al., 1998; Tovey, Porter, & Newman, 2003), are constrained. All these limitations constrain the measurement of neurological efficiency during conceptual design processes.

Cognitive efficiency can also be measured at the level of performance efficiency. The measurement properties of cognitive efficiency have been defined as quantitative increases in gains (for example, knowledge and performance) in relation to costs (for example, time and mental effort). The computation formulas available for calculating cognitive efficiency can be divided into two categories: the deviation model and the likelihood model. The deviation model measures the difference between standardized performance scores and cost scores. The likelihood model compares the ratio between performance and a cost factor. The deviation model is suitable for assessing group performance in different conditions such as training methods, expertise levels, strategy usage, and physiological states (Paas & van Merriënboer, 1993). The likelihood model is always used for assessing individual performance especially when it dynamically varies (Hsu, Chang, Chuang, & Wu, 2008).

In the present study, cognitive efficiency was measured by the difference between the creativity level of design outcomes and the mental effort invested to solve a design problem. The more creative the design solutions and the lower the mental effort, the greater the degree of cognitive efficiency attributed to a given designer during a conceptual design process.

In this chapter, the definition of cognitive efficiency will be stated (Section 4.2). Furthermore, the cognitive efficiency will be compared between experienced and inexperienced participants and between different design methods (Section4.3). Finally, the application of the cognitive efficiency metric will be discussed (Section 4.4).

4.2 Methods

The next three subsections will introduce the evaluation of mental effort and creativity as well as cognitive efficiency calculation.

4.2.1 Mental effort evaluation

Mental effort can be assessed by physiological methods, dual-task methods, and subjective methods (Cennamo, 1993). There are some limitations on applying the first two methods in a design process. Physiological methods will constrain designers' sketching activities and body movements. Dual-task methods require that a second task is implemented at the same break-point of a primary task (that is, a design task). A design process is a series of design activities including framing the design problem, specifying physical parameters, concept generation and evaluation, decision making, sketching, etc. Participants usually perform the task at their own pace, and the order of the design activities is quite different from person to person. Therefore, it is difficult to have all the participants engage in two tasks simultaneously.

Subjective ratings of effort can be used as validation criteria to which the physiological measures are compared (Vicente, Thornton, & Moray, 1987). Johanssen et al. (1979) stated that "Rating scales must be regarded as central to any investigation. If the person feels loaded and effortful, he is loaded and effortful, whatever the behavioral and performance measures may show" (p. 105). Cognitive load may be building up but no observable changes in behavior and performance have appeared if physiological measures are not sensitive and robust enough; conversely, cognitive load may not vary but observable changes in behavior and performance are captured if physiological measures are affected by other factors such as environmental changes (De Waard, 1996; Zijlstra & van Doorn, 1985).

In the human factors literature, mental workload is defined in terms of the interaction between task requirements and human capabilities or resources (Hancock & Meshkati, 1988). Rating scales on mental workload have been widely used in operating tasks, such as aircraft handling and driving (Hancock & Caird, 1993, De Waard, 1996), but have not been examined in design-related tasks. Rating scales that are frequently used in the human factors literature include the National Aeronautics and Space Administration Task Load Index (NASA TLX; Hart & Staveland, 1988) and the Subjective Workload Assessment Technique (SWAT; Reid & Nygren, 1988). Galy et al. used these two multidimensional rating scales in memory tasks in order to study the relation between the subscales of mental workload and the types of cognitive load (Galy, Cariou, & Mélan, 2012). Since the present study focuses on designers' mental effort rather than such factors as physical demand and temporal demand, therefore, a one-dimensional scale of mental effort is appropriate for the design-related task.

4.2.2 Creativity evaluation

The criteria that mark highly creative products have been studied in the literature of creativity. Two important attributes of creative products are novelty and appropriateness (Sternberg, 1999). Novelty means eye-catching, unexpected, and impressive; appropriateness means useful, suitable, and satisfying (Zeng, 2010). Similarly, Goldschmidt et al. measured creativity as a product of practicality and originality and stated that only solutions that are highly rated on both practicality and originality are considered creative (Goldschmidt & Smolkov, 2006). The standard definition is bipartite: creativity requires both originality and effectiveness (Runco & Jaeger, 2012).

The evaluation of creativity usually strongly depends on subjective judgment for lack of objective methods. One reason of this lack is that formalizing an objective measurement leads to a reduction of the product features that are appraised; the other possible reason is that the essential aspects of creativity such as originality and unexpectedness cannot be formalized into an objective instrument (Christiaans, 2002). Therefore, it is necessary to reduce subjectivity within these assessments.

One way is to determine the inter-rater reliability between evaluators. The inter-rater reliability can be computed by inter-judge correlation coefficients (Kim et al., 2007), Kappa statistics (Mackinnon, 2000), and Cronbach's alpha and mean Pearson product-moment correlations (Dorst & Cross, 2001). Another way to improve consistency and reliability of evaluation is to compare the relative degree of difference and unusualness of a design idea in a group of design ideas. For example, originality is computed not only by the number of ideas generated by the participant but also by the number of similar ideas generated by other participants and the total number of ideas generated by all participants (Jansson & Smith, 1991).

In the present study, four measures proposed by Shah et al. (2003), that is, novelty, variety, quality, and quantity were used to evaluate the creativity level of design outcomes. Novelty, variety, and quantity were evaluated by an evaluator who had studied design theory and methodology and had design project experience. Quality was evaluated by the evaluator aforementioned and another evaluator who had equivalent design knowledge and experience. The evaluation process was inspected by a design expert who had years of design experience. One of the two evaluators transcribed the verbal reports generated by the participants before the evaluation process. Neither the evaluators nor the inspector knew the participants' backgrounds before the evaluation process. The evaluation of creativity was based on the design outcomes including sketches and the transcribed verbal protocols. The procedures for calculating the four measures, along with examples are introduced below.

4.2.2.1 Novelty

Novelty measures how unusual or unexpected an idea is compared to other ideas in the same group. To measure novelty, the design problem is first decomposed into its key functions. Every idea generated is analyzed by identifying which function it satisfies and describing how it satisfies the function. Each description is then graded for novelty according to the design outcomes generated by all 23 participants. The novelty score can be computed using the Equation (4.1).

$$O_n = \sum_{j=1}^{n}\left[f_j S_j\right] = \sum_{j=1}^{n}\left[f_j \cdot \left(T_j - m_j\right)/T_j \cdot 10\right] \text{ with } \sum_{j=1}^{n} f_j = 1 \tag{4.1}$$

O_n is the overall novelty score for the design outcomes with n functions. Weights f_j are assigned according to the importance of each function. S_j is the novelty sub score for the function f_j. T_j is the total number of concepts generated by all participants for the function f_j. m_j is the number of the current concept for the current function f_j. The lower the m_j (which means fewer other participants generated the same concept), the higher the novelty. Multiplying by 10 normalizes the expression.

In the original work of Shah et al., the overall novelty score was based on the final design solutions. In the present paper, the overall novelty score represented the novelty of all concepts generated during the design processes even though some of the novel concepts were later dismissed in the final design solutions by the participants. This measure represented the average novelty level of all the concepts generated by each participant.

An example shows the calculation of novelty score O_n. For the design problem, a teaching podium, three main functions ($n = 3$) were defined by an evaluator: accommodate teaching materials (f_1), be movable (f_2), and be adjustable (f_3). Since the space for locating a teaching podium was limited and the podium should not block the students' view, the third function was more important than the other two. The weights were assigned as follows: $f_1 = 0.3$, $f_2 = 0.3$, $f_3 = 0.4$. In our experiment, S_j depended on all concepts generated by all participants. The total number of concepts for each function was $T_1 = 116$, $T_2 = 41$, $T_3 = 23$. Participants could generate more than one concept for one function. To evaluate the variety of all the concepts generated by one participant, the average novelty score of each function was calculated for each participant. For example, one participant generated 5, 1, and 3 concepts for the three functions respectively. The novelty subscore for the concept "slope surface" was $(116 - 9) / 116 \times 10 = 9.22$ (9 out of 20 participants generated the same concepts) and the novelty subscore for the concept "power plug-in" was $(116 - 5) / 116 \times 10 = 9.57$ (5 out of 20 participants generated the same concepts). The novelty subscores for these three functions were $(9.22 + 9.57 + 8.97 + 9.91 + 9.83) /5 = 9.5$, $9.27/1=9.27$, and

(9.57 + 9.57 + 9.57) /3 = 9.57 respectively. The overall novelty score for the design solutions generated by the participant was the sum product of the weights f_j and the novelty subscores S_j, that is, $0.3 \times 9.5 + 0.3 \times 9.27 + 0.4 \times 9.57 = 9.46$.

4.2.2.2 Variety

Variety describes the degree of difference between generated ideas. The measurement is analyzed using a genealogical tree method. At the highest level, design concepts are differentiated by the different physical principles used by each to satisfy the same function. At the second level, concepts that share the same physical principle are differentiated based on different working principles. At the third levels, concepts are differentiated according to embodiments and details. This method of differentiation means that the use of a different physical principle to satisfy the same function makes two design concepts very different (Nelson, Yen, Wilson, & Rosen, 2009). The overall variety score can be computed from the Equation (4.2).

$$O_v = \sum_{j=1}^{n} \left[f_j \cdot \sum_{k=1}^{3} s_k (b_k - 1) \right] \text{ with } \sum_{j=1}^{n} f_j = 1 \qquad (4.2)$$

O_v is the overall variety score for the design outcomes with n functions. Weights f_j are assigned according to the importance of each function. s_k and b_k are sub variety scores and the number of branches respectively at level k (=3 in the present study). The suggested values s_k for the three levels are 10, 6, and 3, which ensure that differences at higher levels will always result in a greater score (Shah et al., 2003). The expression $(b_k - 1)$ represents the number of differentiations at level k. The nodes in the tree carry the count of ideas in each category at each level. Therefore, the number of differentiations in each level gives an indication of the variety of ideas. The higher is the value of b_k, the higher is the variety score. If there is only one branch at a given level, it shows a lack of variety and the score is zero.

An example shows the calculation of variety score for O_v. One participant generated three concepts in total for the function f_3: a hinge to adjust the angle of the top surface, a spring to adjust the interaction between the podium and the desk, and a hook to adjust the position of the podium on the desk. These three concepts belong to two different physical principles ($b_1 = 2$). The hinge and the spring adjust the position by changing the gravitational and elastic potential energy; and the hook works because of geometric matching. The three concepts also belong to three different working principles ($b_2 = 3$) and three different embodiments ($b_3 = 3$). So the variety score for f_3 was $10 \times (2-1) + 6 \times (3-1) + 3 \times (3-1) = 28$. If the variety scores for f_1 and f_2 were 28 and 0 respectively, the overall variety score for all concepts generated by the participant would be $0.3 \times 28 + 0.3 \times 0 + 0.4 \times 28 = 19.6$.

4.2.2.3 Quality

Quality measures how successfully an idea satisfies the product requirements. In the present paper, the quality of design solutions is the sum product of the score of each product requirement and the corresponding weighting factor, as shown in Equation (4.3).

$$O_q = \sum_{r=1}^{m} \left(f_r \cdot S_r \right) \text{ with } \sum_{r=1}^{m} f_r = 1 \tag{4.3}$$

O_q is the overall quality score for the design solutions, and m represents the number of product requirements. The weighting factors f_r are calculated by pairwise comparison of the product requirements, and the sum of the normalized weighting factors is equal to one. The score of each product requirement S_r is given according to the degree of satisfaction, that is, the highest score (10) is assigned if the product requirement is *well satisfied* and the lowest score (0) if it is *not satisfied at all*. The product requirements were obtained from all the potential users of this product such as instructors, students, plus the manufacturer, the seller, and the buyer. The nine requirements for a teaching podium are summarized in Table 4-1.

Table 4-1 Nine requirements for a teaching podium

Requirements	Descriptions
R1	The product should be convenient for instructors to use;
R2	The product should support multimedia teaching (It should be capable of being connected to a power supply and a projector.);
R3	The product should be portable;
R4	The product should fit the structure of classroom (It should fit in the limited space between the chalkboard and the student's desks);
R5	The product should be easily installed (after it is moved to a different classroom);
R6	The product should be conveniently adjusted (so it does not block the students' view);
R7	The product should meet the requirements of manufacturer (It should make use of standard parts as much as possible);
R8	The price of the product should be acceptable to the school (not too expensive);
R9	The product should be stable enough to hold heavy teaching materials such as laptop, textbooks, and lecture notes.

Since the assessments of the quality scores for each product requirement S_r rely on human judgment, it is necessary to limit subjectivity within these assessments (Christiaans, 2002). In order to identify the rationale behind the judged levels of quality and to test the evaluation consistency, two evaluators independently rated the quality against the product requirements twice within one month. One evaluator was among the authors, the other was external. Both evaluators had studied design theory and methodology and had design project experience. They did not know the designers' backgrounds before the evaluation process. The evaluators determined the weighting factors f_r in Equation (4.3), rated the score S_r for each requirement satisfaction, but did not calculate the quality scores O_q during the evaluation process. After the evaluation process, one of the two evaluators counted the quality scores for the four ratings and calculated the final quality scores by averaging the second ratings. For the first rating, the Pearson Product Moment Correlation (Cohen, Swerdlik, & Sturman, 2013) between the scores for quality from the two evaluators is 0.800 ($p < 0.01$); for the second rating, the Pearson Product Moment Correlation is 0.888 ($p < 0.01$). The Pearson Product Moment Correlation between the two ratings from one evaluator is 0.925 ($p < 0.01$) and from the other evaluator is 0.956 ($p < 0.01$).

4.2.2.4 Quantity

Quantity Q_u is represented by the total number of concepts generated during design processes even though some of the concepts are not integrated in the final solutions. Each design concept should meet at least one function. For example, the concept of wheels meets the function of portability. Concepts which were not represented in sketches, for example, concepts generated in the interview session, were not included in the measures of quantity.

4.2.3 Cognitive efficiency measurement

Cognitive efficiency was measured by the difference between the creativity of design outcomes (the benefit) and mental effort (the cost). Cognitive efficiency has four corresponding measures based on the four measures of creativity. To map the units of measurement of mental effort onto those of performance, scores of both mental effort and creativity are normalized by subtracting the grand mean from each score and dividing the result by the grand standard deviation: $P = (P_o - G_P)/\ \sigma_P$, where P is the normalized score for performance, P_o is the original score for performance, G_P is the grand mean of scores for performance, and σ_P is the grand standard deviation of scores for performance; similarly, $M = (M_o - G_M)/\ \sigma_M$, where M is the normalized score for mental effort, M_o is the original score for mental effort, G_M is the grand mean of scores for mental effort, and σ_M is the grand standard deviation of scores for mental effort. The grand mean and the grand standard deviation are based on the data from all the participants. The cognitive efficiency is denoted as $E_c = (P - M)/\sqrt{2}$. In a Cartesian coordinate system represented by P and M, the absolute value of E represents the perpendicular distance from a certain point to the line $P - M = 0$ (see Figure 4-1). This graph provides a visual display of the relationship between mental effort and performance. Data above the line $P - M = 0$ demonstrate higher cognitive efficiency than those below the line, for example, $E_1 > E_2$.

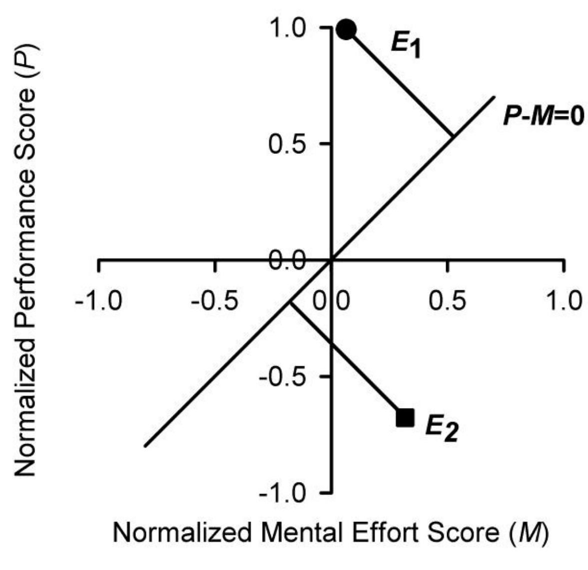

Figure 4-1 Evaluation of cognitive efficiency

4.3 Results and Discussion

The relation between different measures including creativity, mental effort, expertise levels, and cognitive efficiency were investigated. These measures were compared between the mechanical group and the non-mechanical group. Other self-reported measures were also compared between two groups, and factors that affect designers' mental effort were discussed. Furthermore, cognitive efficiency and mental effort were compared between different design methods.

4.3.1 Correlation between different measures

The Pearson Product Moment Correlation between the four measures of creativity, mental effort (RSME), and expertise levels is presented in Table 4-2. The four measures of creativity were related as follows: novelty was significantly related to variety, quality, and quantity ($p < 0.05$); variety was significantly related to quality and quantity ($p < 0.01$); and quality was significantly related to quantity ($p < 0.01$). The relation between quantity and quality supports that if the number of concepts is increased, the quality of the best concepts would also increase (Sweller, 2009). The results did not show that RSME was related to creativity measures and expertise levels. Expertise levels were significantly related to novelty and quality ($p < 0.05$).

Table 4-2 Correlation between creativity measures, RSME, and expertise

Measures	*Creativity*				*RSME*	*Expertise*
	Novelty	*Variety*	*Quality*	*Quantity*		
Novelty	–	0.481 * (0.020)	0.580 ** (0.004)	0.541 ** (0.008)	0.238 (0.275)	0.446 * (0.033)
Variety		–	0.730 ** (< 0.001)	0.966 ** (< 0.001)	0.349 (0.103)	0.298 (0.167)
Quality			–	0.703* (< 0.001)	0.288 (0.183)	0.481* (0.020)
Quantity				–	0.368 (0.084)	0.261 (0.230)
RSME					–	−.005 (0.835)

*: $p < 0.05$; **: $p < 0.01$

The Pearson Product Moment Correlation between the four measures of cognitive efficiency and expertise levels is presented in Table 4-3. Only cognitive efficiency scores of quality showed a significant relation with expertise levels. Since cognitive efficiency was measured based on RSME, the four measures of cognitive efficiency were definitely related to each other and RSME (all the p values < 0.01, data not shown in Table 4-3).

Table 4-3 Correlation between cognitive efficiency measures and expertise

Measures	*Cognitive Efficiency*			
	Novelty	*Variety*	*Quality*	*Quantity*
Expertise	0.399 (0.059)	0.301 (0.162)	0.442 * (0.035)	0.273 (0.208)

*: $p < 0.05$

4.3.2 Comparison between expertise levels

The 23 participants were divided into two groups: the mechanical group ($n = 9$) and the non-mechanical group ($n = 14$). The expertise levels of participants in the inexperienced group were less than one point (< 1), and the average score was about zero. The expertise levels of participants in the experienced group were more than one point (≥ 1), and the average score was about three.

The four measures of creativity and mental effort ratings for the two groups are presented in Figure 4-2. The mechanical group outperformed all the four creativity measures than the non-mechanical group. The novelty ($t(21) = 2.971$, $p = 0.007$, $d = 1.3$), variety ($t(21) = 3.315$, $p = 0.003$, $d = 1.3$), quality ($t(21) = 4.251$, $p < 0.001$, $d = 1.8$), and quantity ($t(21) = 2.838$, $p = 0.010$, $d = 1.1$) measures show significant differences between the two groups (*d* is Cohen's *d*; Cohen et al., 2013). The averaged RSME score for the non-mechanical group was marginally higher than that for the mechanical group, but the difference failed to reach statistical significance ($t(21) = -0.460$, $p = 0.325$). The result indicated that the design task did not seem easier for the mechanical group even though they had more experience in design than the non-mechanical group.

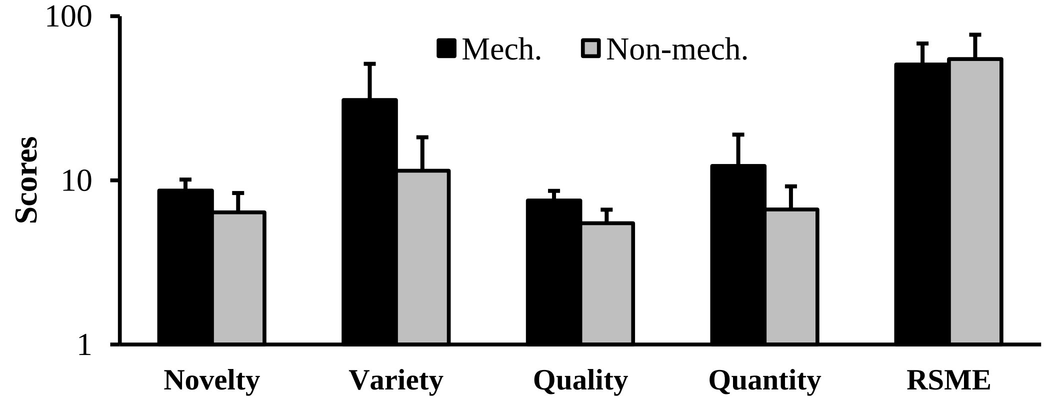

Figure 4-2 Comparison of creativity measures and mental effort between two groups

The cognitive efficiency scores of novelty, variety, quality, and quantity were calculated separately for the two groups. The averaged group scores of cognitive efficiency are compared in Figure 4-3. Since the cognitive efficiency measures reflected relative performance in a group, the scores for the mechanical group were positive while for the non-mechanical group were negative. There were significant differences in the four efficiency measures between the two groups (Novelty: $t(21) = 2.801$, $p = 0.011$, $d = 1.2$; Variety: $t(21) = 3.447$, $p = 0.002$, $d = 1.5$; Quality: $t(21) = 3.957$, $p < 0.001$, $d = 1.7$; Quantity: $t(21) = 3.075$, $p = 0.006$, $d = 1.3$;). The comparison indicated that the participants with higher expertise levels performed significantly higher cognitive efficiency than those with lower expertise levels.

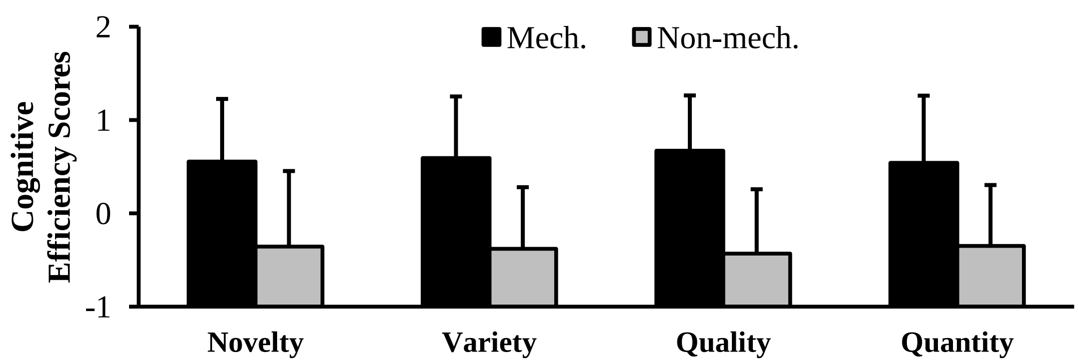

Figure 4-3 Comparison of cognitive efficiency measures between two groups

4.3.3 Comparison of other self-report measures and time

Participants' ratings for the difficulty level of the design task, interest level in the design problem, and the degree of satisfaction with their own design solutions were compared between the two groups. The data did not support a significant difference for difficulty levels of the design task ($t(21) = 1.027$, $p = 0.316$) between the two groups. The data also failed to support that there were significant differences for the degree of satisfaction ($t(21) = 0.734$, $p = 0.471$) and interest levels ($t(21) = -0.514$, $p = 0.613$) between the two groups.

In this study, each participant worked on the design task at his or her own pace. Time spent on completing the design task varied greatly from person to person (49 ± 39 min for the experienced group and 38 ± 21 min for the inexperienced group). The differences for time spent on the task between the two groups failed to reach statistical significance ($t(21) = 0.876$, $p = 0.391$). However, the time allocation was radically different between the two groups. The experienced group spent 25% of their total time either analyzing the product requirements prior to concept generation or defining the design problem; however, the inexperienced group only spent 7% of their time on these tasks. The results were consistent with that of a study which found that professional designers spent more time defining and structuring ill-defined design problems than engineering students (Björklund, 2013).

Table 4-4 lists the Pearson Product Moment Correlation between RSME, self-rated difficulty levels of the design task, self-rated interest levels in the design problem, self-rated degree of satisfaction with design solutions, and time spent on completing the task. The self-rated difficulty levels of the design task were highly related to the mental effort ratings (r = 0.685, p < 0.001). In addition, the frequency distributions of difficulty level scores showed that the most frequent scores were three and two respectively for the experienced and inexperienced designers. The results may indicate that design experience reported by the experienced designers did not relieve their mental effort because they perceived higher difficulty levels for the same design task than the inexperienced designers. The self-rated difficulty levels were also related to time spent on solving the design task (r = 0.441, p = 0.035). It was not surprising that the participants would spend more time on problem solving if they perceived the challenge of the design problem or they thought the problem was complex.

Table 4-4 Correlation between self-reported measures and time

	Difficulty	*Interest*	*Satisfaction*	*Time*
RSME	0.685* (< 0.001)	0.232 (0.288)	0.143 (0.516)	0.399 (0.060)
Difficulty		0.230 (0.292)	−0.084 (0.703)	0.441* (0.035)
Interest			−0.009 (0.968)	0.087 (0.695)
Satisfaction				−0.067 (0.761)

*: $p < 0.05$

Mental effort can be divided into two types: task-related effort and state-related effort (Mulder, 1986). Task-related effort is mainly determined by the intrinsic demands, that is, the difficulty of the task; while state-related effort is required to protect performance from the detrimental influence of the designers' physiological state, for example, interest in the design problem and the degree of satisfaction with design solutions (both of which are critical parts of motivation). In this study, the mental effort ratings were positively related to the self-rated difficulty levels of the design task rather than other factors including time, interest level, and degree of satisfaction (see Table 4-4). The data suggested that the mental effort that the participants reported was task-related rather than state-related. The mechanical group invested higher task-related mental effort than did the non-mechanical group presumably because the mechanical designers better understood the challenge of the design task. Previous studies have also found that experts dedicate a substantially greater effort than novices while elaborating on their understanding of a problem (Casakin, 2004). Other previous studies have found that invested mental effort, defined as the number of non-automatic mental elaborations necessary to solve a problem, was significantly influenced by the perceived complex/ambiguous features of material encountered (Salomon, 1983).

4.3.4 Comparison between design methods

In order to further analyze the contribution of different design methods to cognitive efficiency, the 23 participants were divided into three categories according to the design methods they applied. In the first category, 9 out of 23 participants (8 mechanical and one non-mechanical) applied the systematic design method: analyzing customers' requirements, specifying the requirements by function decomposition, generating alternative design concepts for each function, and evaluating those concepts to propose the final design solutions. In the second category, 7 out of 23 (one mechanical and 6 non-mechanical) participants analyzed customers' requirements and immediately focused on one design feature of the product. They thought about this feature and focused on the first design concept they generated without considering alternative design concepts. They then invested a great deal of effort in creating detailed drawings of their original concepts rather than improving them or generating alternatives. In the third category, 7 out of 23 participants (all belonged to the non-mechanical group) did not explicitly analyze customers' requirements in detail before generating their initial concepts. They first considered the general concept of a teaching podium according to their own experience, then referred to the description of the design task and modified the original design concepts iteratively until they were satisfied with their design.

The cognitive efficiency scores of quality for the three design methods are graphically compared in Figure 4-4. Method 1 obtained the highest quality score and efficiency score, while Method 3 got the highest mental effort score and the lowest quality and efficiency scores. Method 2 got the lowest mental effort score. Method 1 outperformed the other two methods.

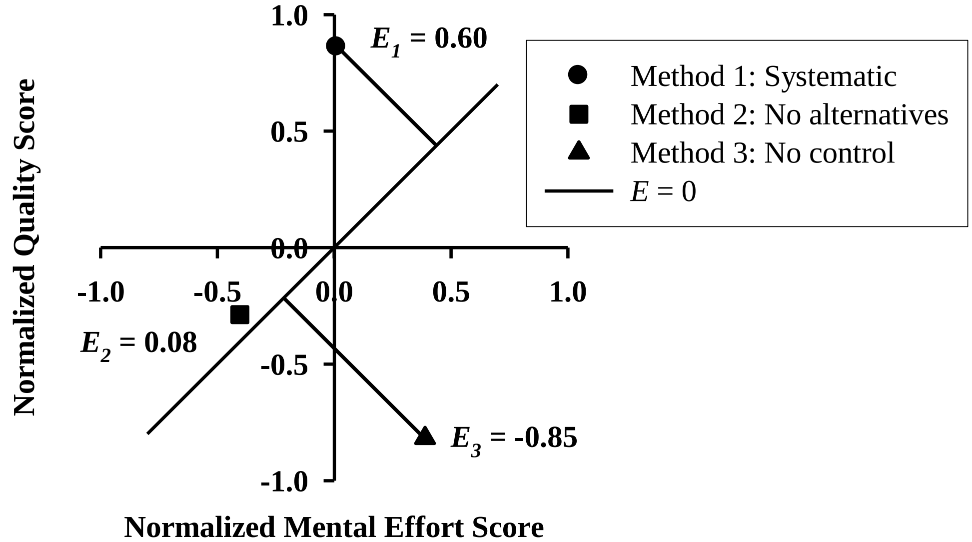

Figure 4-4 Cognitive efficiency measures for three design methods

The quality ratings of design outcomes and the corresponding cognitive efficiency scores for the three design methods are compared in Figure 4-5. For the measures of cognitive efficiency, significant differences existed between Method 1 and Method 3 ($p < 0.001$, $d = 2.3$), as well as between Method 2 and Method 3 ($p = 0.011$, $d = 2.5$). For the ratings of quality, significant differences existed between Method 1 and Method 2 ($p = 0.004$, $d = 1.8$), as well as between Method 1 and Method 3 ($p < 0.001$, $d = 2.2$). These results support that the systematic method outperformed Method 3. Method 2 did not improve design outcomes but did enhance cognitive efficiency compared with Method 3. For the scores of mental effort, no significant differences existed between the three methods ($p > 0.05$, $d < 0.2$).

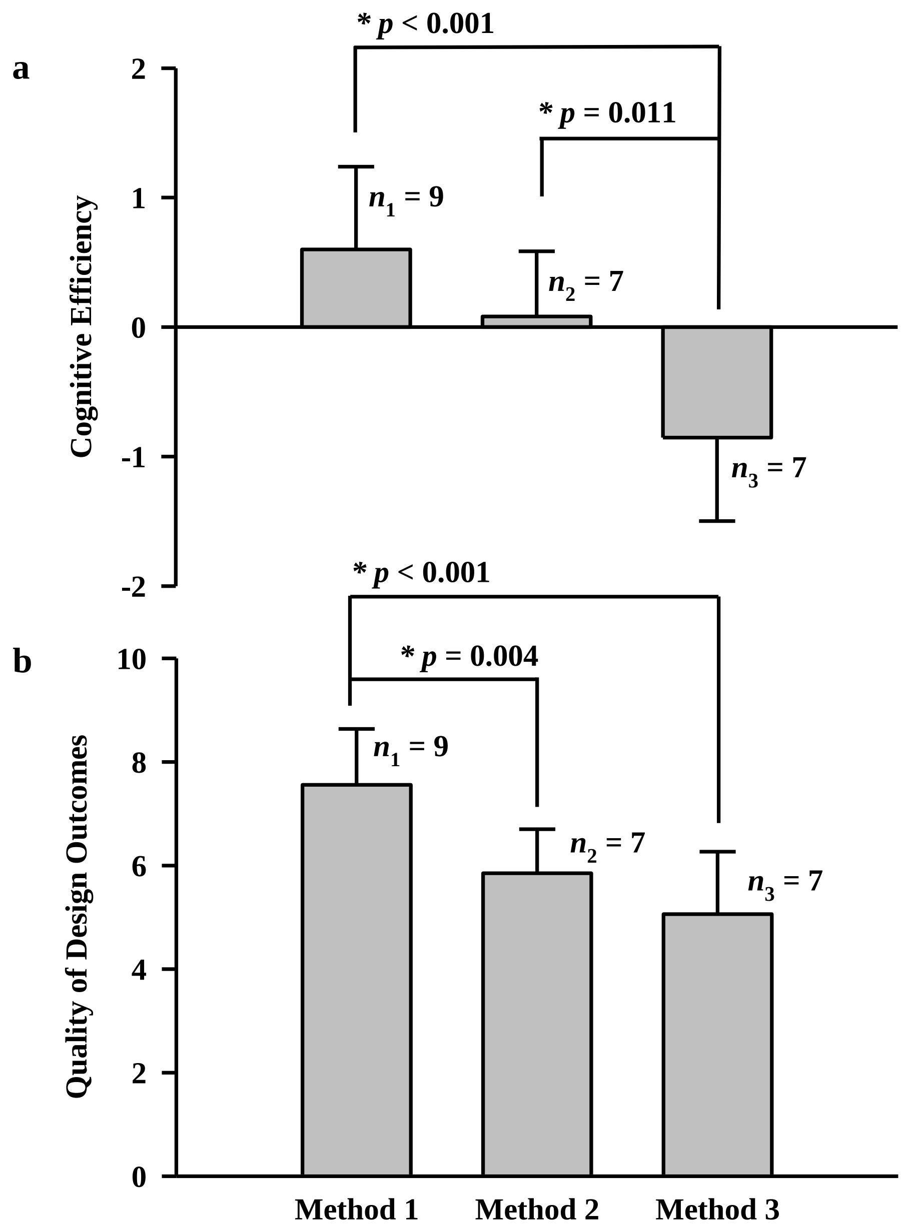

Figure 4-5 Comparison of cognitive efficiency and quality measures for three design methods

4.4 Application of Cognitive Efficiency

The present study developed a method to assess designers' performance in terms of cognitive efficiency. The cognitive efficiency measures can be applied to evaluating designers' performance because the measures were found to be related to designers' expertise levels (see Table 4-3). The four measures of cognitive efficiency can be used in different situations. For engineering professional certification, efficiency in quality may be the most important; for innovation competitions and artwork development, efficiency in novelty and variety may be more useful than in quality. The four measures should not be substituted for each other, and it is difficult to describe the significance of an overall measure consolidating all four measures.

Cognitive efficiency is a supplement to the evaluation methods such as outcomes-oriented measures (creativity level of design outcomes) and designer-oriented measures (designers' mental effort). Outcomes-oriented measures do not reflect designers' cognitive demands. The assessment of mental effort is a valuable addition to the available methods of performance measurement because particular training or task environments may sometimes have no significant impact on performance measures (Paas & van Merriënboer, 1993). Designer-oriented measures are also not sensitive enough because tasks that require very high and very low levels of mental effort both discourage human performance (Paas et al., 2004; Svensson et al., 1997), and it is very difficult to find an optimal level of mental effort for each individual. Cognitive efficiency considers both designers' demands and design outcomes. The three measures should not be substituted for each other because they focus on different aspects: the designer, the design outcomes, and the relationship between the designer and the design outcomes. In Figure 4-4, the three evaluations are demonstrated simultaneously by the x-coordinates, the y-coordinates, and the distances to the reference line $E = 0$. The measure proposed in the current study not only focuses on the relationship between the designer and the design outcomes, but also presents the other two evaluations.

The cognitive efficiency measures can also be applied to evaluating design methodologies and strategies (as shown in Figure 4-4). The systematic method was found to outperform the other two methods in the quality of design outcomes and in the corresponding cognitive efficiency. The design strategies identified in the present study can also be used for problem-solving in other fields. In engineering design, designers use three types of knowledge: knowledge to generate ideas, knowledge to evaluate ideas, and knowledge to structure the design process (Ullman, 2009). The first two types of knowledge are domain-specific. Idea generation comes from natural ability and experience; idea evaluation comes from experience and formal training. However, knowledge about the design process is largely independent of domain-specific knowledge (Ullman, 2009). In the present study, the three design methods (as shown in Figure 4-4) leading to different levels of cognitive efficiency belong to the third type of knowledge.

In addition, the practical applications of cognitive efficiency evaluation include designer training and design process improvement. Research on expert performance and expertise has shown that important characteristics of experts' superior performance are acquired through experience and that the effect of practice on performance is larger than that of talent (Ericsson, Krampe et al., 1993). Learners and operators are encouraged to practice. It has been well accepted that practice improves performance while reducing the effort necessary to complete the task; therefore, the problem-solving skill is usually assessed by outcome performance or mental effort. However, the present study suggests that, in an open-ended design task, expertise in design may not necessarily reduce mental effort but does improve design outcomes and cognitive efficiency (see Figure 4-2 and Figure 4-3). In summary, in the conceptual design stage, the evaluation of design outcomes alone or designers' mental effort alone may not be sufficient to have an accurate assessment of design training.

4.5 Summary

This chapter proposed a method that can quantitatively describe cognitive efficiency. Cognitive efficiency was measured by the difference between the creativity of design outcomes (the benefit) and mental effort (the cost). Cognitive efficiency has four corresponding measures based on the four measures of creativity. The four measures of cognitive efficiency can be used in different situations. The 23 participants were divided into a mechanical group and a non-mechanical group according to their educational background and work experience in the field of mechanical engineering. The mechanical group demonstrated significantly higher cognitive efficiency scores than the non-mechanical group. The creativity measure of quality and corresponding cognitive efficiency scores of quality were related to the participants' expertise levels.

Cognitive efficiency evaluation considers both designers' cognitive demands and design outcomes. The three measures should not be substituted for each other because they focus on different aspects: the designer, the design outcomes, and the relationship between the designer and the design outcomes. The method proposed in this study can simultaneously demonstrate the three measures graphically: how creative the design outcomes are, how much effort designers have experienced to generate the outcomes, and how efficiently the design outcomes are generated given different expertise levels and strategies.

Studies outside the field of engineering design have found that cognitive efficiency can be influenced by factors such as prior knowledge, working memory capacity, motivation, and use of strategy (Hoffman, 2012). Experienced designers have more domain-specific and non-specific prior knowledge than inexperienced designers. Furthermore, it has been proposed elsewhere that a designer's cognitive capacity can be extended by prior knowledge and experience in solving design problems according to the theory of chunks of information (Ullman, 2009). Studies have shown that experts' cognitive processing is structured such that it stays within the limits of human short-term memory (Kavakli & Gero, 2003). Another study found that experts' cognitive activity and productivity in design processes can be almost three times higher than novices' (Kavakli, Suwa, Gero, & Purcell, 1999). Therefore, designers' cognitive capacity and their organization of cognitive activity can affect cognitive efficiency.

High motivation is found to be related to having high interest in a problem and having confidence to successfully solve the problem (Glynn, Brickman, Armstrong, & Taasoobshirazi, 2011). However, in the present study, motivation may not be a critical factor affecting cognitive efficiency because the differences for self-reported interest in the design task and the degree of satisfaction between the two groups failed to reach statistical significance.

In the present study, cognitive efficiency was affected not only by design experience but also by design methods applied by the participants. The participants who applied the systematic design method received the highest cognitive efficiency scores compared with those who applied the other two design methods. The use of effective design methods could help designers improve cognitive efficiency even if they lack experience and domain-specific knowledge. Cognitive efficiency evaluation is anticipated to identify design strategies and compare the effectiveness of design methods applied in design processes. In the next three chapters (Chapter 5, Chapter 6, and

Chapter 7), the relations between cognitive efficiency and complexity measures will be investigated to identify design strategies that relate to high cognitive efficiency. Chapter 5 will focus on strategies of problem structuring, Chapter 6 will focus on strategies of organizing cognitive actions, and Chapter 7 will focus on strategies of linking design ideas.

Chapter 5 Complexity of Problem Structuring [2]

5.1 Introduction

Problem structuring is a process of using knowledge and external information to construct the problem space (Restrepo & Christiaans, 2004; Simon, 1973). Problem space, the particular representation of the task environment in the memory of problem solvers, determines the possible strategies that can be used for problem solving (Newell & Simon, 1972; Simon, 1978). The application of design strategies can cause the differences between design processes and outcomes (Kruger & Cross, 2006). Designers approach design problems in different ways, and the selection of either problem- or solution-oriented approach has an effect on the way designers structure the problem; problem-oriented designers did a better job of structuring the problem and produced outcomes with higher creativity than solution-oriented designers (Restrepo & Christiaans, 2004).

Problem structuring activities not only dominate at the beginning of the design task, but also re-occur periodically throughout the task (Goel & Pirolli, 1992). The processes of structuring and formulating the problem are frequently identified as key features of design expertise (Cross, 2004). Previous studies have shown that expert designers and novices employed different problem structuring strategies (summarized in Table 5-1). The differences in applying strategies in problem structuring between experts and novices are in decomposition modes and control strategies.

[2] Part of this chapter has been accepted by the Journal of Design Research (Sun, Yao, & Carretero, 2015b).

Table 5-1 Comparison of problem-structuring strategies between expert and novice designers

No.	Expert (or experienced)	Novice (or non-experienced)	Reference
1	Explicit problem-decomposing strategies	Implicit problem-decomposing strategies	(Ho, 2001; Liikkanen & Perttula, 2009)
2	Breadth-first	Depth-first	(Ho, 2001)
3	Working forward (top-down)	Working backward (bottom-up)	(Ho, 2001)
4	Use Limited Commitment Mode control strategy (an extension of the breadth-first control strategy) more actively	Decide design concepts earlier	(Kim et al., 2007)
5	Adopt a conjectural approach to framing or perceiving design problems in terms of relevant solutions (generative reasoning)	Tend to use more problem analysis (deductive reasoning)	(Lloyd & Scott, 1994)
6	Demonstrate superior extent, depth, and level of detail in the initial mental representations	Less verbal segments on problem structuring	(Björklund, 2013)

Problem decomposition is one of the most essential problem-solving techniques (Newell & Simon, 1972). Two modes of decomposition in design have been identified: explicit and implicit (Ho, 2001). Explicit decomposition refers to the deliberate analysis of a function structure at the beginning of the design process; while in implicit decomposition, the function structure is not openly sought or revealed. This proposition is called the dual-mode view of decomposition (Liikkanen & Perttula, 2009). Studies have found that novice designers do not use explicit decomposition in conceptual product design (Ho, 2001; Liikkanen & Perttula, 2009; Ullman, Stauffer, & Dietterich, 1986; also see Table 5-1). Some studies implied that decomposition might support idea generation in non-design contexts (Dennis, Valacich, Connolly, & Wynne, 1996) and might facilitate productivity (Kruger & Cross, 2006). However, there is not enough evidence to show that the application of explicit decomposition is necessary and beneficial for idea generation (Liikkanen & Perttula, 2009). It is not clear whether the application of explicit decomposition should be encouraged in design education.

Control strategies are the cognitive strategies that designers use to control the design process. Two categories of control strategies have been identified: breadth-first and depth-first. Breadth-first approaches maintain a top-down and hierarchical structure to the process of solution development. Experts tend to apply top-down (or working forward) and breadth-first approaches (see Table 5-1). However, studies increasingly show that experts also use variants of standard breadth-first approaches such as incomplete breadth-first and opportunistic depth-first strategies (Ball & Ormerod, 1995). Sometimes, the experts neglected one of the essential sub-goals and developed only one or two principles in a concept. The phenomena could be explained in the following way: searching memory for a solution to fulfil a sub-goal can produce several solutions in a short time; in this situation, the naturally easy thing is to select one of the solutions as a starting point for the next idea (Liikkanen & Perttula, 2009). Therefore, it is likely cost-effective for experts to temporarily exclude themselves from the breadth-first category and to pursue a depth-first category. However, there seems to be no direct evidence to show which kind of control strategy is beneficial for cognitive cost, that is, the expenditure of mental resources which include characteristics such as working memory capacity and existing knowledge stored in long-term memory.

In summary, very little formal experimental evidence exists currently to indicate which problem structuring strategies applied by experts could actually be beneficial for engineering design. Previous studies have identified different design strategies for different design problems among designers with different fields and levels of expertise. It is difficult to compare the results from different cases. It is also difficult to identify which strategies are unique for expert designers or which are just personal differences, especially when data are collected from a small sample of experts and novices. Therefore, this study aims at exploring a metric which can be used for evaluating the effectiveness of these strategies for different kinds of design problems and for comparing the performance among designers with different expertise levels. The results are expected to provide evidence for design strategy usage that could be taught in engineering education.

The effectiveness of problem structuring strategies is often evaluated based on design concepts generated by designers. Characteristics such as quantity, quality, novelty, and variety of ideas have been used to prove the effectiveness of idea generation (Liikkanen & Perttula, 2009; Shah, Kulkarni, & Vargas-Hernandez, 2000; Shah et al., 2003). Self-evaluation instruments and social communication between group members were also used for the effectiveness metrics (Liikkanen, Hämäläinen, Häggman, Björklund, & Koskinen, 2011). Designers' cognitive demands may influence idea development. Studies have found that efficient human performance depends on satisfying demands (Hancock & Caird, 1993). Bilda and Gero (2007) have observed that the performance of cognitive activity and perception activity dropped due to high cognitive demands when the designers were blindfolded and could not sketch. Therefore, it would be valuable to consider designers' cognitive demands (that is, their desired level of mental effort as they work on a design problem) as a part of the evaluation of effectiveness in the conceptual design process.

This chapter proposes an effectiveness metric of problem structuring in order to evaluate which strategies are better or more effective for structuring a problem or how effectively a design problem is structured. The effectiveness metric of problem structuring is based on a model shown in Figure 5-1. The framework for problem-solving behavior comprises three components: task environment, problem space, and human information-processing system (Newell & Simon, 1972). The human information processing system is related to the task environment by the problem space, which is personally perceived and constructed in the working memory of a designer. The input of the processing system is the mental effort invested by designers (that is, cognitive cost), and the output is the design concepts which can be measured by the quality of design outcomes (that is, cognitive benefit). The effectiveness of problem structuring can be represented as the ratio of output to input (that is, benefit to cost). Previous studies have shown that designers perceived an open-ended design problem differently and solved the problem accordingly; the mental effort that designers experienced is positively related to the difficulty levels perceived by them (Sun, Yao, & Carretero, 2015a). Thus, the input mental effort is determined not only by the design task itself but also by how difficult/complex the task is perceived/structured in the problem space. Therefore, in order to compare the effectiveness of problem structuring among individuals, the input is the mental effort invested in each unit of complexity of problem structuring. This model is in accord with literature on problem structuring methods stating that in order to evaluate whether one method is more successful than another, process gain or loss and the measures of the participant's perception of the process are considered; in addition, it is meaningful to investigate whether the outcomes are sufficiently appropriate to warrant the effort expended in problem structuring (White, 2006).

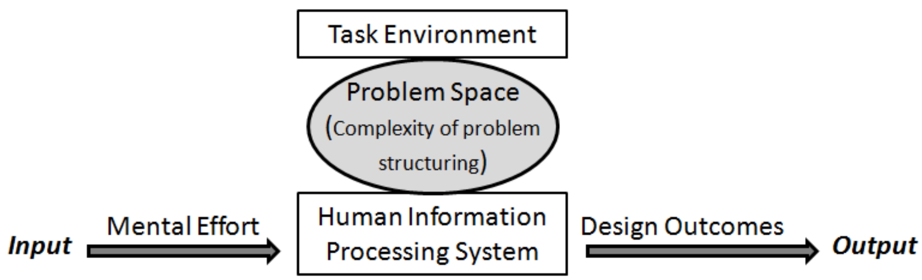

Figure 5-1 Schematic diagram of the effectiveness model

Representing problem structuring is challenging because the design problem space evolves in a design process and exchanges information with the solution space (Maher, 2000; Maher & Tang, 2003). Since an engineering design process is a process of satisfying functional requirements, the problem space is updated with the functions (Maher & Tang, 2003). After designers identify the main goal of the task, they apply control strategies to control the processing of different sub-goals and attempt to achieve each sub-goal by searching for the solution models existing in their minds. In engineering design, each sub-goal can be related to a subfunction, which should be satisfied by a particular physical structure. By the breadth-first control strategy, the main function is divided into several subfunctions (by analogy with tree branches growing from a trunk), and later on the subfunctions are achieved one by one. By the depth-first control strategy, the first subfunction is proposed and matched with an existing structure before the second subfunction emerges. If one subfunction cannot be matched with an existing solution, the subfunction may be divided into several subfunctions at a lower level until all the subfunctions are satisfied by solutions. The process of function decomposition provides information about the co-evolutionary process of the problem space and solution space. Therefore, function decomposition can be used for representing problem structuring as personally perceived and constructed in a designer's mind.

In this chapter, a numerical method is proposed to evaluate the effectiveness of problem structuring strategies. Problem structuring is represented by a tree structure of function decomposition, which will reveal how designers perceived and constructed an open-ended design problem (Section 5.2.1). The complexity of the tree structure is then defined (Section 5.2.2). The effectiveness metric is calculated as the ratio of output to input of the information processing system (Section 5.2.3), where the output is the quality of design outcomes and the input is the mental effort invested by designers. Finally, the effectiveness metric is applied to identify the benefits of such problem structuring strategies as decomposition modes and control strategies (Section 5.2.4). The results present the relation between the complexity measures, effectiveness scores, expertise levels, and the creativity of design outcomes (Section 5.3). The factors that affect the effectiveness metric and the strategic orientation are also discussed (Section 5.4).

5.2 Methods

5.2.1 Problem structuring representation

Each participant's problem structuring process was graphically represented by a particular tree structure. The tree structures were built based on the sketches and transcriptions of verbal protocols. In order to reduce inconsistency and subjective bias, the decomposition was completed according to a rubric procedure (see Figure 5-2). The first step was to identify the basic functions based on the requirement list written down by the participants at the beginning of their design processes (Step 1 in Figure 5-2). Figure 5-3 shows an example of the requirement list. The participant wrote down four basic requirements: accommodate laptop and other materials, fit in limited space, be movable and adjustable, and be stable. Later he divided the requirements into six subfunctions (that is, accommodate laptop, accommodate other materials, fit in limited space, be movable, be adjustable, and be stable). He generated design concepts accordingly to satisfy those requirements (that is, flat table with Velcro pads to hold laptop, wells to put small stuff in, base and top that can slide under a table, clamp on cylinder to raise height, wheels that move up and down to allow movement and stability, and heavy base; see Figure 5-4). Each subfunction was related to a specific design solution. These six subfunctions were at the second level of the tree structure. The main function at the first level for a teaching podium was to support teaching.

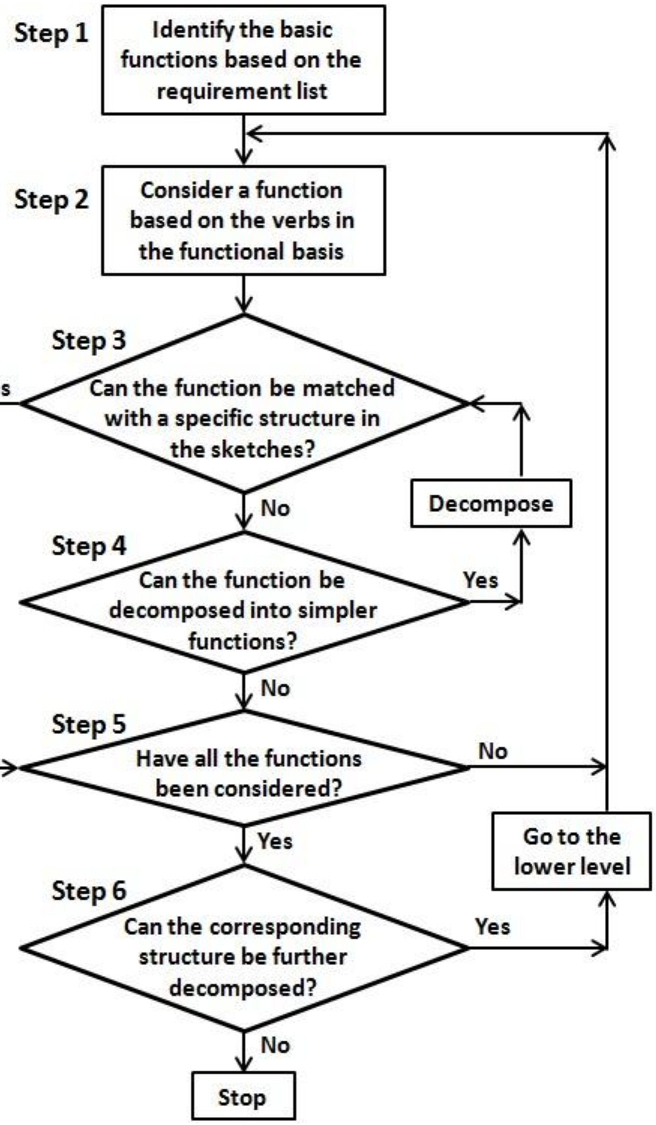

Figure 5-2 Function decomposition steps

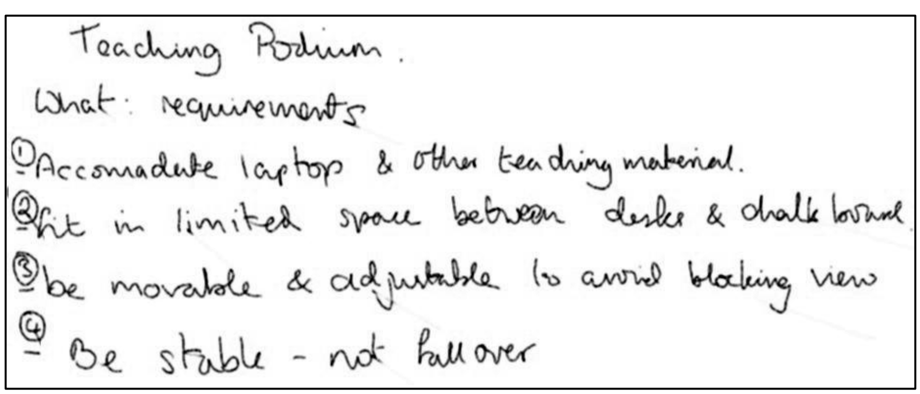

Figure 5-3 Requirement list by a participant

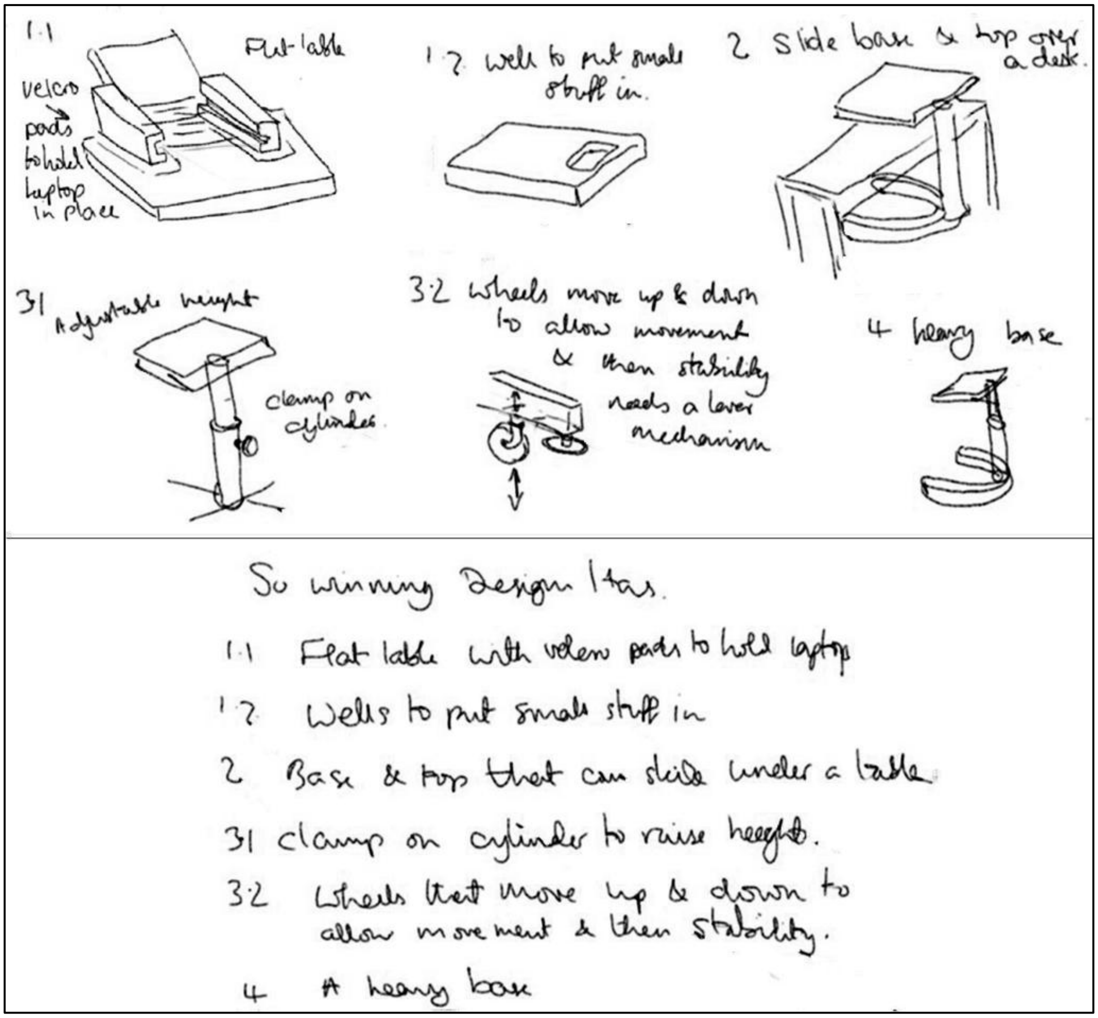

Figure 5-4 Design concepts satisfying requirements

If the participants did not explicitly write down any requirements, the subfunctions were extracted from sketches and verbal protocols. When a verb in the verbal protocol can be related to a subfunction of the podium and at the same time linked to a particular structure in the sketch, this verb was extracted to represent a subfunction. An example is shown in Figure 5-5 and Figure 5-6. According to the participant's verbal protocol, the first idea that occurred to him was to position a laptop for instructors. In the sketch, he drew a box-shaped podium with a flat top surface; the second level of the podium was to position other teaching materials. Later he realized that the flat top may not be comfortable for reading and changed the surface to a gentle slope. In this situation, the laptop may slide down, so a holder was added at the bottom edge of the slope to secure the laptop. The solution “flat surface” changed the participant’s view of the problem, so he modified the problem by adding a subfunction “secure laptop.” He also added two doors to secure the materials. Subfunctions “secure laptop” and “secure materials” were the supplements to subfunctions “position laptop” and “position materials” respectively and thus were put at a lower level in the tree. Afterwards, the participant thought about other subfunctions and generated some concepts to satisfy the subfunctions. The five subfunctions at the second level of the tree structure, according to the representation of the design task in the memory of the participant, included “position laptop,” “position other materials,” “stabilize the flat top,” “regulate the height,” and “change the position.” The five subfunctions were not all generated at the beginning of the design process. The tree structure in Figure 5-6 represents the participant’s way of viewing the design task. The information about the functional requirements and the design solutions is contained in the tree structure. Sometimes a subfunction or a design concept was not included in the final design solutions, but the tree branch still existed in the tree structure (for example, the concept of “four legs” in Figure 5-6). If more than one concept was generated to meet a requirement, those concepts were parallel to each other in the tree structure (for example, “four legs” and “single stand” in Figure 5-6), and each parallel branch was further analyzed until it could not be decomposed. The experimenter constructed the tree structures twice to ensure the procedure was reliable.

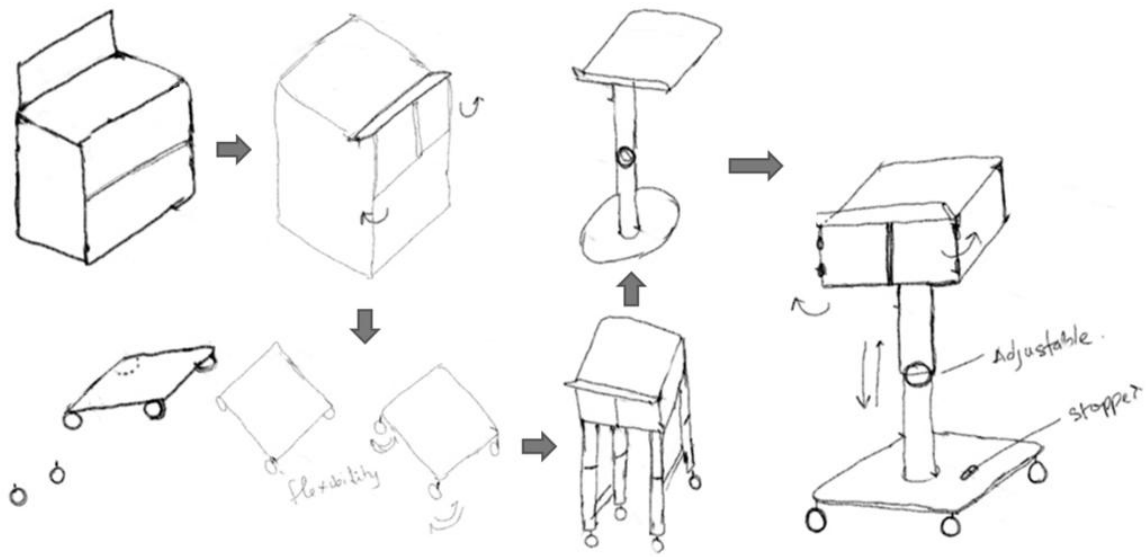

Figure 5-5 Sketches showing a design process

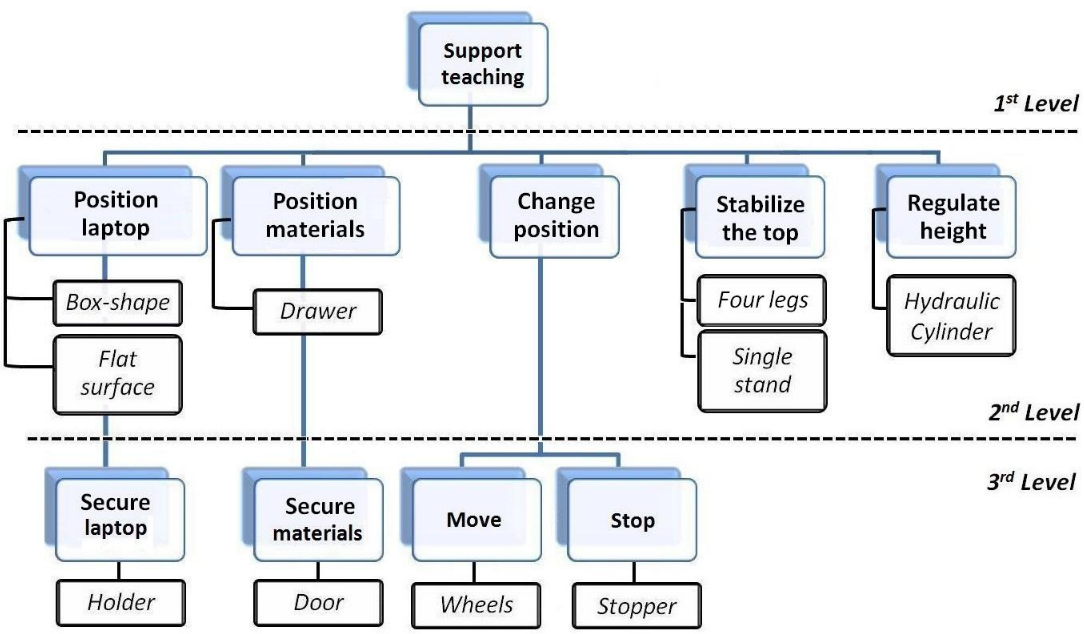

Figure 5-6 Example of function decomposition applied to a design problem

In this study, all the functions and subfunctions are represented based on a standard functional basis (Step 2 in Figure 5-2). The basis is created with the intent to ensure consistency of function models by using controlled vocabularies and rules

(Stone & Wood, 2000). The basis contains 53 verbs and 45 nouns and is organized in a three-level hierarchy. Previous studies have shown that the secondary level of the functional verbs is used most often by different functional models (Caldwell, Sen, Mocko, Summers, & Fadel, 2008). The vocabulary at the secondary level is also the most beneficial one for constructing function models because it provides a good balance between information content and information density (Sen, Caldwell, Summers, & Mocko, 2010). Therefore, this study applies 21 verbs at the secondary level in order to ensure consistency and generalization of function models (see Table 5-2). The definitions of these 21 function verbs can be accessed in a web-based design repository (Caldwell et al., 2008; http://function2.mime.oregonstate.edu:8080/view/index.jsp).

Table 5-2 Functional basis verb hierarchy

(Hirtz, Stone, McAdams, Szykman, & Wood, 2002)

Primary level	Secondary level
Branch	Separate
	Distribute
Channel	Import
	Export
	Transfer
	Guide
Connect	Couple
	Mix
Control Magnitude	Accurate
	Regulate
	Change
	Stop
Convert	Convert
Provide	Store
	Supply
Signal	Sense
	Indicate
	Process
Support	Stabilize
	Secure
	Position

Each function or subfunction in the tree structure must be related to a specific structure, which is a design concept (Step 3 in Figure 5-2; see the example in Figure 5-4). In addition, the function decomposition should be conducted until the specific structure cannot be further decomposed (Step 4 in Figure 5-2). A function or a subfunction is a description of an operation to be performed by a device or artifact (Stone & Wood, 2000). In Figure 5-7, the Velcro holder (the sign ellipsis in the figure represents subfunctions except for "position laptop") satisfied the subfunction of "position laptop." The participant did not provide the details of the Velcro along with the connection between the flat surface and the Velcro. Therefore, the Velcro holder is the "final" specific structure that could not be further decomposed (Step 6 in Figure 5-2). Figure 5-8 shows another example that satisfies the same subfunction shown in Figure 5-7. In Figure 5-8, the adjustable device consists of five components: a pair of clamps positioning the laptop, a pair of rods changing the position of the clamps, a pole stabilizing the structure, a sleeve pipe coupling the pole and the clamp, and a knob securing the rods. The five components satisfy five subfunctions at the third level of the tree-structure and cannot be further decomposed (Figure 5-8b). The design concept in Figure 5-8 contains more components than the one in Figure 5-7. Thus the tree-structure in Figure 5-8 is more complex than that in Figure 5-7.

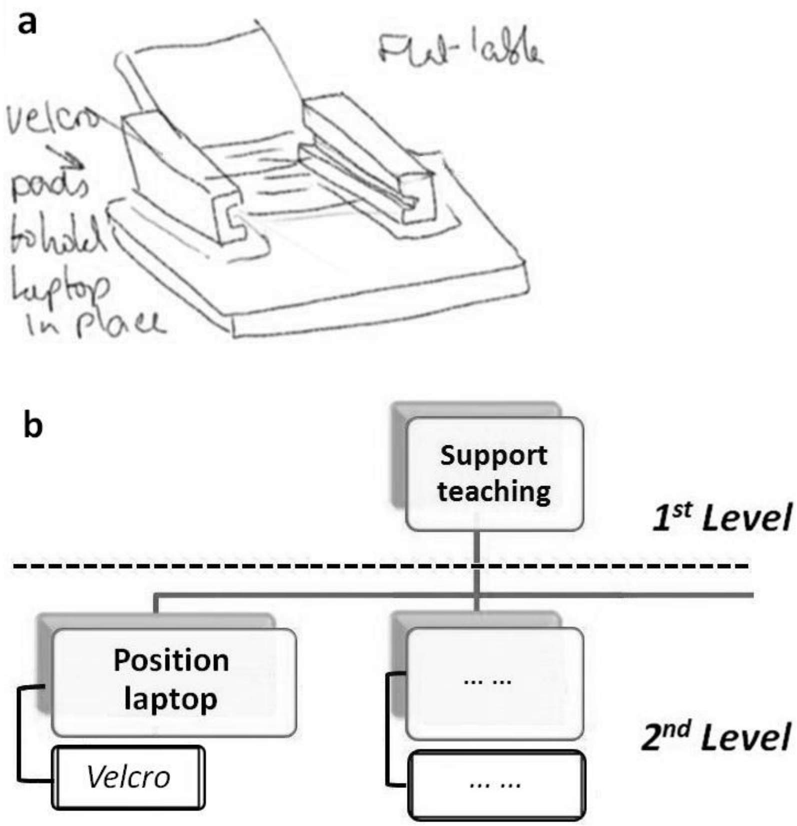

Figure 5-7 A design concept of positioning a laptop

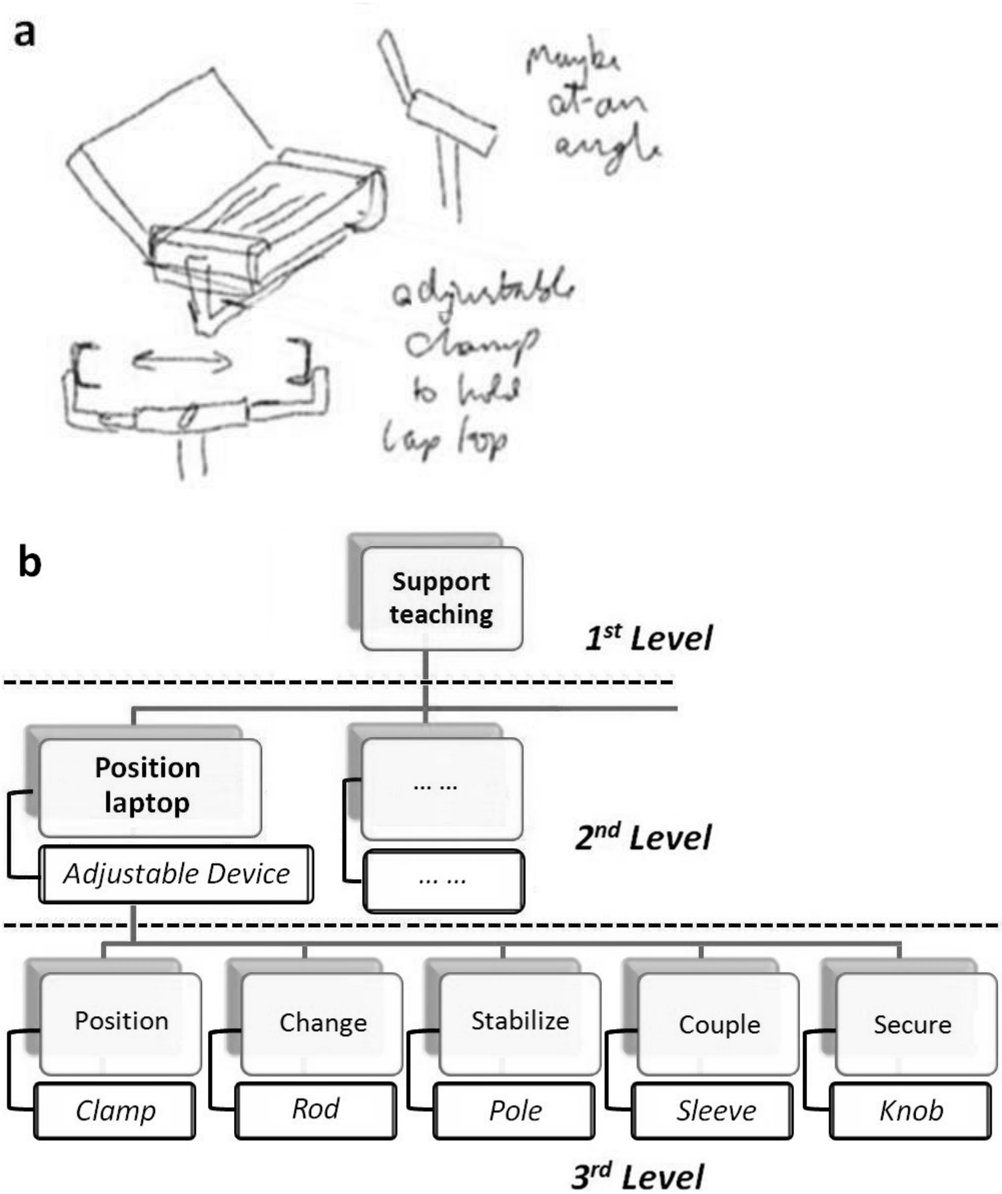

Figure 5-8 Another design concept of positioning a laptop

Figure 5-9 compares different design solutions with different complexities. Figure 5-9a shows a simple flat top supported by a tripod; the two specific structures perform two subfunctions. The connection between the flat top and the tripod is unknown. In Figure 5-9b, a device named "turning table," which can rotate the slope top in different directions, connects the slope top and the pillar support. However, the details of the device mechanism are unknown. In Figure 5-9c, a chute and a screw thread realize the sliding and rotating mechanism, respectively. Therefore, function decomposition can represent not only the complexity but also the solvability of design solutions (the degree that the problem is solved).

Figure 5-9 Design solutions from low to high complexity

5.2.2 Complexity of the tree structure

The number of levels in the decomposition is indicative of the complexity of the tree structure. If it is assumed that the complexity depends on the number of functions and the depth of their functional trees (hierarchies), then a metric, C_T, for the complexity of the tree structure, can be defined by the following formula.

$$C_T = \sum_{j=1}^{m} j \cdot F_j \tag{5.1}$$

where m is the number of tree levels, and F_j is the number of functions at level j. In Figure 5-6, $m = 3$, $F_1 = 1$, $F_2 = 5$, $F_3 = 4$, and $C_T = 1\times1 + 2\times5 + 3\times4 = 23$.

5.2.3 Effectiveness metric of problem structuring

The effectiveness of problem structuring, E_p, can be represented as the ratio of output to input of the human information processing system (that is, benefit to cost), as shown in Equation (5.2). The input mental effort M_O was normalized by the complexity of problem structuring C_T because the designers perceived different difficulty levels of an open-ended design problem and solved the problem accordingly. O_q represents quality scores. Since the dimensions of quality, mental effort, and complexity were different, before applying Equation (5.2), each measure was divided by the maximum value of this measure in the group. Therefore, the normalized measures of quality, mental effort, and complexity were in the range of 0 to 1, and the values represented the relative performance of participants in the group. As an example, a participant reported 68 scores on the rating scale of mental effort; the complexity of problem structuring calculated by Equation (5.1) was 23; design outcomes generated by the participant were rated as 5.7; the maximum values of the corresponding measures for all the whole group (including 23 participants) were 96, 137, and 8.8, respectively; the effectiveness E_p calculated by Equation (5.2) was (5.7/8.8) / {(68/96) / (23/137)} = 0.15.

$$E_p = \frac{Output}{Input} = \frac{Benefit}{Cost} = \frac{O_q}{M_O / C_T} \tag{5.2}$$

5.2.4 Identification of strategies for problem structuring

The effectiveness metric of problem structuring proposed in the present study was applied to investigate the benefits of different decomposition modes and control strategies. The two decomposition modes, explicit and implicit decomposition, were distinguished according to the function structure. In explicit decomposition, the function structure was deliberately analyzed at the beginning of the design process (see the example shown in Figure 5-3); however, in implicit decomposition, the function structure was not explicitly revealed (see the example shown in Figure 5-5). Different categories of control strategies were identified according to the order of constructing function structures. In the breadth-first category, all the requirements and basic functions were listed first, then each basic function was decomposed, and finally each subfunction was satisfied by different solutions. In the depth-first category, the solution was found to satisfy one basic function before another function was proposed. Mixed control strategy may also exist when both breadth-first and depth-first strategies were used. For example, in the tree structure shown in Figure 5-6, if all the five subfunctions at the second tree level were listed one by one before any solutions were generated, the control strategy belonged to the category of breadth-first; otherwise, if each of the five subfunctions was followed immediately by corresponding solutions, the depth-first strategy was used. Any other situations belonged to the category of mixed strategy.

5.3 Results and Discussion

5.3.1 Correlation between the complexity and other measures

The relations between the complexity C_T and other measures including creativity, mental effort, time effort, expertise level, difficulty level, and cognitive efficiency are shown in Table 5-3. Complexity C_T was significantly related to the four measures of creativity and the cognitive efficiency of variety and quantity. The complexity measure was determined by the depth and width of the tree-structure, as shown in Equation (5.1). The depth of the tree was determined by the complexity of design concepts as well as the solvability of those concepts (see an example in Figure 5-9). The width of the tree was determined by the number of functions/subfunctions as well as the number of design concepts satisfying those functions/subfunctions. Thus the complexity values of tree structures were significantly related to the quality and quantity of design concepts. Meanwhile, since novelty and variety were highly related to quantity (see Table 4-2), the complexity C_T were also significantly related to novelty and variety (see Table 5-3). The complexity measure indicated, to a certain extent, how successfully the design problem was solved.

Table 5-3 Correlation between tree-structure complexity values and other measures

Measures	*Creativity*				*RSME*	*Time*
	Novelty	*Variety*	*Quality*	*Quantity*		
Complexity C_T	0.552 ** (0.006)	0.938 ** (< 0.001)	0.609 ** (0.002)	0.956 ** (< 0.001)	0.377 (0.076)	0.786 * (< 0.001)
Measures	*Cognitive Efficiency*				*Expertise*	*Difficulty*
	Novelty	*Variety*	*Quality*	*Quantity*		
Complexity C_T	0.142 (0.518)	0.488 * (0.018)	0.194 (0.375)	0.512 * (0.013)	0.305 (0.157)	0.472 * (0.023)

$n = 23$, **: $p < 0.01$; *: $p < 0.05$

Complexity C_T was also significantly related to time spent on completing the design task and difficulty levels reported by the participants (see Table 5-3). It was not surprising that the more time spent on generating design concepts, the more concepts were generated, and so the higher the complexity of problem structuring. The difficulty level of the design task was determined by not only the task itself but also by how designers perceived the problem in their minds. The higher the difficulty level was rated, the more complex the design problem was structured and constructed. Data did not support significant relations between complexity C_T and RSME and between C_T and expertise levels. Complexity C_T appeared not to relate to the cognitive efficiency of novelty and quality.

5.3.2 Comparison between two groups

The effectiveness measure describes the relationships between the quality of design outcomes, mental effort experienced during problem solving, and the complexity of problem structuring. The measures of quality, RSME, complexity C_T, and effectiveness were compared between the mechanical and non-mechanical groups (see Table 5-4). Significant differences occurred in quality, complexity C_T, and effectiveness, which indicated that the mechanical group generated higher quality design outcomes, constructed more complex problem spaces, and performed higher effectiveness of problem structuring than the non-mechanical group. The reason may come from the prior domain-specific knowledge, experience in design, strategy use, and design methods that the mechanical group members have experienced in the mechanical engineering program.

Table 5-4 Comparison of different measures between two groups

Measures	*Quality*	*RSME*	*Complexity C_T*	*Effectiveness*
Mech. Group	7.5 ± 1.1	50.8 ± 17.2	46.3 ± 37.0	0.54 ± 0.32
Non-mech. Group	5.5 ± 1.1	54.8 ± 22.1	17.6 ± 8.9	0.15 ± 0.07
Signifiance	4.251 ** $p < 0.001$ $d = 1.8$	−0.460 $p = 0.650$ $d = 0.2$	2.810 * $p = 0.010$ $d = 1.1$	4.516 ** $p = 0.001$ $d = 1.7$

n=23; **: $p < 0.01$; *: $p < 0.05$; d is Cohen's d

In Table 5-4, the difference in mental effort reports between the two groups is not statistically significant (also see Figure 4-2). The design task was not easier for the mechanical group than for the non-mechanical group. Expertise in design did not significantly reduce mental effort probably because the mechanical group was able to understand the challenge of the design task and to identify the contradiction between the requirements. The difficulty level of the design task was determined not only by the task itself but also by designers' perceptions. Therefore, in Equation (5.2), the self-reported mental effort ratings are normalized by designers' perceptions of the design task, that is, the complexity values of problem structuring.

5.3.3 Relation between the effectiveness metric and expertise level

The relation between the effectiveness metric and expertise level is shown in Figure 5-10. The mechanical group (data points in black circles) had a higher expertise level and performed at a higher effectiveness level than the non-mechanical group (data points in grey square). For the mechanical group, the relation between the effectiveness value and the expertise level showed a pattern of two phases: at first the effectiveness value increased with the expertise level and then decreased later. The Pearson Product Moment Correlation coefficient r between the effectiveness value and the expertise level was only 0.387 (n = 23, p = 0.068). The results implied that the effectiveness measure was not determined only by the expertise level. Some other factors besides expertise level may exist, for example, the design strategies applied in design processes.

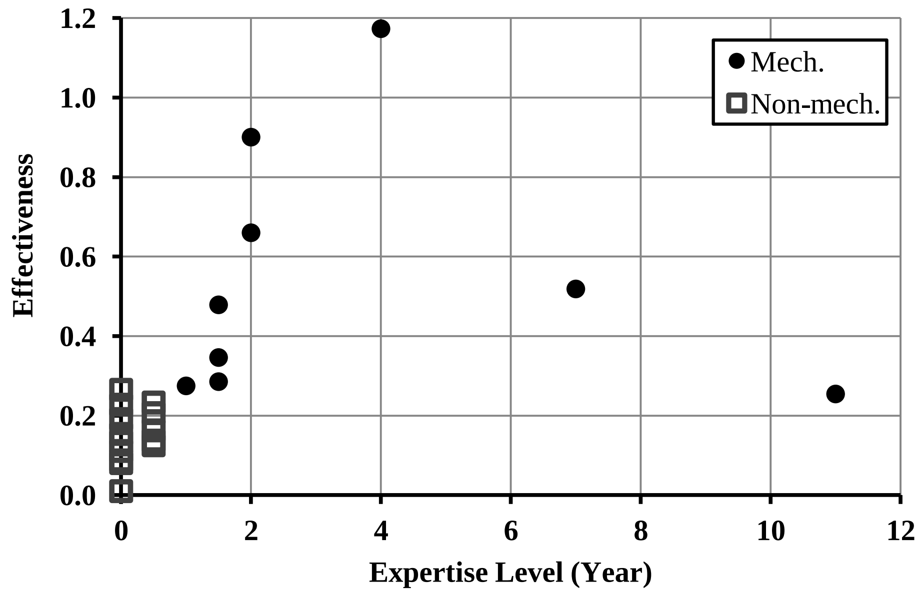

Figure 5-10 Relation between the effectiveness metric and expertise level

5.4 Application of Effectiveness Metric

5.4.1 Selection of problem structuring strategies

The decomposition modes and control strategies used by participants were compared in Table 5-5, as well as the effectiveness measure and their expertise levels. Eight out of nine mechanical group members applied explicit decomposition, while 13 out of 14 non-mechanical group members used implicit decomposition. The results supported previous studies that novice designers seldom applied explicit decomposition (Liikkanen & Perttula, 2009) but experts tended to use explicit decomposition (Ho, 2001). Most of the mechanical group members, except for one, applied the breadth-first or the mixed control strategy. Most of the non-mechanical group members applied the depth-first strategy, except for two participants using the mixed strategy. The results showed that the mixed strategy existed in both experienced and non-experienced designers. The phenomenon implied that the mixed strategy might not be a domain-specific strategy because non-experienced designers who had no domain-specific knowledge would use the mixed strategy.

Table 5-5 Decomposition modes and control strategies used by participants

Group	Subject Number	Effectiveness Value	Expertise Level	Decomposition Mode	Control Strategy
Mech.	1	0.51	7	Explicit	Mixed
	2	0.30	11	Implicit	Depth-first
	4	1.19	4	Explicit	Breadth-first
	9	0.33	1.5	Explicit	Mixed
	14	0.32	1	Explicit	Mixed
	15	0.85	2	Explicit	Mixed
	16	0.36	1.5	Explicit	Breadth-first
	19	0.49	1.5	Explicit	Breadth-first
	23	0.60	2	Explicit	Mixed
Non-mech.	3	0.23	0.5	Implicit	Depth-first
	5	0.28	0	Implicit	Depth-first
	6	0.12	0.5	Implicit	Depth-first
	7	0.10	0	Implicit	Depth-first
	8	0.14	0	Implicit	Depth-first
	10	0.13	0	Implicit	Mixed
	11	0.09	0	Implicit	Depth-first
	12	0.17	0	Implicit	Mixed
	13	0.21	0.5	Implicit	Depth-first
	17	0.25	0	Explicit	Depth-first
	18	0.21	0	Implicit	Depth-first
	20	0.25	0.5	Implicit	Depth-first
	21	0.01	0	Implicit	Depth-first
	22	0.13	0.5	Implicit	Depth-first

Problem decomposition is considered as a knowledge-sensitive problem-solving technique. According to the cognitive model of design idea generation (Liikkanen and

Perttula, 2009), implicit decomposition is a cognitive activity following an automatic recognition attempt, and explicit decomposition is a complementary activity for verifying the initial implicit decomposition of the problem. In this model, implicit decomposition is an inextricable part of the problem interpretation phase and is intimately coupled with recognition. In engineering design, designers use three types of knowledge: knowledge to generate ideas, knowledge to evaluate ideas, and knowledge to structure the design process (Ullman, 2009). When task-relevant knowledge is retrieved during a recognition attempt, the recovered knowledge can be used for deducing a function structure of the solution (that is, implicit decomposition of the problem). Experts may have more knowledge and experience in structuring the design process than novices. Experts can recognize and recall more complex solutions due to more domain-specific knowledge organized in bigger chunks than novices (Akin, 1986). For the same reason, experts might be able to find an alternative function structure later on by restarting decomposition explicitly. In contrast, novice designers may only retrieve incomplete or unfit matches that still provide enough information for implicit decomposition (Liikkanen and Perttula, 2009). Therefore, experts were observed to use explicit decomposition while novice designers tended to use implicit decomposition. A similar expertise effect on decomposition modes has also been observed in industrial design (Ho, 2001) and electronics (Ball, Evans, Dennis, & Ormerod, 1997).

The selection of decomposition modes may also be determined by the types of design task and design domains. A previous study (Liikkanen and Perttula, 2009) showed that the explicit decomposition mode may have limited applicability in the design of radically new kinds of products or in a less holistic and solution-centred domain; thus designers tended to use more straightforward methods and strategies over analytical ones. Experimental conditions such as no instructions to participants, limited time and commitment, and relatively low complexity and difficulty levels of design tasks may also affect the selection of different decomposition modes (Liikkanen and Perttula, 2009). In the present study, the participants completed a design task in a quiet research lab without any interruption and any limitation on the number of sketches and time. No instructions on design methods and design solutions were provided to the participants during the design processes. The design task was open-ended and selected to accommodate all participants; that is, inexperienced designers could also generate design concepts even if they had not enough domain-specific knowledge. Therefore, experimental conditions are unlikely to explain the selection of different decomposition modes by the two groups in the present study.

The mechanical group tended to use the breadth-first or mixed control strategy probably because this group perceived the design problem as being more complicated than the non-mechanical group. Those who applied the breadth-first/mixed control strategy perceived and structured the design problem with a complexity value of 43.3 on average, but the value was only 17.8 for those who applied the depth-first control strategy; a significant difference existed in the complexity values ($t(21) = 2.457$, $p = 0.023$, $d = 1.0$).

In the present study, those who applied implicit decomposition were likely to use the depth-first control strategy (see Table 5-5); out of 14 participants who applied implicit decomposition, 12 applied the depth-first strategy. Meanwhile, explicit decomposition seemed to be related to structured control strategies; out of nine participants who applied explicit decomposition, only one applied the depth-first strategy. However, a previous study observed that decomposition modes and control strategies were two independent issues (Liikkanen and Perttula, 2009). The different observations from the two studies may be caused by different experimental conditions. In the present study, participants were allowed to generate as many pages as they desired without any time limitation; however, two participants mentioned in their retrospective protocols that they would use “more formal design methods” if they had “plenty of time” to do the task or if they could access “more materials outside the experiment lab.” Their expressions indicated that experimental conditions and restrictions on time or materials may have an effect on their choices of design strategies.

5.4.2 Comparison of problem structuring strategies

In order to further analyze the effect of problem structuring strategies, the effectiveness metric was compared among the participants who used different decomposition modes and control strategies. In Figure 5-11, the averaged effectiveness scores and expertise levels are compared between two groups who applied explicit and implicit decomposition. The participants who applied explicit decomposition ($n = 9$) had a higher expertise level and performed higher effectiveness than those who applied implicit decomposition ($n = 14$). There was a significant difference in the effectiveness measure between the two decomposition modes ($t(21) = 4.406$, $p < 0.001$, $d = 1.7$). The results supported that explicit decomposition was beneficial for the effectiveness of problem structuring.

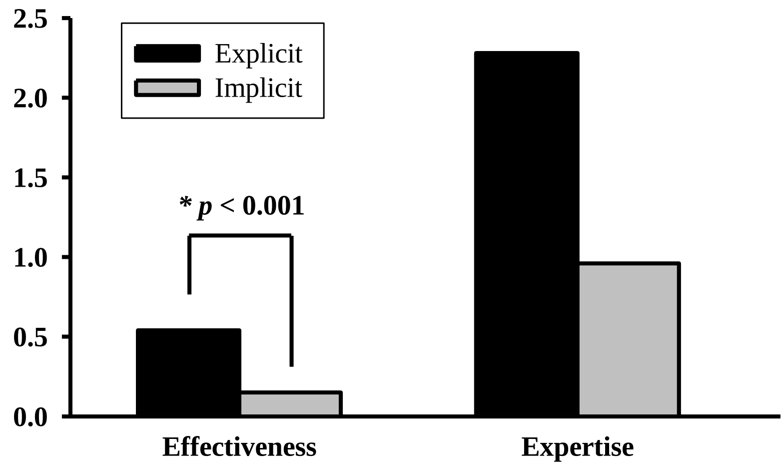

Figure 5-11 Comparison of two decomposition modes

In Figure 5-12, the averaged effectiveness scores and expertise levels are compared between three groups who applied the breadth-first, the mixed, and the depth-first control strategy. The participants who applied the breadth-first strategy (n = 3) performed with higher effectiveness than those who applied the mixed (n = 7) or depth-first strategy (n = 13). A significant difference existed in the effectiveness measure between the breadth-first and the depth-first strategy ($t(14) = 4.316$, $p < 0.001$, $d = 1.6$) and also between the mixed and the depth-first strategy ($t(18) = 3.017$, $p = 0.007$, d = 1.2). The results indicated that the breadth-first strategy and the mixed strategy occurred with higher effectiveness compared with the depth-first strategy. In addition, the quality ratings for those who applied the breadth-first strategy and the depth-first strategy were not significantly different ($t(14) = 1.986$, $p = 0.067$), but significant difference existed in the effectiveness metrics. This result indicated that the effectiveness metric was able to identify the benefit of strategy usage even if the design outcomes were not improved.

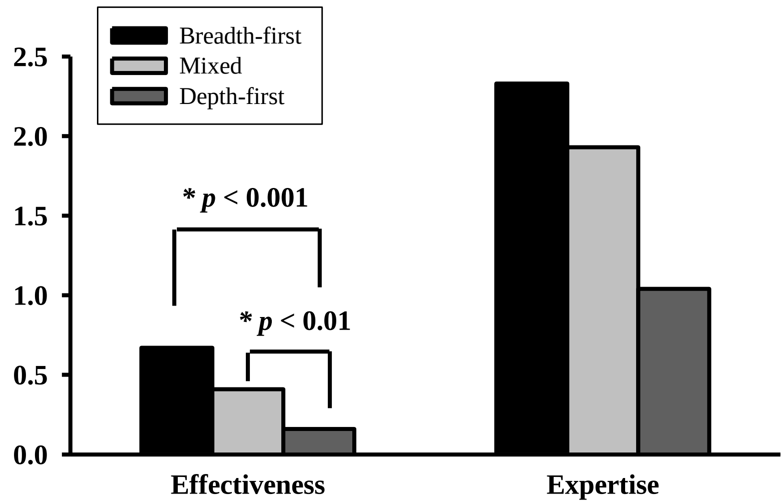

Figure 5-12 Comparison of different control strategies

The data did not support a significant difference between the breadth-first strategy and the mixed strategy ($t(8) = 1.086$, $p = 0.309$). The mixed strategy appeared not to be more effective than the breadth-first strategy presumably because of small samples. Only 3 out of 23 participants (all in the mechanical group) applied the breadth-first strategy, and 7 out of 23 participants applied a mixed strategy (5 in the mechanical group and 2 in the non-mechanical group). The other reason may come from the small gap in expertise levels between the two groups. The mechanical group members had three years of work experience on average, while the non-mechanical group members had zero.

The differences in effectiveness measures were significant between different decomposition modes and between different control strategies (see Figure 5-11 and Figure 5-12). However, no significant differences were observed in mental effort ratings. It seemed that applying the explicit decomposition mode and the breadth-first (or mixed) strategy did not contribute to reducing designers' overall mental effort, which can be explained as follows: mental effort was task-related and depended on personal perceptions of the design task; effective strategies, such as explicit decomposition and the breadth-first (or mixed) strategy, helped to improve the quality of design outcomes given the same mental effort invested in solving a design task with the same complexity perceived.

5.5 Significance and Summary

Although previous studies support that the effectiveness of idea generation is a critical feature between experts and novices, there seems to be no specific measure that can be used to describe this feature. The effectiveness metric proposed in the present study can identify this feature among different expertise levels (Figure 5-10). The metric also supported that using analytical methods benefited problem structuring (see Figure 5-11 and Figure 5-12) and improved design outcomes (see the quality measures in Table 5-4). In addition, since the complexity of problem structuring can be quantified into numerical units, the effectiveness of problem structuring can be calculated and compared numerically. The effectiveness metric measures the relative performance within a group. The group can include different designers completing one design task, or one designer completing several similar design tasks, or one designer using different design methods. The application of the effectiveness metric in different situations should be examined in future study. The results are expected to identify effective design methods and benefit design training/education.

The effectiveness metric meets the challenge of representing the process of problem structuring in a tree structure, which satisfies two critical features of problem structuring: "*decomposability*" and "*abstraction hierarchies*" (Goel and Pirolli, 1992).

Moreover, the effectiveness metric extends the application of complexity measures in engineering design, which measures the size of the composite, the degree of interconnections, and the difficulty level of solving a design problem (Summers and Shah, 2010). Studies have dealt with the issue of measuring complexity in terms of design problems (Griffin, 1993), design processes (Jin and Li, 2007), and design products (Kannapan, 1995). However, the complexity measures have not been used for studying problem spaces in designers' minds. The measure of tree-structure complexity used in the present paper describes the number of product functions, the connections between those functions, and the solvability of those functions (see an example in Figure 5-9).

The effectiveness measure was found to be related to designers' expertise levels and problem structuring strategies. The mechanical group demonstrated significantly higher effectiveness than the non-mechanical group. The participants who applied explicit decomposition performed at a significantly higher level of effectiveness than those who applied implicit decomposition. The participants who applied the breadth-first or mixed strategy performed at a significantly higher level of effectiveness than those who applied the depth-first strategy. The effectiveness measure provides direct evidence that the explicit decomposition mode and the breadth-first strategy are beneficial for the effectiveness of concept generation. The mechanical group tended to use the analytical methods due to the training they had received, while the non-mechanical group tended to use the straight-forward methods. This study suggests that the explicit decomposition mode and the breadth-first strategy should be encouraged in design education, although not all the experienced designers apply them all the time.

Chapter 6 Complexity of Cognitive Actions [3]

6.1 Introduction

A cognitive process is composed of a series of cognitive actions, which can be defined by encoding verbal protocols. Previous studies have identified different categories and structures of design actions. Suwa and Tversky (1996) classified the contents of what designers see, attend to, and think of into four information categories: depicted elements and their perceptual features, spatial relations, functional thoughts, and knowledge. According to these information contents, different categories of design actions were defined corresponding to different levels of human information processing (Suwa, Purcell, & Gero, 1998).

Subcategories and actions such as drawing actions and goals actions have also been used to study the structure of cognitive actions (Kavakli & Gero, 2002). A structure named concurrent cognitive actions (the coexistence of cognitive actions) has been identified. This structure occurred when certain groups of cognitive actions increased or decreased in parallel with each other. A case study found evidence for a clear structural organization in the expert's concurrent cognitive actions, and the structural interdependency between the categories of cognitive actions might be a reason for the expert's high performance in the design process (Kavakli & Gero, 2002). However, the relation between cognitive actions and cognitive efficiency has not been directly studied. The current study aims at exploring whether and how some categories and structures of cognitive actions are related to cognitive efficiency. The results are expected to identify

[3] Part of this chapter has been submitted to a journal.

what categories and structures of cognitive actions are related to high cognitive efficiency.

Studying cognitive actions in real-time design is particularly full of methodological challenges since cognitive activity is easily disturbed by any obtrusive experimental techniques and not visible to unobtrusive techniques. For example, neurological signals, such as EEG, are likely sensitive to designers' physiological status and body movement, such as sketching activity. Eye tracking techniques require designers to position at a distance from the screen (van Gog, Paas, & van Merriënboer, 2005) and demand cautious interpretation on designers' perception (Sun, Xiang, Chai, Yang et al., 2014). Measuring design outcomes including sketches and verbal protocols is also challenging because the measurement is based on unstructured data and thus a systematic method is required to keep the measurement objective and consistent. This chapter developed an information based approach to representing the complexity of design actions. Cognitive actions were defined based on a bottom-up hierarchy of human information processing. Methods will be introduced in the next subsection.

6.2 Method

6.2.1 Coding cognitive actions

The free-hand sketched entities and retrospective verbal protocols were used for coding designers' cognitive actions. The scheme of coding was derived from previous studies on cognitive activity in design processes (Suwa, Purcell et al., 1998) and modified after intensive review of sketches and verbal protocols collected for the present study. The original method of the scheme was designed for studying architects' cognitive activity, and the main target of the analysis was verbal protocols including words, phrases, and sentences that were used as evidence of each subclass of coded cognitive actions. In the present study, the main target of the analysis was freehand sketches, as well as information perceived and processed during and after sketching processes. Verbal protocols were supplements to interpreting non-visual data, that is, cognitive activity that was not able to be recorded in visual data such as sketches and gestures.

Each sketching process was segmented by a significant pause. Each segment presents a coherent proposition of an entity in the sketch. The coherent proposition can be a design concept or an intention; an entity can consider a structure or a function of the product being designed. Figure 6-1 shows the sketches and verbal protocols in a segment. In this segment, a concept of “flat platform” was generated to satisfy the subfunction of “accommodate laptops” listed in the requirements by the participant. The entity in this segment was a flat platform with a laptop on the top of it.

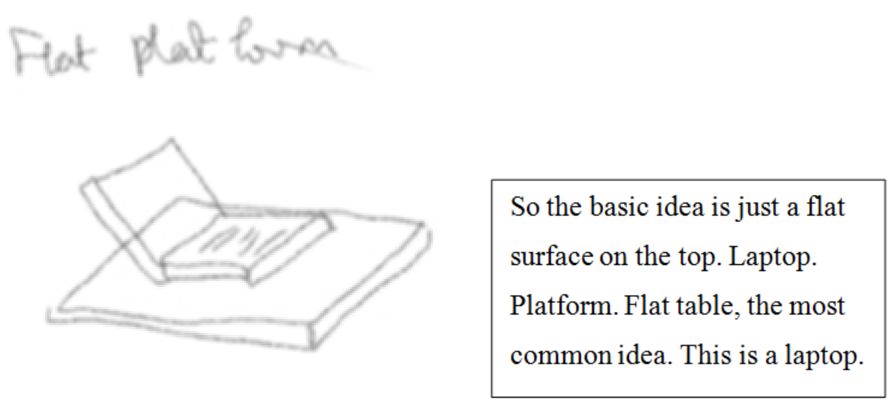

Figure 6-1 Example of a design segment: sketches and verbal protocols

Each segment consists of different cognitive actions, which are divided into four categories: physical, perceptual, functional, and conceptual. The four categories correspond to the levels at which incoming information is thought to be processed in human cognition. Past literature in cognitive science supports the proposition that information coming into human cognitive processes is processed first sensorily, then perceptually and semantically. The upper levels of information processing have an inherent dependency on lower levels. Physical actions correspond to the sensory level, perceptual actions to the perceptual level, and both functional and conceptual to the semantic level.

The specifications and examples of the cognitive actions for the four categories are listed in Table 6-1. The specifications are modified to accommodate mechanical engineering design processes. (1) Physical actions are those having relevance to sketches such as sketching activities, looking at sketches, and creating new sketches. (2) Perceptual actions refer to attending to physical features and physical relations of depicted elements in sketches. Basic information contained in engineering sketches includes the mechanical elements depicted and the connections among the elements or between the elements and their environment. Thus physical features include shape, dimension, material, mass, force, stiffness, and so on; physical relations include positions, mechanical connections, alignment, intersections, and so on. (3) Functional actions are related to the considerations of functions and behaviors of products (Gero & Kannengiesser, 2004). For mechanical engineering design, the function can be specifically referred to as "a physical interaction between two objects of interest, each of which may be a component of a design or the design itself and its environment (Deng, 2002, p 344)." Behavior is related to the physical state of a design: "either it changes temporally, thus causing a state transition, or it can remain unchanged, thus maintaining a static state (Deng, 2002, p 347)." Functional actions also include the issues of interactions between products and users when designers consider customer requirements; for example, “the lecturer can *move* the podium, so it would not *block* students’ view.” (4) Conceptual actions refer to concept evaluation and judgment, as well as retrieval of knowledge from long-term memory.

Table 6-1 Specifications and examples of cognitive actions

(modified from (Suwa, Purcell et al., 1998))

Category	Specifications	Examples
Physical	Make depictions	Lines, circles, arrows, words
	Look at previous depictions	Look or read design task
	Other physical actions	Move a pen, move elements, gesture
Perceptual	Add physical features	Shapes, dimensions, materials
	Add physical relations	Positions, mechanical connections, alignment, intersection
Functional	Attend to product functions	Physical interaction such as push, support, hold
	Attend to product behaviors	Physical state such as steady, rolling, moving
Conceptual	Compare concepts	Similar to another mechanism
	Make evaluations	Like-dislike, good-bad
	Set up goals	Suggest what need to be done
	Retrieve knowledge	-

Figure 6-2 presents an example of encoding. The transcript of verbal protocols and encoded actions are shown in Figure 6-3. In this segment, the participant roughly sketched the front view of the podium he designed. He drew “a rectangle to represent a lectern” and “a rod and a circle to represent wheels.” He also thought about the mechanism of controlling the movement of the podium by changing the direction of wheels. In this segment, three physical actions referred to drawing the rectangle, the bar, and the circle. Three perceptual actions referred to the shape and positions/directions of the podium and wheels. The functional action referred to the physical states of the wheels. The conceptual action referred to the control mechanism of movement although the participant had not a clear idea about the details. Five transitions occurred between the four categories of actions. All the verbal protocols were transcribed, segmented, and encoded. The first three verbal protocols were analyzed twice to examine the reliability.

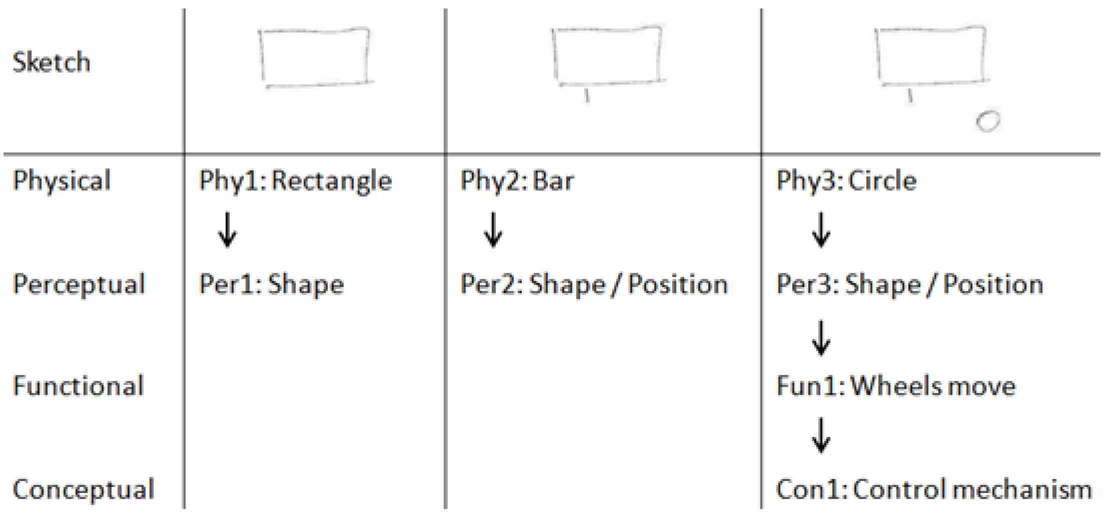

Figure 6-2 Example of cognitive actions and transitions in a design segment

Segment	Transcription	Physical	Perceptual	Functional	Conceptual	Transitions
#5	I am thinking how to fix the lectern and how to rapidly move it. I draw a rectangle to represent a lectern from the perspective of instructors. I draw a rod and a circle to represent wheels. I have no idea the directions of the wheels. Neither do I have ideas about how to control the direction of the wheels, e.g. a button? Change the direction to another direction. I haven't thought about the details of the mechanical device about the button.	3	3	1	1	5

Figure 6-3 Example of segmentation and protocol coding

6.2.2 Kolmogorov complexity

This subsection introduces Kolmogorov complexity to measure information contained in cognitive actions and transitions (for example, how to convey information in Figure 6-3). A protocol segment is considered to be a message which constitutes a sequence of events: cognitive actions and transitions between these actions. Information theory provides a mathematical measure for information contained in a message produced by a discrete source (Shannon, 1948). A message constitutes a sequence of events, which are selected from a predefined, finite list of allowed events or controlled vocabulary (Sen et al., 2010). So an event is a unit element of information in the message. The source is discrete and linear if the events occur distinctly and sequentially (Sen et al., 2010). Thus, each event occurs with a known probability. Since different parts of the brain are responsible for different brain functions, the four categories of cognitive actions proposed in the present study and transitions between them may be conducted by different neurons in different areas of the brain. Therefore, cognitive actions and transitions in a segment can be considered as independently discrete random variables.

The Kolmogorov complexity $K_\mu(x)$ of a string x with respect to a universal computer μ is defined as (Cover & Thomas, 2006)

$$K_\mu(x) = \min_{p:\, \mu(p)=x} l(p) \tag{6.1}$$

where x is a finite length binary string and μ is a universal computer. $l(p)$ denotes the output of the computer μ when presented with a program p. Thus $K_\mu(x)$ is the shortest description length of x over all descriptions interpreted by computer μ. An important technique for thinking about Kolmogorov complexity is that one person can describe a sequence to another person, and then the number of bits in that communication is an upper bound on the Kolmogorov complexity.

According to Kolmogorov complexity, the amount of information in a string is the size of the smallest computer program generating that string (Kolmogorov, 1965). The quantity of information in a string can be measured directly based on its internal structure, that is, “modules” and “relations” (Braha & Maimon, 1998b). In the present study, the string is a segment; the modules are the cognitive actions; and the relations are the transitions between the cognitive actions. For simplicity, it is assumed that cognitive demands for cognitive actions at different levels of information processing are the same. Also, transitions from one information-processing level to another need the same cognitive resources. Therefore, the independent variables, that is, the cognitive actions and transitions in a segment, are assumed to be identically distributed.

Let X_i be a random variable with a probability mass function $p(x_i)$. Variable X_i (i=1, 2, …, Λ) is either one category of design actions or one transition from one information-processing level to another, where Λ is the length of a design segment, that is, the sum number of total cognitive actions (N) and total cognitive transitions (L). The probability mass function of each variable is $p(x_i) = 1/(\rho+v)$, where ρ and v are the numbers of unique cognitive actions and unique cognitive transitions respectively. The probability of the sequence (X_1, X_2, …, X_Λ) is $p(x_1, x_2, \dots x_\Lambda) = 1/(\rho+v)^\Lambda = 1/\lambda^\Lambda$. According to information theory, the information contained in a particular design segment with length Λ is equal to the joint entropy H_j in Equation (6.2) (Shannon, 1948). Therefore, the information contained in a design segment is a function of the length of the segment ($\Lambda = N + L$) and the size of basic elements ($\lambda = \rho + \upsilon$) (Ameri et al., 2008) as shown in Equation (6.3).

$$H_j(X_1, X_2, \cdots, X_\Lambda) = -\sum p(x_1, x_2, \cdots, x_\Lambda)\log_2(p(x_1, x_2, \cdots, x_\Lambda))$$
$$\text{with } \sum p(x_1, x_2, \cdots, x_\Lambda) = 1 \tag{6.2}$$

$$H_j(X_1, X_2, \cdots, X_\Lambda) = -\sum \frac{1}{\lambda^\Lambda}\log_2\left(\frac{1}{\lambda^\Lambda}\right) = \Lambda \log_2 \lambda \tag{6.3}$$

In the example shown in Figure 6-2, the numbers of unique cognitive actions and transitions were 4 and 3 respectively, so the size of basic elements was 7 ($\lambda = \rho + \upsilon = 4+3$). The numbers of total cognitive actions and transitions were 8 and 5 respectively, so the length of the segment was 13 ($\Lambda = N + L = 8 + 5$). Information contained in the sequence of the segment was $\varepsilon_h = 13 \times \log_2(7) = 36.5$.

The measure of Kolmogorov complexity for a segment may be viewed as the smallest program reconstructing the message without directly viewing it. A person not observing the segment needs to ask another person who can see the segment at least a number $13 \times round(\log_2(7))$ of binary questions to reconstruct the segment. The function *round* approximates the numeric value to the nearest higher integer. The binary questions are answered *yes* or *no*. An assumption in this scenario is that both persons know the size and length of the segment. The elements of the segment can be referred to {*A* = physical action, *B* = perceptual action, *C* = functional action, *D* = conceptual action, *E* = transition from physical action to perceptual action, *F* = transition from perceptual action to functional action, and *G* = transition from functional action to conceptual action}. The length of the segment is represented as "*AEB AEB AEBFCGD*." For example, the possible questions and answers for the first unit "*A*" in the sequence are: (1) Is the action or transition in the list of {*A*, *B*, *C*, *D*}? The answer is *yes*. (If the answer is *no*, the next question would ask whether the action or transition is in the list of

{*E*, *F*, *G*}.) (2) Is the action or transition in the list of {*A*, *B*}? The answer is *yes*. (If the answer is *no*, the next question would ask whether the action or transition is in the list of {*C*, *D*}.) (3) Is the action or transition in the list of {*A*}? The answer is *yes*. After asking the three questions, the person who did not see the segment can identify the first unit in the sequence as "*A*." In order to identify the total 13 units in the sequence, the person needs to repeat the three questions 13 times.

The measure of Kolmogorov complexity for a whole design process can be calculated by adding all the measures of segments. So the measure is affected by the length of a design process, that is, the number of segments in a verbal protocol. Some designers generated more design concepts and then had more segments than others. More segments would lead to more cognitive actions and transitions. Therefore, Kolmogorov complexity measure was normalized by dividing it by the quantity of design concepts generated in the design process. In Equation (6.4), C_A represents the complexity of cognitive actions, H_j is the Kolmogorov complexity for each segment of a verbal protocol, O_u is the quantity of design outcomes, and n is the number of segments in this protocol.

$$C_A = \sum_{i=1}^{n} \left(H_j\right)_i \Big/ O_u \tag{6.4}$$

The complexity measure of cognitive actions was proposed to examine factors that may affect cognitive efficiency. Two opposite assumptions about the relation between Kolmogorov complexity and cognitive efficiency may exist. One assumption is in accord with the neurological efficiency hypothesis that a large amount of cognitive actions lead to high consumption of brain energy; therefore, high complexity of cognitive actions is related to low cognitive efficiency. The other assumption is that high complexity of cognitive actions refers to high cognitive efficiency. This assumption is based on the existing studies analyzing the mental iterative behaviors of designers and the contribution of expertise to improving cognitive efficiency. Studies have shown that creative design involves more mental iterations than routine design (Jin & Chusilp, 2006) and that more skillful designers do more mental iterations (Adams, 2001). More mental iterations obviously relate to more cognitive actions and transitions. Also, studies in neuroscience have found that expertise or high intelligence levels are strongly related to high neurological efficiency (Fink et al., 2009; Jausovec, 2000). Therefore, more cognitive actions and transitions may contribute to higher cognitive efficiency. That is to say, Kolmogorov complexity may be positively related to cognitive efficiency.

6.3 Results and Discussion

6.3.1 Relation between the complexity and cognitive efficiency

Table 6-2 lists the Pearson Product Moment Correlation between the measures of the complexity C_A, cognitive efficiency, RSME, and expertise levels. The complexity C_A was significantly related to the cognitive efficiency scores of quality ($r = -0.511$, $p = 0.013$). When the complexity C_A was higher, the cognitive efficiency scores were lower. This result was in accord with the neurological efficiency hypothesis that the more the mental resources consumed, the lower the cognitive efficiency.

Table 6-2 Correlation matrix between Kolmogorov complexity and other measures

Measures	Cognitive Efficiency			RSME	Expertise
	Novelty	*Variety*	*Quality*		
Complexity C_A	−0.296 (0.171)	−0.349 (0.103)	−0.511 * (0.013)	0.589 * (0.003)	−0.279 (0.197)

n=23, *: $p < 0.05$

In addition, the complexity C_A was significantly related to the RSME reported by the participants ($r = 0.589$, $p = 0.003$). It is not surprising that the higher the complexity of cognitive actions, the higher the mental effort invested to solve the design task. There was no significant relationship between the complexity C_A and expertise level ($r = -0.279$, $p = 0.197$). Experienced designers appeared to have no more complex cognitive actions than inexperienced designers.

Figure 6-4 shows the relation between Kolmogorov complexity and cognitive efficiency (of quality) in detail. The mechanical group performed higher cognitive efficiency than the non-mechanical group given the same complexity C_A values.

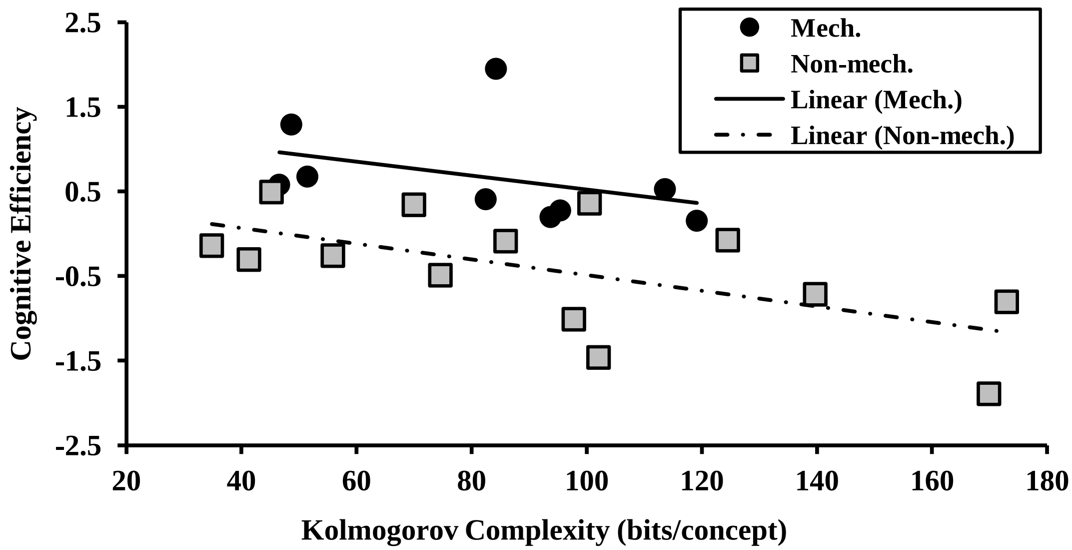

Figure 6-4 Relation between Kolmogorov complexity and cognitive efficiency

6.3.2 Complexity fluctuation in design processes

Figure 6-5 shows different patterns of complexity fluctuation in the design process. The *x*-coordinates were the serial numbers of segments (of verbal protocols) divided by the total number of segments of each verbal protocol. As a result, the *x*-coordinates were normalized between 0 and 1 for all the participants. The number of data points in Figure 6-5 represents the number of segments (of verbal protocols). The complexity values fluctuated from zero to over 200. The value of zero happened only when physical actions did not lead to a higher level of information processing in a segment; the perceptual, functional, and conceptual actions could not be identified in sketches. In this situation, the participants retrieved pages they had generated, moved their hands, or read the design problem once again. The very low complexity value (even as low as zero) in a segment may indicate a cognitive status switch or strategy use switch at that moment. For example, in Figure 6-5c, the complexity value of the fourth segment is zero; in this segment, the participant could not access information in long-term memory when he was trying to complete a design concept (he moved hands but did not sketch anything); later he moved back to retrieve the previous pages; but he failed to collect useful clues from the previous pages, so he gave up, went back to the present page, and started to thinking about another design concept.

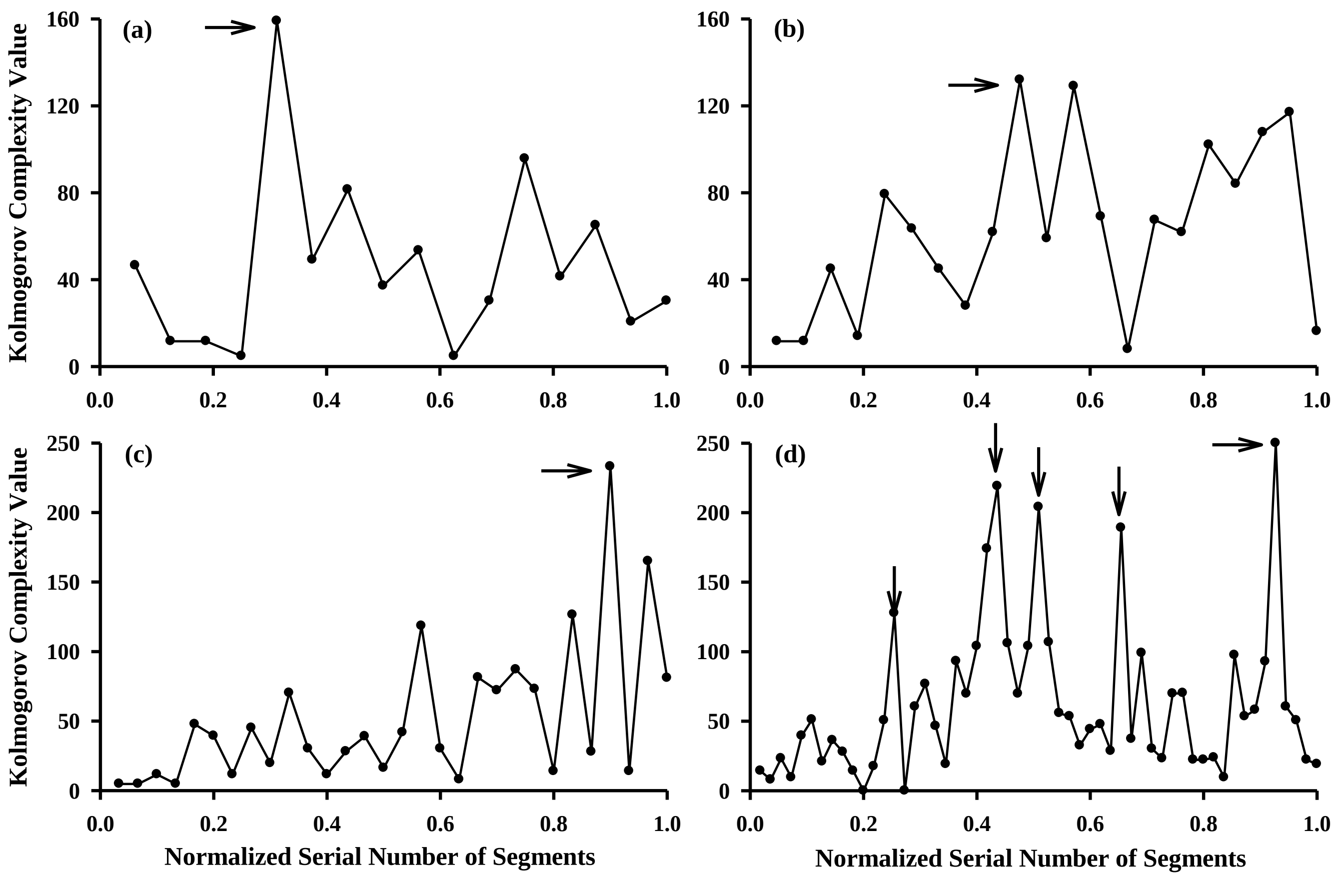

Figure 6-5 Different patterns of complexity fluctuation in design sessions

The standard deviation (SD) of complexity values was found to be related to RSME (r = 0.593, p = 0.003; see Table 6-3). The higher the variation of complexity data, the more frequently a thinking process was interrupted, and the less coherent the thinking process might be; therefore, the higher the mental effort was reported. This result implied that the SD of complexity values may be able to represent the variation of information flow processed in segments through design sessions. The SD values did not correlate with cognitive efficiency, the quality of design solutions, and expertise levels (see Table 6-3). The results implied that a temporary break of information processing may affect mental effort but not change design outcomes and cognitive efficiency. Moreover, the frequency of breaks did not appear to be significantly different between individuals with different levels of expertise in design.

Table 6-3 Relation between the complexity *SD* values and other measures

Measures	*Cognitive Efficiency of Quality*	*RSME*	*Quality*	*Expertise*
Standard Deviation of Complexity Values	−0.320 (0.136)	0.593 * (0.003)	0.211 (0.333)	−0.146 (0.506)

*: $p < 0.05$;

The complexity values arrived at a maximum (horizontal arrows shown in Figure 6-5) when the number of cognitive actions was much more than that in other segments. In this situation, the participants may generate an early conjecture to solve the design problem, sketch a basic structure of the product, describe some critical features of the product, or combine all the design concepts. The maximal values can occur at the beginning ($x < 1/3$), in the middle ($1/3 \leq x < 2/3$), or near the end ($x \geq 2/3$) of design sessions. Only 4 out of 23 participants had the maximal values occur at the beginning of design sessions (see an example in Figure 6-5a). These participants generated initial solution conjectures or critical features at the beginning of design sessions and fixed on the conjectures/features during the remainder of design sessions. Furthermore, 9 out of 23 participants had the maximal values occur in the middle of design sessions (see an example in Figure 6-5b). Another 10 out of 23 participants had the maximal values happen near the end of design sessions (see an example in Figure 6-5c). These participants intended to finalize the design processes by combining all the design concepts they had generated. Therefore, the time that the maximal values occurred varied with the design methods used in the design sessions.

Table 6-4 lists the Pearson Product Moment Correlation between the time that the maximal complexity values happened and other measures including cognitive efficiency, mental effort, and expertise levels. In this study, the time that the maximal complexity values occurred was significantly related to RSME and three measures of cognitive efficiency including novelty, variety, and quality. The results indicated that the later the design solutions arrived, the higher the mental effort reported and the lower the cognitive efficiency performed. The time that the maximal complexity values happened was not related to the creativity of design outcomes and designers' expertise levels. Experience in design did not affect the timing of the design solutions/conjectures arrived in the early stage of design sessions, and the quality of design solutions would not be affected by when the design solutions were generated.

Table 6-4 Relation between the time for maximal complexity values and other measures

Measures	*Cognitive Efficiency*				*RSME*	*Expertise*
	Novelty	*Variety*	*Quality*	*Quantity*		
Time for Max. Complexity	−0.485 * (0.019)	−0.425 * (0.043)	−0.449 * (0.031)	−0.374 (0.078)	0.616 * (0.002)	0.040 (0.855)

*: $p < 0.05$;

6.3.3 Comparison between design methods

In Figure 6-5d, the complexity curves demonstrated several peaks (see vertical arrows). In this design session, the participant used the systematic method. He analyzed requirements and specified the design problem at the beginning of the session, generated more than one design concept for each divided subfunction, built standard criteria to evaluate those concepts, and completed final design solutions after evaluation. This result implied that the distribution of complexity values in design sessions may be different if different design methods were used.

The distributions of complexity values for the three design methods (defined in Section 4.3.4) are compared in Figure 6-6. For the three methods, most of the complexity values (about 86%) were less than 100. The frequency values were no more than 10% when the complexity values were over 100. If a design segment only contains a cycle that starts from a physical action to perceptual, then to functional, and finally to a conceptual action, the length of this segment ($\Lambda = N + L$) is 7 and the size of basic elements ($\lambda = \rho + \upsilon$) in this segment is 7 too. According to Equation (6.3), the information contained in this segment is $7 \times \log_2 7 = 19.65$. If the complexity value of a segment was less than 100, no more than 5 cycles occurred in this segment (100/19.65=5.09). The distributions in Figure 6-6 indicated that most of the time the participants could not process more than 5 cycles from physical to conceptual actions. The restriction may be determined by the limitations of human information processing and designers' expertise levels. Occasionally, the participants could process as many as 10 cycles in one design segment. In this situation, the complexity value was over 200 (200/19.65=10.18). Since each complexity value was independently calculated by a logarithmic function in Equation (6.3), the distribution of complexity values was comparable to a logarithmic function.

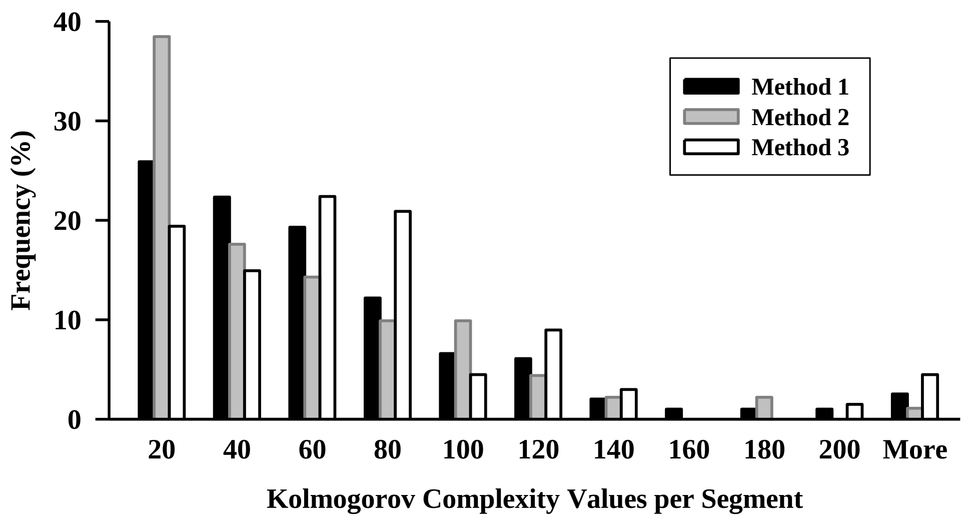

Figure 6-6 Comparison of complexity value distribution for three design methods

For Method 1 (the systematic method), the frequency value for bin 20 was close to the value for bin 40, that is 26% *vs.* 22%; however, for Method 2 (the no-alternative method), the frequency value for bin 20 was over twice as high as the value for bin 40, that is 38% *vs.* 18%. This result implied that the participants who applied Method 2 performed many more segments with low complexity values than those who applied Method 1. The segments with low complexity values may be due to some excess physical actions caused by thought breaks and cognitive status change. The distribution for Method 3 (the no-control method) shows a different pattern compared with that for Methods 1 and 2. The frequency values for the bins from 20 to 80 did not gradually decrease and showed a relatively random pattern. This may be because the participants who used Method 3 did not structure their design sessions; therefore, the cognitive actions and the information content of those actions were relatively random. In addition, for Method 3, relatively fewer segments with low complexity values occurred compared with Method 1 and 2, which may be because the participants completed the design task without considering the design conditions and the conflicts of requirements and so their thought processes were free of restrictions. The mean numbers of segments in each design session for the three methods were 22, 13, and 10. A significant difference existed in the mean numbers of segments between Method 1 and Method 3 (Mann-Whitney Rank Sum Test, $T = 34.5$, $p = 0.009$).

6.3.4 Contribution of cognitive actions to cognitive efficiency

Since the complexity measure is a combination of the four categories of cognitive actions, in order to further investigate the contribution of each category, the relations between the number of each category of cognitive actions and other measures including cognitive efficiency, RSME, and expertise are examined in Table 6-5. The number of each category of cognitive actions/transitions was normalized by the quantity of design concepts. The results in Table 6-5 show that cognitive efficiency measures were significantly related to the number of physical and perceptual actions ($p < 0.05$). More physical and perceptual actions for each design concept led to lower cognitive efficiency.

Table 6-5 Correlation matrix between cognitive actions and other measures

Measures	*Cognitive actions*			
	Physical	*Perceptual*	*Functional*	*Conceptual*
Cognitive Efficiency	−0.429 * (0.041)	−0.481 * (0.020)	−0.371 (0.081)	−0.206 (0.346)
RSME	0.475 * (0.022)	0.521 * (0.011)	0.539 ** (0.008)	0.174 (0.426)
Expertise	−0.238 (0.275)	−0.190 (0.385)	−0.195 (0.373)	−0.420 * (0.046)

*: $p < 0.05$; **: $p < 0.01$;

However, the functional and conceptual actions did not directly correlate with cognitive efficiency as expected (see Table 6-5). The percentages of cognitive actions at high levels (the functional and conceptual actions) were much less than those at low levels of information processing (the physical and perceptual actions), that is, 27% (= 16% + 11%) *vs.* 73% (= 47% + 26%; data shown in Table 6-5). It may be assumed that small percentages of functional and conceptual actions may need less cognitive effort and thus may have weaker effect on cognitive load compared with the physical and perceptual actions. But this assumption may not be true because the functional actions were highly related to mental effort (see Table 6-5).

RSME ratings were significantly related to all the cognitive actions ($p < 0.05$) with the exception of the conceptual actions. Those who reported higher mental effort conducted relatively more physical, perceptual, and functional actions per design concept than those who reported lower mental effort. This result implied that concept evaluation did not appear to be an effort-consuming job, compared with physical movements, visual perceptions, and idea generation.

In addition, the number of conceptual actions negatively correlated with designers' expertise levels. Experienced designers did not evaluate/judge each design concept as frequently as inexperienced designers although the former generated more design concepts than the latter. Experienced designers tended to evaluate design concepts after a standard criterion was built. The stages of goal set-up, concept generation, and evaluation were clearly separated. By contrast, inexperienced designers did not structure the problem at the beginning and preferred to judge a design concept just after it was generated. The original idea was fixed on instantly after the evaluation or replaced with a new one until it was satisfactory. As a result, the inexperienced designers performed more conceptual actions for each design concept than experienced designers and demonstrated lower cognitive efficiency. The result suggested that setting up goals as well as separating concept generation and evaluation may benefit cognitive efficiency.

6.3.5 Comparison of cognitive actions and transitions

In order to further investigate the relations among cognitive actions and transitions, four categories of cognitive actions and six possible transitions (only from the low to high levels of information processing) in a design session can be described by a matrix (see an example in Table 6-6). The four diagonal elements of the matrix represent the number of the four categories of cognitive actions. The non-diagonal components in this matrix represent the possible transitions from one information-processing level to another. The four matrix elements in the first row represent physical actions as well as transitions from the physical to perceptual, functional, and conceptual actions, respectively. Table 6-6 lists the averaged percentages of different categories of cognitive actions and transitions averaged for all the participants. Since transitions between cognitive actions only happened from the low to high levels of information processing, the values of the diagonal elements were equal to the sum of the other elements in the same columns. Thus, seven elements in the matrix were independent, and the other three elements in parenthesis were dependent. The sum of the seven independent elements was normalized to 100%. In total, about 47% belonged to the physical actions, 26% to the perceptual actions, 16% (= 3% + 13%) to the functional actions, and only 11% (= 4% + 2% + 5%) to the conceptual actions. The percentages were similar to those that have been reported for architects (Suwa, Purcell et al., 1998).

Table 6-6 A matrix showing design actions and transitions

	Physical	Perceptual	Functional	Conceptual
Physical	47%	26%	3%	4%
Perceptual	−	(26%)	13%	2%
Functional	−	−	(16%)	5%
Conceptual	−	−	−	(11%)

About half of physical actions (54% = 26% / 47%) led to a higher level of perceptions, for example, shapes or dimensions of an object. The other half of physical actions included hand gestures, body movements, reading materials, or flipping between pages. These movements may suggest hesitation, cognitive state changes, or cognitive strategy switches. The functional actions came from two parts: the physical and perceptual actions. Those from perceptual actions were more than four times (13%

vs. 3%) as many as those from physical actions. The former functional actions happened when the object physical interactions / states were based on the visual perceptions of object physical features and relations; the latter functional actions happened when the product functions / behaviors were not presented by the perceptions of product physical features (the participants wrote down the functions and behaviors by notes rather than by sketches).

Only 6% (= 3% / 47%) and 9% (= 4% / 47%) of physical actions led to higher functional and conceptual actions respectively. About half (= 13% / 26%) of perceptual actions led to functional actions. Only 31% (= 5% / 16%) of functional actions transitioned to conceptual actions. About half (=5% / 11%) of conceptual actions came from functional actions. The other half of conceptual actions came from physical and perceptual actions. The results support the bottom-up hierarchy of information processing.

If the systematic design method was applied, a design session can be divided into several stages: requirements analysis, design specification, concept generation, and concept evaluation. Each design stage has its own dominant cognitive actions and transitions. An example of the occurrence of cognitive actions and transitions in a design session is shown in Figure 6-7. The *x*-coordinate is the serial number of segments. The sum of the four categories of cognitive actions was normalized to 100%. The physical actions occupied around half of all actions (also see the statistics shown in Table 6-6). The percentage of physical actions decreased in the middle of the design session (segments 10~35), which is the stage of concept generation. The decrease was due to the occurrence of functional actions. In this stage, the transitions *Per.−Fun.* and *Fun.−Con.* frequently occurred, and the occurrence of perceptual and functional actions was related to each other. The correlations between the perceptual and functional actions were also observed in the stage of functional exploration for a practising architect (Suwa, Purcell et al., 1998). The transitions *Phy.−Per.* occurred almost throughout the design session, but the transitions *Phy.−Fun.* occurred only when the product functions were considered without visual perceptions of product physical states/relations.

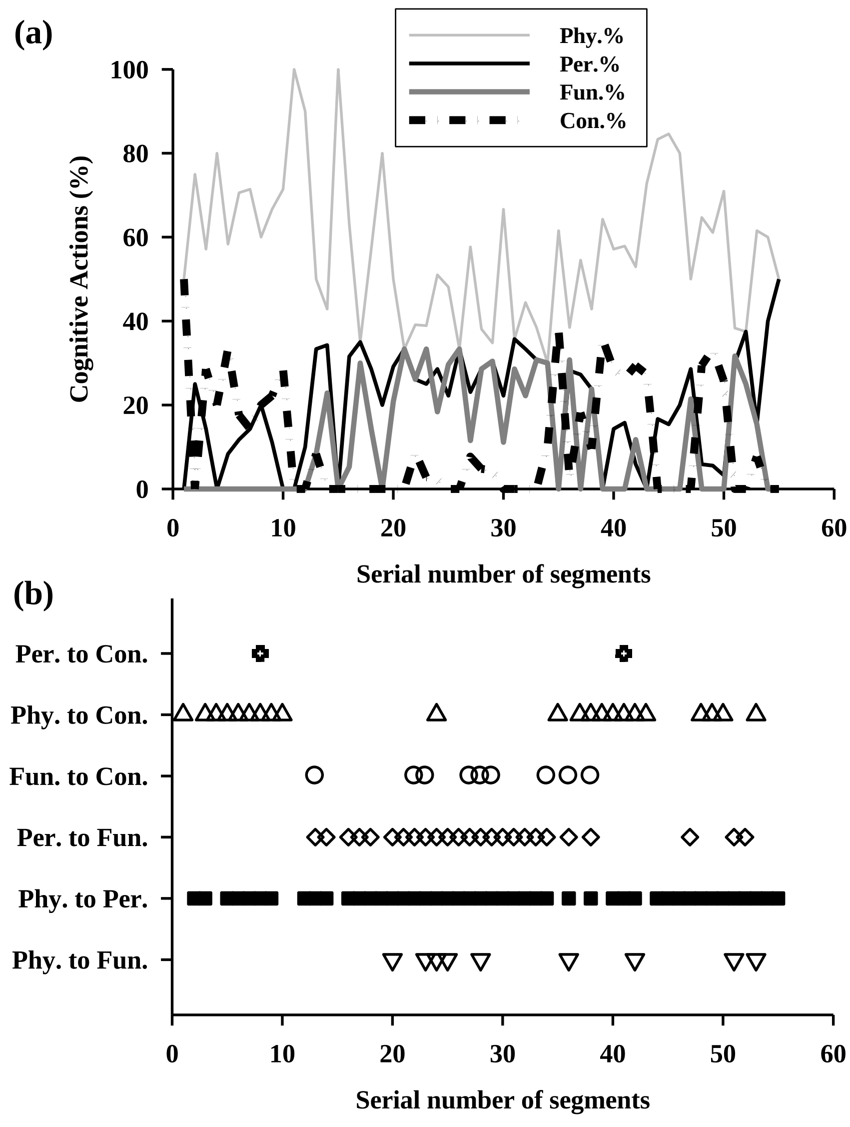

Figure 6-7 Comparison of cognitive actions and transitions in a design session

The conceptual actions frequently occurred at the beginning of the design session (segments <10) when the participant was framing and structuring the design problem.

The design goals were set up based on requirements analysis. At this early stage, physical features, such as shapes, dimensions, and materials, and physical relations, such as positions, contacts, and connections, were seldom considered. The conceptual actions also occurred near the end of the design session (segments >35) when the participant was finalizing the design session by evaluating and combining all the design concepts. Only a few conceptual actions occurred in the stage of concept generation when the design concepts were evaluated just after they were generated.

One inexperienced designer who applied the systematic design method demonstrated a similar pattern of data shown in Figure 6-7. However, those experienced designers who did not use the systematic design method demonstrated a different pattern. No dominant cognitive actions and transitions were observed in every stage of the design sessions. Therefore, the occurrence of cognitive actions was more likely affected by the structure of design sessions than by designers' expertise levels. This may partially explain why no significant differences were observed in the number of cognitive actions (except for the conceptual actions) between the experienced and inexperienced designers (see the relation between the actions and expertise in Table **6-5**).

6.4 Significance and Application

This chapter proposed a complexity measure of information contained in sketches and verbal protocols. The complexity measure C_A can quantify the occurrence of cognitive actions and transitions at different levels of human information processing. Low complexity value in a design segment represented a small amount of cognitive actions, which implied thought break or design intent switch; while high complexity value represented high productivity of idea generation. The variation of complexity values in a design session was found to be related to mental effort reported by the participants. The time that the maximal complexity values occurred, which represented the time that a critical design solution arrived, was also related to mental effort. The higher the variation of complexity values and the later the peak values occurred, the higher the mental effort was rated. Therefore, the complexity measure can indicate the fluent flow of design thoughts in a whole design session (for example, Figure 6-5).

The complexity measure C_A can also help to identify effective design methods. The patterns of fluctuation and distribution of complexity values varied with different design methods (see Figure 6-5 and Figure 6-6). The generation of a conjecture design solution at the early design stage is beneficial for reducing mental effort and thus improving cognitive efficiency (see Table 6-4). The efficient design methods identified in the present study are also supported in the fields outside engineering design. An experienced software developer argued that efficient software development methodology is to do testing after all the code is completely done (Bryan, 2011). The advantage of this approach is that the developer can focus on the design of the code rather than think about other activities such as the missing requirements, the requirements satisfaction, the evaluation of the code design, and the implementation for that code (Bryan, 2011). In order to develop software efficiently, the developers should also know the whole process of code design. Producing a requirements document, specification document, and a design document (pseudo code) gives the developer ample opportunity to think about the code and design the code well from the start (Bryan, 2011). In addition, it is very important to create a quick prototype that can be shown to get early feedback. All the efficient practices are in accord with the results from the present study in the field of engineering design.

In addition, the complexity measure C_A identifies the contribution of sketching activity and perceptions to cognitive efficiency (see Table 6-5). In the present study, the experienced participants were able to sketch efficiently by using appropriate representations, that is, conceptual sketches. However, the inexperienced participants sometimes used either presentation drawings (for example, with colors and shadows) or technical drawings (for example, exploded view drawing), which were simply labored re-workings of conceptual sketches but not furthering the design concepts. After the experiment, some inexperienced participants mentioned that they felt it was difficult to sketch down the structure elements in their minds; they thought their sketches were not exactly what they "saw" in their memory. The ability to quickly sketch and visualize ideas plays an important role in the early stage of design (Yang & Cham, 2007). In addition, the experienced participants were able to think of more non-visual physical properties than the inexperienced individuals from the perceptions of sketches, such as stability, strength, and failure, which led to further mechanical analysis and productive design ideas. Therefore, efficient sketching representations and effective perceptions of sketches may lead to a relatively high level of overall cognitive efficiency for experienced participants.

The cognitive actions were described in a bottom-up hierarchy of information processing. Dividing cognitive actions into four categories corresponding to three levels of information processing can give insight into which level of information processing should be focused on in order to enhance cognitive efficiency. The coding scheme also benefits studying cognitive efficiency at the neurological level. Studies in neuroscience have found that the visual input is analyzed in a cascade of cortical regions. Therefore, cognitive actions at the neurological level can be linked to cortical processors in the human brain. For example, perception can be linked to low-level cortical processors, such as the primary visual cortex, and semantics can be linked to high-level cortical processors, such as the inferior temporal cortex (Bar, 2003). If both cognitive efficiency and cognitive actions can be observed by neuroscience technologies, the relation between cognitive efficiency and cognitive actions can also be examined at the neurological level.

In addition, cognitive actions in other design process models can be corresponded to the three levels of information processing. Consequently, the relation between cognitive actions and cognitive efficiency in this study can be extended to other design process models. For example, one of the most prominent models in engineering design is the function-behavior-structure (FBS) model, which considers designing as a process of transforming posited functions into a design description of an artifact that can perform these functions. This model includes an explicit representation of the cognitive processes of designing, where eight steps characterize the relationships between three fundamental variables: function, behavior, and structure.

In this model, the function is defined as “the design intentions or purposes,” and the behavior is defined as “how the structure of an artifact achieves its functions” (Gero et al., 1992, p 193). In the present study, the definition of functional action is related to the considerations of both functions and behaviors in the FBS model. The participants usually generated design concepts to satisfy functions and subfunctions (that is, functions in the FBS model) at the stage of concept development, and they frequently considered the achievements of the design goals (that is, behaviors in the FBS model) when judging and evaluating the design concepts near the end of design sessions. Setting up design goals when framing and structuring the design problem at the beginning of design sessions is defined as conceptual action at the highest level of information processing because this action is based on knowledge in designers' long-term memory. The present study included functional and conceptual actions in the category of semantic information processing for the purpose of studying designers' cognitive efficiency.

The four categories of cognitive actions and six categories of cognitive transitions between those actions can be related to the five steps in the FBS model (see Table 6-7). The remaining three steps (Steps 6 to 8) reformulate the earlier steps by searching for a new structure and expected behaviors or functions until the evaluation is satisfactory. The relation between the steps of the FBS model and information categories is not linear because each step can involve several levels of information processing. Steps 2 (synthesis) and 3 (analysis) are the most frequently referred to physical and perceptual actions, both of which are found to significantly correlate with cognitive efficiency (see Table 6-5). Therefore, synthesis and analysis are the two critical steps that can be improved to enhance cognitive efficiency.

In this study, cognitive efficiency was measured based on the overall mental effort reported by the participants instantly after the design sessions. Although the relation between RSME and each category of cognitive actions and transitions can be roughly assessed in Table 6-5, the mental effort invested by each participant on each design activity such as concept generation and evaluation was unknown. In future work, if cognitive efficiency can be measured at the neurological level in real-time design sessions, the relation between conceptual actions and cognitive efficiency during each design stage can be re-evaluated in more detail. In addition, studies in neuroscience have found that the visual input is analyzed in a cascade of cortical regions. Therefore, cognitive actions at the neurological level can be linked to cortical processors in the human brain. For example, a low level of perception can be linked to low-level cortical processors, such as the primary visual cortex, and a high level of semantics can be linked to high-level cortical processors, such as the inferior temporal cortex (Bar, 2003). If both cognitive efficiency and cognitive actions can be observed by neuroscience technologies, the relation between cognitive efficiency and cognitive actions can also be examined at the neurological level.

Table 6-7 Steps in the FBS model corresponding to cognitive actions and transitions

FBS model	Information categories
Step 1: formulation. Transform the posited functions to a description of behavior that is expected to enable this function.	Step 1 can be related to transitions *Phy.−Fun.* and *Phy.−Con.*, by which the product functions/behaviors are considered without visual perceptions as well as design goals are set up.
Step 2: synthesis. Transform the expected behavior into a structure for the artifact to be designed that is intended to exhibit this behavior.	Step 2 can be related to physical actions and transitions *Phy.−Per.* by which a structure is sketched down and its physical features are perceived. Conceptual actions may also happen when knowledge is retrieved from long-term memory.
Step 3: analysis. Derive the actual behaviors of the structure.	Step 3 can be related to functional actions and transitions *Per.−Fun.*, by which physical states and interactions are perceived from sketches.
Step 4: evaluation. Comparison of the actual and expected behaviors.	Step 4 can be related to conceptual actions and transitions *Fun.−Con.*, by which design concepts are evaluated.
Step 5: documentation. Production of the design description.	Step 5 can be related to physical actions and transitions *Phy.−Fun.* and *Phy.−Con.*, by which the product functions/behaviors are summarized.

6.5 Summary

This chapter proposed a complexity measure of information contained in unstructured data. The free-hand sketched entities and retrospective verbal protocols were used for coding designers' cognitive actions. The cognitive actions were coded into four major categories: physical, perceptual, functional, and conceptual according to a bottom-up hierarchy of information processing. The complexity of cognitive actions, represented as a logarithmic function of the number of cognitive actions and transitions at different levels of information processing, was found to correlate with cognitive efficiency measures (Table 6-2). The result was in accord with the neurological efficiency hypothesis that the more the mental resources consumed, the lower the cognitive efficiency. The complexity values appeared to not be related to the expertise levels of designers (Table 6-2), but the variation and frequency distribution of complexity values were controlled by the design methods used (Table 6-3 and Figure 6-6). In addition, the complexity measure can indicate the fluent flow of design thoughts and help to identify effective design methods (Figure 6-5).

Not all cognitive actions and transitions equally contributed to design outcomes and cognitive efficiency. The numbers of physical and perceptual actions were related to cognitive efficiency (Table 6-5), which suggested that sketching activity and the perceptions of sketches are two critical factors affecting cognitive efficiency. The transitions from the physical to the perceptual and from the perceptual to the functional were two dominant transitions that frequently occurred during the stage of concept development and were found to be related to mental effort (Figure 6-7). The present study observed that generating a solution conjecture but not fixing on it during the early design stage was beneficial for cognitive efficiency (see Table 6-4 and the discussion in Section 6.3.2); the other is to divide such design activities as goal set-up, concept generation, and evaluation into different stages (see Table 6-5 and the discussion in Section 6.3.4).

Chapter 7 Complexity of Idea Links

7.1 Introduction

Design ideas in a design process (segments in a verbal protocol) are not independent, and some ideas are linked to others. A process like idea mapping (or mind mapping) has been found to improve idea development. Idea links have been studied to provide insight on design activities, especially at the early stage of idea development. Quantitative tools have been developed to visualize and measure the structure of idea links. Examples include flow graph to indicate the level of design strategy usage (Kim et al., 2007), distance graph to reveal the degree of idea development (Cai et al., 2010), link matrix to study the visual means of expression in group design (van der Lugt, 2000), and linkography to assess design productivity (Goldschmidt, 1990).

Linkography is a technique used to discern the relationships among design segments to form links (Goldschmidt, 1995). In protocol analysis, if two design segments are related to each other, they are connected by two straight lines perpendicular to each other (see Figure 7-1; the protocols are partially shown due to the limit of space). The graphical representation of a design process traces the associations of every design segment and displays the structure of the idea generation processes.

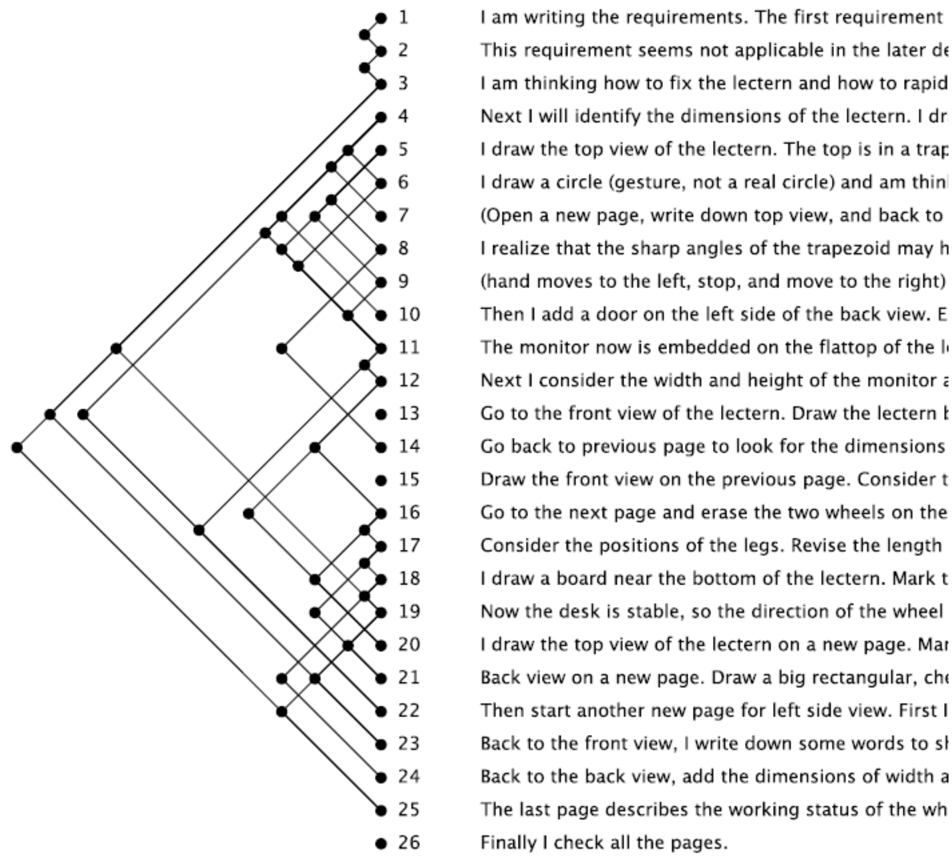

Figure 7-1 Linkograph of verbal protocol by a participant

Different linkograph patterns have been identified and related to the quality of design processes. Back-links connecting to previous moves record the path that led to a move's generation, while fore-links connecting to subsequent moves bear evidence relating to their contribution to the production of further moves (Goldschmidt, 1995). Chunks are a group of moves that are almost exclusively linked among these moves; webs are a large number of links among a relatively small number of moves. More chunks and webs are related to more creative design (Cai et al., 2010). A well-integrated creative process is found to be related to a large network of links and a balance of link types (van der Lugt, 2000, 2003).

Some metrics based on the links in a linkograph have been used as indicators of the quality of concept generation. Link index and critical links are counted as indicators of design productivity (Goldschmidt, 1995), and the link density index is used to measure design fixation (Perttula & Sipila, 2007). The definition of links based on “lateral transformation” and “vertical transformation” is used to represent both the breadth and the depth of the problem space explored in design (Cai et al., 2010). The entropy of links is interpreted as idea development opportunities and a measure of design creativity (Kan & Gero, 2008; Kan & Gero, 2009). Unrelated design segments indicate no converging ideas, hence a very low opportunity for idea development; however, a fully saturated linkograph indicates no diversity of ideas, hence also less opportunity for quality outcomes (Kan et al., 2007). The higher entropy of fore-link and back-link implies a richer idea generation process as they reveal a higher degree of uncertainty.

In summary, these empirical studies attempt to use linkography as a measure of the quality of design processes and the quality of concept generation. However, the relation between idea links and cognitive efficiency has not been studied. It is still unknown whether too few or too many idea links would degrade cognitive load and affect cognitive efficiency. The present study aims to examine whether the metrics of links (including the number, distance, and entropy of idea links) are related to the metrics of performance (including design outcomes, mental effort, and cognitive efficiency), and whether the relations change with designers’ expertise levels.

7.2 Methods

7.2.1 Definition of linkograph measures

The segmentation of sketching processes was the same with that in Section 6.2.1. Each sketching process was segmented by a significant pause, and each segment presents a coherent proposition of an entity in the sketch (also see the example shown in Figure 6-1). If a segment revisited another previous segment and improved the design concept, modified it, or added details, the two segments were connected by two straight lines perpendicular to each other and the nodes were marked in dark (see Figure 7-1). If no improvement was identified, the two segments were not connected, for example, representing the same design concept in different perspective views or just adding some notes.

The linkograph measures include link index, critical segments, link distance, and the entropy of links. Link index is the ratio between the number of links and the number of design segments. Critical segments have connections to at least three other segments. For example, in Figure 7-1, Segment 4 is connected to five other segments, so it is a critical segment. Segment 11 is also a critical segment.

Link distance is an index for the distribution of all nodes during a design session. The centroid or the average position of all nodes represents how far the linked segments are apart in the vertical and horizontal directions (Kan & Gero, 2008). In Figure 7-2, the four nodes are treated as four points in a Cartesian coordinate system, where x is the direction of segment series and y is perpendicular to x. The four nodes connect segments (1, 2), (2, 3), (2, 4), and (1, 5). The corresponding coordinates for the nodes are calculated by Equation (7.1), that is, (1.5, 1), (2.5, 1), (3, 2), and (3, 4). Therefore, the link distances are $x = (1.5 + 2.5 + 3 + 3) / 4 = 2.5$ and $y = (1 + 1 + 2 + 4) / 4 = 2$, respectively. A higher link distance x indicates that more nodes appear near the end of a design session. A higher link distance y indicates longer linking lengths.

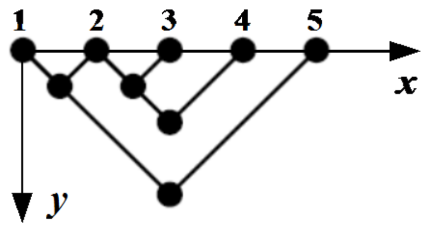

Figure 7-2 Example of link distance

$$\begin{cases} x_i = \left(node_i(1) + node_i(2)\right)/2 \\ y_i = node_i(2) - node_i(1) \end{cases} \tag{7.1}$$

7.2.2 Shannon entropy of idea links

A quantitative tool, Shannon's entropy of information, is used to interpret linkograph. The entropy H of a random variable with a probability mass function p is defined by (Shannon, 1948):

$$H = -\sum_{i=1}^{n} p_i \log(p_i) \text{ with } \sum_{i=1}^{n} p_i = 1 \tag{7.2}$$

In Equation (7.2), n is the number of possible outcomes. The entropy H is a measure of the average uncertainty in the random variable. It is the number of bits on average required to describe the random variable. So the amount of information carried by a message is based on the probability of the occurrence of a known random variable. If there is only one outcome, there is no uncertainty (when $n = 1$, $p_i = 1$, and $H = 0$).

In Figure 7-3, a linkograph with 8 segments is shown as an example. The random variable is the idea link between two segments; it has two possible outcomes: "*ON*" or

"*OFF*." The linked nodes (black dots except those in the first row) are considered as "*ON*" and the unlinked nodes (gray dots) as "*OFF*." In Figure 7-3, there are in total $8 \times (8-1) / 2 = 28$ nodes for links; 11 out of 28 are existing links and the other 17 are unlinked. The percentage for linked nodes is $11 / 28 = 39.3\%$, and the percentage of unlinked nodes is $17 / 28 = 60.7\%$. The probability of occurrence of each outcome (either *ON* or *OFF*) will be $p(ON) = 0.39$ and $p(OFF) = 0.61$, respectively. According to Equation (7.3), the entropy of whole idea links H_l is 0.97.

$$H_l = -p(ON) \times \log_2(p(ON)) - p(OFF) \times \log_2(p(OFF))$$
$$\text{where } p(ON) + p(OFF) = 1 \tag{7.3}$$

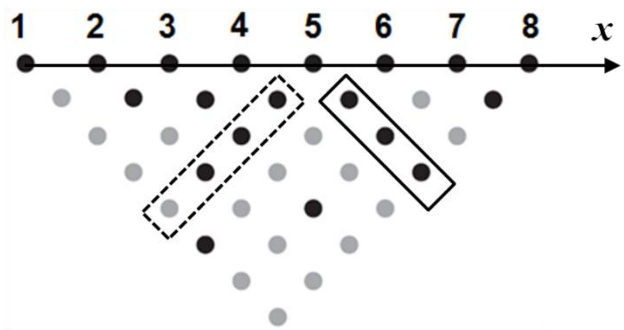

Figure 7-3 Example of entropy measurement

Equation (7.3) is interpreted in Figure 7-4. The maximum entropy is one when $p(ON)$ or $p(OFF)$ equals 0.5. When $p(ON)$ is less than 0.5, H_l is increased with $p(ON)$; when $p(ON)$ is more than 0.5, H_l is decreased with $p(ON)$. A previous study argued that the higher entropy indicated a higher degree of uncertainty, and therefore higher opportunity for idea development (Kan, Bilda, & Gero, 2006; Kan et al., 2007). The present study aims at investigating the relation between the degree of the uncertainty of idea links and cognitive load. The assumption is that the higher the degree of uncertainty, the higher the cognitive load.

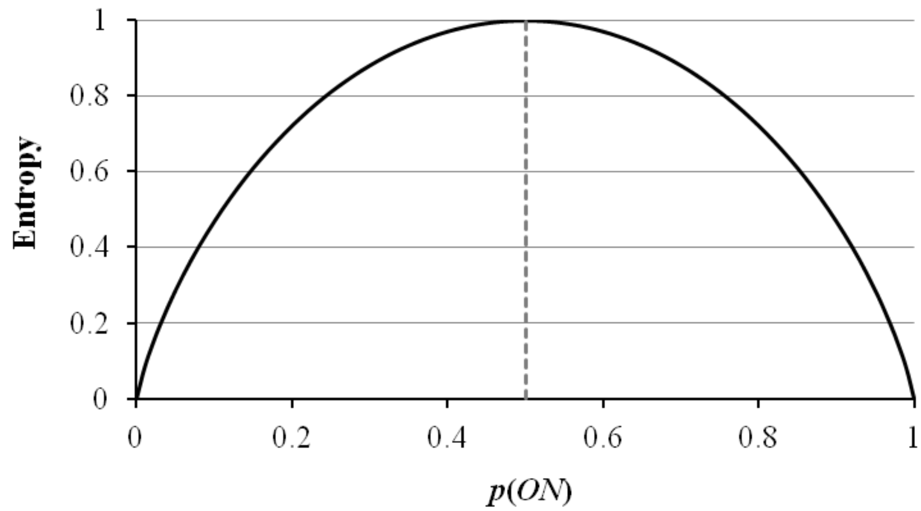

Figure 7-4 Entropy measure of idea links

Equation (7.3) calculates the entropy of whole links in Figure 7-3. The link entropy of each individual segment can also be calculated. Two rectangles are marked in Figure 7-3 as an example for calculating. For Segment 5, the solid rectangle includes the nodes connecting Segment 5 and forward segments, that is, Segment 6, 7, and 8; while the dashed rectangle includes the nodes connecting Segment 5 and backward segments, that is Segment 1, 2, 3, and 4. There are three possible positions for nodes inside the solid rectangle, and all of them are linked. The probabilities of linking and unlinking are $p(ON) = 1$ and $p(OFF) = 0$, respectively. According to Equation (7.3), the fore-link entropy for Segment 5 is 0. Similarly, the back-link entropy for Segment 5 is 0.81. The accumulative entropy for fore-links or back-links is the sum of individual entropy for the all segments in a design session. The present study will investigate which link entropy (whole-link H_l, fore-link H_f, or back-link H_b) is related to cognitive efficiency and thus how to improve cognitive efficiency by analyzing idea links.

7.3 Results and Discussion

7.3.1 Comparison of linkograph measures

Since two design sessions from the non-mechanical group were too short to build enough idea links, only 21 design sessions were analyzed in this chapter; 9 were from the mechanical group, and the other 12 were from the non-mechanical group. Out of 23 design sessions, 8 had critical segments, which were connected to at least three other segments, and 6 of them applied the systematic design method. One design session during which the systematic design method was applied had as many as 37 critical segments out of 55 segments. The critical segments occurred at the beginning of design sessions when design requirements were proposed, and these requirements were considered (the segments were revisited and improved) during the later stage of concept generation. The critical segments also happened near the end of design sessions when several design concepts were evaluated and compared (the segments were revisited and improved). The application of the systematic design method helped to build connections between design segments.

Table 7-1 lists the Pearson Product Moment Correlation of linkograph measures. The link index significantly correlated with all the other linkograph measures except for the entropy of whole links. The entropy measure of whole links was not related to other measures. The link index, fore-link entropy, and back-link entropy were highly and linearly related to each other since the correlation coefficients were over 0.9 and the p values were less than 0.001. That is because the scores for fore-link or back-link entropy increased with the number of design segments in a design session.

Table 7-1 Correlation matrix between linkograph measures

Measures	*Link distance* *x*	*Link distance* *y*	*Entropy H_l* (whole-links)	*Entropy H_f* (fore-links)	*Entropy H_b* (back-links)
Link index	0.713 * (< 0.001)	0.729 * (< 0.001)	0.356 (0.113)	0.935 * (< 0.001)	0.909 * (< 0.001)
Link distance *x*		0.852 * (< 0.001)	−0.304 (0.180)	0.873 * (< 0.001)	0.888 * (< 0.001)
Link distance *y*			−0.188 (0.413)	0.836 * (< 0.001)	0.873 * (< 0.001)
Entropy H_l (whole-links)				0.053 (0.820)	−0.023 (0.921)
Entropy H_f (fore-links)					0.961 * (< 0.001)

*: $p < 0.05$

The linkograph measures were compared between the mechanical and non-mechanical groups (see Table 7-2). The mechanical group had a significantly higher link index and entropy scores for fore-links and back-links than the non-mechanical group. The data did not support significant difference in the link distance and whole-link entropy between the two groups; therefore, the centroid positions of link nodes and the saturation of linking were not significantly different between the two groups.

Table 7-2 Comparison of linkograph measures between two groups

Linkograph Measure	t-test (n = 19; d is Cohen's d)	Significance ($p < 0.05$ & $d > 0.8$)
Link index	$t = 3.411$, $p = 0.003$, $d = 1.4$	Yes
Link distance x	$t = 1.453$, $p = 0.163$, $d = 0.7$	No
Link distance y	$t = 1.803$, $p = 0.087$, $d = 0.6$	No
Entropy H_l (whole-links)	$t = 1.435$, $p = 0.168$, $d = 0.6$	No
Entropy H_f (fore-links)	$t = 2.411$, $p = 0.026$, $d = 1.0$	Yes
Entropy H_b (back-links)	$t = 2.811$, $p = 0.011$, $d = 1.2$	Yes

The relation between link index and link entropy is further examined in Figure 7-5. Fore- and back-link entropy linearly increased with link index, which was in accord with the results in Table 7-1. Most of the data points for the fore-links were below those for the back-links; 7 out of 9 mechanical group members and 5 out of 12 non-mechanical group members had higher scores for back-link entropy than fore-link entropy. The mechanical group appeared to revisit design ideas backward more frequently than the non-mechanical group. A previous study also found that the senior architect and junior architect had higher entropy scores for back-links than fore-links; by contrast, the landscaper had higher scores for fore-links than back-links (Kan & Gero, 2008). The two studies suggested that experienced participants tended to enhance the design concepts that they had generated, while inexperienced participants rarely further considered and improved their design concepts, probably due to the lack of domain-specific knowledge.

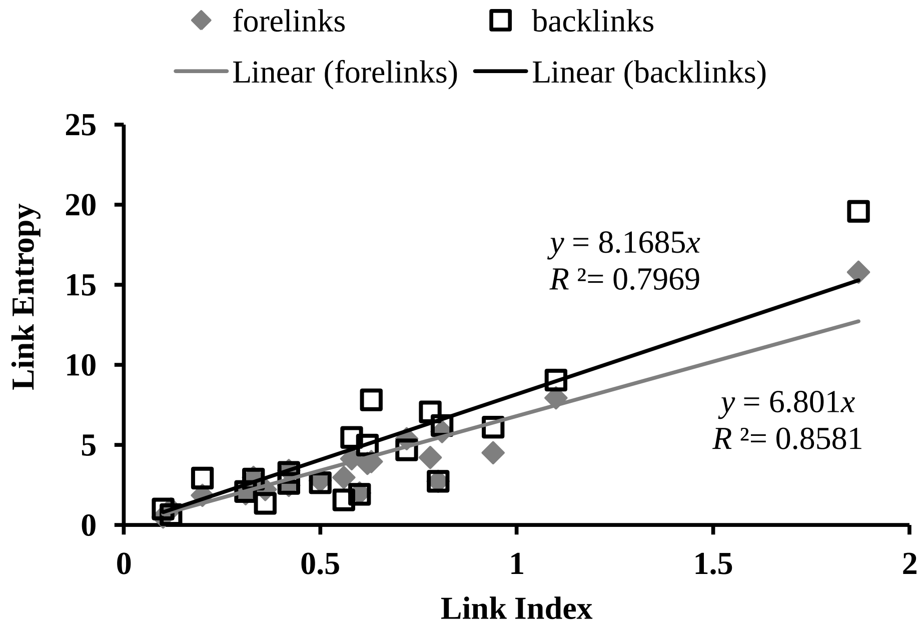

Figure 7-5 Relation between link index and entropy measures

In addition, the back-link entropy can be twice as high as the fore-link entropy when the systematic method was used (data from participant S15). Linked nodes near the end of a design session had larger weight in the fore-link entropy scores than the nodes at the beginning of the design session because the nodes near the end had fewer possible positions for linking forward; that is, the probability of linking $p(ON)$ was likely larger (see Equation (7.3) and Figure 7-4). Similarly, linked nodes at the beginning of a design session had larger weight in the back-link entropy scores than the nodes at the end of the design session. When different design methods were applied, the degree to which one segment was linked to other segments varied in the design process. For example, if a systematic method was used, the segments at the beginning of the design process would be intensively linked to some segments in the middle stage due to the connection between requirement identification and concept generation. If the final design solution was integrated from several subsolutions, the segments near the end of the design process would be intensively linked to the segments in the middle stage, during which subfunctions were proposed and satisfied. Therefore, the application of design methods determined the distribution of linked nodes and had an effect on the fore- and back-link entropy scores.

7.3.2 Relation between linkograph measures and expertise levels

In Table 7-3, only the whole-link entropy is significantly related to expertise levels. The whole-link entropy is a function of the probability of linking, $p(ON)$, and the relation between $p(ON)$ and the entropy is shown in Figure 7-6. All the 21 data points are located on the left of the dashed line, which represents $p(ON) = 0.5$. One square (mechanical group member) and one circle (non-mechanical group member) data points were separated from other data points because the numbers of segments for the two design sessions were very small (=5), and so the denominators of $p(ON)$ were small and $p(ON)$ values were relatively large. Most of the entropy values were between 0.2 and 0.6, and accordingly the $p(ON)$ values were between 5% and 15%. The whole-link entropy values for the two groups were not significantly different (see also Table 7-2; $t(19) = 1.435$, $p = 0.168$). However, the most frequent entropy value for the mechanical group was 0.4, while for the non-mechanical group the value was 0.3. The experienced participants appeared to demonstrate higher uncertainty of idea links than the inexperienced participants. Therefore, the whole-link entropy may be used as an indicator of expertise levels: the higher the entropy values, the higher the expertise levels.

Table 7-3 Relation between linkograph measures and expertise levels

	Link index	*Link distance x*	*Link distance y*	*Entropy H_l* whole-links	*Entropy H_f* fore-links	*Entropy H_b* back-links
Expertise	0.408 (0.067)	0.093 (0.689)	0.146 (0.529)	0.514 * (0.017)	0.223 (0.332)	0.248 (0.279)

*: $p < 0.05$

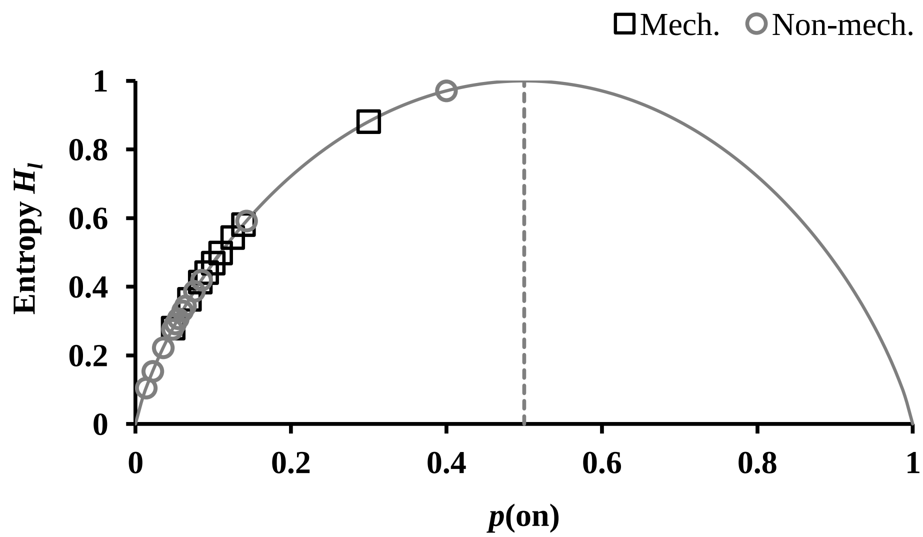

Figure 7-6 Whole-link entropy measurement of idea links

7.3.3 Relation between linkograph measures and design outcomes

The Pearson Product Moment Correlations between the linkograph measures and the creativity measures of design outcomes are listed in Table 7-4. The link index and the fore- and back-link entropy were significantly related to the four creativity measures. The whole-link entropy was not related to the creativity measures. Link distances *x* and *y* were related to the creativity measures except for novelty scores. The results indicated that idea links contributed to design outcomes.

Table 7-4 Correlation between the linkograph measures and creativity measures

Measures	*Creativity*			
	Novelty	*Variety*	*Quality*	*Quantity*
Link index	0.465 * (0.034)	0.823 * (< 0.001)	0.506 * (0.019)	0.797 * (< 0.001)
Link distance x	0.406 (0.068)	0.828 * (< 0.001)	0.480 * (0.028)	0.880 * (< 0.001)
Link distance y	0.342 (0.130)	0.865 * (< 0.001)	0.504 * (0.020)	0.852 * (<0.001)
Entropy H_l (whole-links)	0.012 (0.959)	−0.045 (0.846)	−0.074 (0.750)	-0.135 (0.559)
Entropy H_f (fore-links)	0.463 * (0.034)	0.895 * (< 0.001)	0.499 * (0.021)	0.914 * (< 0.001)
Entropy H_b (back-links)	0.483 * (0.027)	0.929 * (< 0.001)	0.602 * (0.004)	0.920 * (< 0.001)

*: $p < 0.05$

7.3.4 Relation between linkograph measures and cognitive efficiency

The Pearson Product Moment Correlations between the linkograph measures and cognitive efficiency as well as mental effort are listed in Table 7-5. The cognitive efficiency has four measures. The link index, link distance *y*, and the back-link entropy were significantly related to the efficiency scores for variety and quantity. The whole-link entropy was not related to efficiency measures and mental effort. The fore-link entropy was related to the efficiency scores for quantity. No linkograph measures seemed to be related to the efficiency measures of novelty and quality.

Table 7-5 Correlation between the linkograph measures and efficiency measures

Measures	*Cognitive Efficiency*				*RSME*
	Novelty	*Variety*	*Quality*	*Quantity*	
Link index	0.160 (0.490)	0.506 * (0.019)	0.211 (0.359)	0.489 * (0.025)	0.220 (0.338)
Link distance x	−0.111 (0.631)	0.280 (0.220)	−0.039 (0.868)	0.323 (0.153)	0.479 * (0.028)
Link distance y	−0.008 (0.973)	0.467 * (0.033)	0.134 (0.563)	0.459 * (0.036)	0.305 (0.179)
Entropy H_l (whole-links)	0.209 (0.363)	0.165 (0.474)	0.143 (0.537)	0.093 (0.689)	−0.229 (0.318)
Entropy H_f (fore-links)	0.018 (0.937)	0.424 (0.055)	0.063 (0.785)	0.442 * (0.045)	0.380 (0.089)
Entropy H_b (back-links)	0.090 (0.697)	0.512 * (0.018)	0.204 (0.375)	0.509 * (0.019)	0.315 (0.165)

*: $p < 0.05$

In Table 7-5, only link distance *x* was related to mental effort. Although the distance *x* value was highly affected by the number of segments in each design session (see Equation (7.1)), the number of segments was not significantly related to mental effort ($n = 21$, $r = 0.379$, $p = 0.091$). Higher link distance *x* indicated that the centroid of nodes appeared closer to the end of a design session; therefore, the result implied that the later the previous design ideas were revisited/modified/enhanced, the more mental effort was reported. This result was in accord with that shown in Table 6-4, that is, the later the critical features of design solutions arrived (when the maximal complexity of design actions occurred), the more mental effort was reported. Both results suggested that generating and improving conjectural solutions in the early stage of design helped to relieve mental effort.

The link distance *y* represents the length of linking. It is assumed that a longer linking length demands more cognitive resources and hence causes higher mental effort. In Figure 7-7, the link distance *y* was related to mental effort only for the mechanical group (r = 0.733, p = 0.025). Some non-mechanical group members reported that their mental effort was less than 37 ("*some effort*") presumably because they did not identify the challenge of the design task, that is, conflict exists in requirements. The others reported that their mental effort was over 60 ("*rather much effort*") presumably because they felt they did not have enough domain-specific knowledge and sketching skills to solve the design problem. If the two types of non-mechanical group members were separated, the mental effort appeared to increase with the link distance *y* for each type.

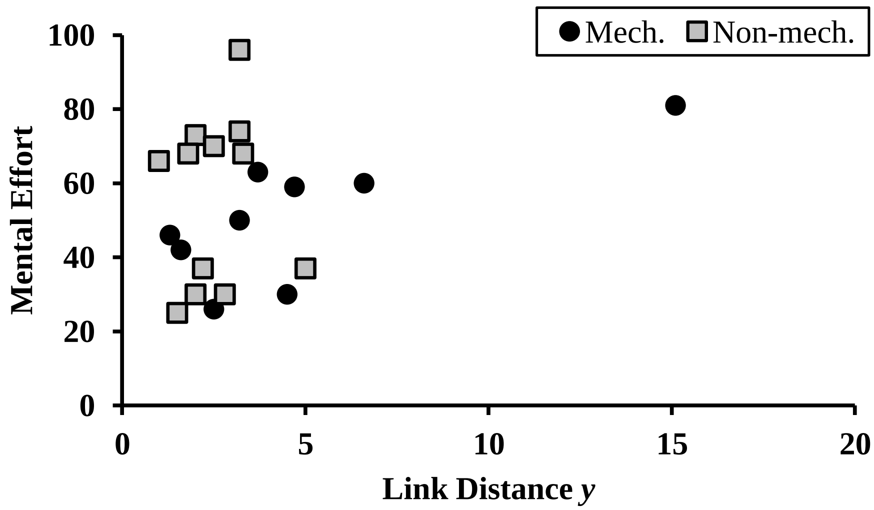

Figure 7-7 Relation between link distance *y* and mental effort

In addition, the application of effective design methods helped the participants to effectively revisit design ideas that were generated previously. In Figure 7-8, the frequency distributions of link distance *y* for different design methods are compared. For the non-systematic design method, the link distances were not able to reach design ideas over 7 segments away, and around 60% of the distance data were no more than 2 segments. However, for the systematic design method, more than 70% of the distance data were over 2 segments, and around 40% of the distance data were over 7 segments. The effective design methods could make the designers revisit their previous design ideas as far as over 30 segments.

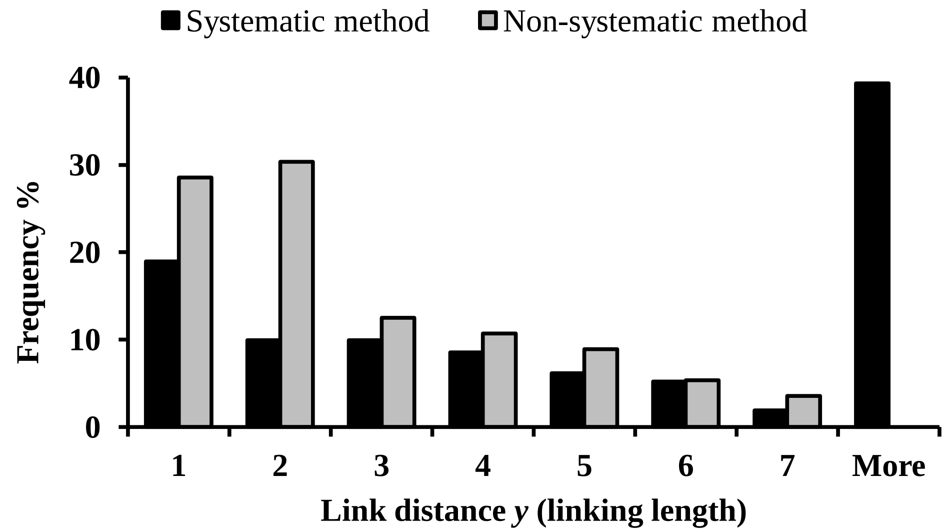

Figure 7-8 Frequency distribution of link distance *y*

Entropy, the measurement of uncertainty, was found to be not related to cognitive load (measured by self-reported mental effort). The assumption that a higher degree of uncertainty leads to higher cognitive load was not supported by the data. A possible reason was that the overall cognitive load was rated at the end of a design session while the fore- or back-link entropy was accumulated during the design session. In future work, if cognitive load at each design segment could be monitored, the relation between entropy and cognitive load could be dynamically observed during the design session. The other reason may come from the counting of links. Links were not counted when previous design ideas were revisited but not improved. Actually, the non-mechanical group members sometimes went back to read their previous design ideas without improvement due to the lack of ability to improve the ideas. The mechanical group members sometimes revisited previous design ideas without improvement by just combining them into the final design solutions. In both situations, mental effort was invested, but links were not counted. Therefore, the percentages of linked nodes were undercounted and the entropy may be under- or over-estimated according to Equation (7.3). In future work, if effective cognitive load (which effectively contributes to the fulfillment of a design task) could be separated from overall cognitive load and be measured with real-time signals such as eye mean pupil diameter change rate, the relation between effective cognitive load and the uncertainty of idea links could be investigated (Sun, Yao, & Carretero, 2015a).

7.4 Summary

In this chapter, the linkograph measures including link index, critical segments, link distance, and link entropy were compared among 21 participants with different expertise levels. The mechanical group demonstrated significantly higher link index, more critical segments, and higher fore- and back-link entropy than the non-mechanical group. The relations between the linkograph measures and the performance measures including creativity and cognitive efficiency were also examined. The correlation between the measures is summarized in Table 7-6 (significant correlations marked by "√"). The whole-link entropy was related to expertise levels. Meanwhile, other linkograph measures including link index and fore- and back-link entropy were related to the creativity measures. No linkograph measures were found to be related to the cognitive efficiency scores for novelty and quality.

The link distances *x* and *y* were related to mental effort. The results suggested that generating and improving conjectural solutions in the early stage of design could help to relieve mental effort. In addition, the application of effective design methods helped the participants to organize their design processes and effectively revisit and improve previous design ideas.

Table 7-6 Significant correlation between the linkograph and performance measures

Measures		Expertise Levels	Creativity				Mental Effort	Cognitive Efficiency			
			Novelty	*Variety*	*Quality*	*Quantity*		*Novelty*	*Variety*	*Quality*	*Quantity*
Link index			√	√	√	√			√		√
Link distance x				√	√	√	√				
Link distance y				√	√	√	√		√		√
Entropy	Whole-links H_l	√									
	Fore-links H_f		√	√	√	√					√
	Back-links H_b		√	√	√	√			√		√

√: significantly correlated

Chapter 8 Summary and Future Work

8.1 Summary

This study first developed a method which assessed designers' cognitive demands and performance in terms of cognitive efficiency (Chapter 4). The cognitive efficiency measure not only focused on the relationship between designers and their design outcomes, but also graphically presented the other two evaluations: the creativity of design outcomes and the effort invested to generate the outcomes. Cognitive efficiency has four measures corresponding to the four measures of creativity. The four measures of cognitive efficiency can be used in different situations and should not be substituted for one another.

Moreover, the information based approaches were applied to quantifying unstructured data including sketches and verbal protocols. The design sessions along with the participants' cognitive processes were described from three different perspectives: the effectiveness of problem structuring (Chapter 5), the complexity of cognitive actions (Chapter 6), and the entropy of idea links (Chapter 7). In Chapter 5, problem structuring was represented by a tree structure of function decomposition, which revealed how the participants perceived and constructed an open-ended design problem, and the effectiveness of problem structuring was used for assessing problem structuring strategies, such as decomposition modes and control strategies. In Chapter 6, cognitive actions were defined in a systematic way by encoding sketches and verbal protocols into a bottom-up hierarchy of human information processing, and the complexity of cognitive actions were used for identifying the fluent flow of design thoughts and the contribution of sketching activity and perceptions to cognitive efficiency.

In Chapter 7, idea links were graphically presented in a linkograph, and the saturation, centroid, length, and uncertainty of linking were used to study the process of idea development.

In addition, the information-based measures were used to compare the performance of groups with different expertise levels and applying different design methods. The relations between the information based measures and cognitive efficiency were also investigated to examine critical factors that affect cognitive efficiency. Table 8-1 summarizes the relation between different complexity/entropy measures and cognitive efficiency as well as expertise levels. The complexity measures were related to different aspects of cognitive efficiency. The results suggest that enhancing (or decreasing) the complexity would benefit corresponding cognitive efficiency. For example, the complexity of tree structure C_T correlated with the efficiency scores for variety and quantity, indicating that enhancing the breadth and depth of the tree structure (of problem structuring) can be helpful for improving the efficiency scores for variety and quantity. Similarly, the back- and fore-link entropy of idea links correlated with the efficiency for quantity, which suggests that re-considering a previously generated design idea and adding new features is beneficial for the efficiency scores for quantity. Moreover, the complexity of cognitive actions correlated with the efficiency scores for quality. Excess cognitive actions including physical and perceptual actions for each design concept led to lower cognitive efficiency scores for quality (see the results in Table 6-5). The whole-link entropy of idea links did not correlate with the efficiency measures but with the participants' expertise levels. The experienced participants tended to demonstrate a higher uncertainty of idea links than the inexperienced participants. Therefore, the whole-link entropy may be used as an indicator of expertise levels: the higher the entropy values, the higher the expertise levels. Table 8-2 summarizes the description of the complexity measures and the corresponding answers to the three research questions proposed in Section 1.3.

Table 8-1 Relation between complexity measures and cognitive efficiency

Complexity Measures	*Cognitive Efficiency*				*Expertise*
	Novelty	*Variety*	*Quality*	*Quantity*	
Complexity C_T (*Problem Structuring*)		+ (Table 5-3)		+ (Table 5-3)	
Complexity C_A (*Cognitive Actions*)			– (Table 6-2)		
Entropy H_l (*Whole-links*)					+ (Table 7-3)
Entropy H_f (*Fore-links*)				+ (Table 7-5)	
Entropy H_b (*Back-links*)		+ (Table 7-5)		+ (Table 7-5)	

+: positively correlated; −: negatively correlated; the tables in the bracket provided the original data.

Table 8-2 Summary of the complexity measures

Complexity or Entropy Measures	Answers to the three research questions (proposed in Section 1.3)			Suggestions for design education
	Q1: How are designers' cognitive processes quantitatively described?	Q2: Do the quantitative measures relate to designers' performance?	Q3: Do the quantitative measures relate to designers' expertise levels?	
C_T (Problem Structuring)	The complexity C_T describes how complex a design problem is constructed in a designer's mind. The complexity C_T also represents the *solvability* of design solutions (Figure 5-9).	The complexity C_T was related to the four measures of creativity, as well as the cognitive efficiency scores of variety and quantity (Table 5-3).	The complexity C_T was different between the two groups (Table 5-4).	Explicit decomposition and the breadth-first control strategy are beneficial for problem structuring.
C_A (Cognitive Actions)	The complexity C_A describes how much information is contained in a design session. The complexity C_A also represents the component *size* of a cognitive process.	The complexity C_A was related to mental effort and the cognitive efficiency scores of quality (Table 6-2).	The complexity C_A was not related to expertise levels. The fluctuation of C_A values in a design session was related to design methods used.	Generating a design conjecture at the beginning of a design session is beneficial for relieving mental effort and enhancing cognitive efficiency.
H_l, H_f, and H_b (Idea links)	The entropy measures describe the *connection* of design segments in a design session and the uncertainty of linking forward or backward.	The entropy H_f and H_b were related to the creativity and cognitive efficiency measures (Table 7-4 and Table 7-5);	The entropy H_l was related to expertise levels (Table 7-3).	The effective design methods could make the designers effectively revisit and improve their previous design ideas.

8.2 Contributions

This study proposed information based approaches to systematically describing designers' cognitive processes. The results of this study provide information for designers' performance evaluation, design method comparison, design strategy identification, and design expertise development. The contributions of this study are listed as follows:

Evaluation of designers' performance

Considering design outcomes alone is not enough. Designers' cognitive demands/costs should be integrated in the evaluation of performance. The relation between cognitive demands and design outcomes can be examined by cognitive efficiency, which describes how designers invest mental effort to achieve the design outcomes. Cognitive efficiency has been found to be related to designers' expertise levels and the design methods used.

Comparison of design methods

The systematic design method outperformed the other two methods, "*no alternatives*" and "*no control*," in the levels of creativity and cognitive efficiency (Figure 4-5). Not all the experienced participants applied the systematic design method. The use of effective methods could help make up for a lack of experience and knowledge. The application of effective design methods helped the participants to better structure the design space (Figure 5-11 and Figure 5-12), better control the cognitive actions (Figure 6-6), and more easily access their previous design ideas (Figure 7-8). The effective design methods should be encouraged in design education even though not all the experts applied these methods all the time.

Identification of design strategies

The present study identified effective/efficient design strategies. The explicit decomposition and the breadth-first control strategy were more effective in problem structuring than the implicit decomposition and the depth-first strategy (Figure 5-11 and Figure 5-12). The generation of a conjectural solution at the early stage of design is beneficial for relieving mental effort and thus improving cognitive efficiency (see Table 6-4). Moreover, setting up design goals as well as separating concept evaluation from concept generation benefits cognitive efficiency; so do efficient sketching representations and effective perceptions of sketches (Section 6.3.4 and Section 6.4).

Development of expertise in design

The mechanical group outperformed the non-mechanical group in the levels of creativity and cognitive efficiency (Figure 4-2 and Figure 4-3). The mechanical group perceived a higher difficulty level of the design task and constructed more complex problem structures mentally than the non-mechanical group (Table 5-4). The experienced participants preferred to use explicit decomposition and structured control strategies because of training received (Table 5-5). The experienced participants tended to evaluate/judge design concepts after standard criteria were established and thus conducted fewer conceptual cognitive actions for each design concept than the inexperienced participants (Table 6-5). The experienced participants were able to sketch efficiently by using appropriate representations, that is, conceptual sketches, and "read off" more non-visual physical properties than the inexperienced individuals from the perceptions of sketches. The mechanical group also demonstrated more idea links per design segment (that is, link index) and higher entropy of linking forward or backward (H_f and H_b) than the non-mechanical group (Table 7-2). Furthermore, the mechanical group appeared to revisit design ideas backward more frequently than initiate new ideas forward; while the non-mechanical group tended to link ideas more forward than backward. The uncertainty of idea links ε_w was also related to expertise levels (Table 7-3).

In addition, the approaches proposed in the present study contribute to the literature of design cognition.

Encoding of cognitive processes

In the present study, the main target of encoding was based on sketches rather than verbal protocols. Describing cognitive actions in a bottom-up hierarchy of information processing can give insight into which level of information processing should be focused on in order to enhance cognitive efficiency. These four categories of cognitive actions are model-independent and thus can be linked to other design process models (Table 6-7), which can help to identify which steps in other design process models are related to cognitive efficiency.

Complexity of cognitive processes

Complexity in engineering design measures the size of the composite, the degree of interconnections, and how difficult it is to solve or analyze a design problem. Studies have dealt with the issue of measuring complexity in terms of design problems, design processes, and design products. The present study extends the application of complexity measures for studying designers' cognitive processes. The complexity measures of problem structuring and cognitive actions, together with the entropy of idea links, describes the solvability, size, and connection of the cognitive processes, respectively (see Table 8-2).

8.3 Limitations

The experiments were conducted in a controlled environment. Participants were asked to complete a specific design task in an unspecified period. There are some limitations regarding design task, participants' expertise levels, and the measure of cognitive load. The applications of results of the present study may also have some limitations when extended to other design areas outside mechanical engineering.

Design behavior and performance vary with design tasks (Atman et al., 2005). It is important to consider the length, the context specificity, and the complexity of the task (Atman et al., 2005). To accommodate all participants, the design task selected for the present study was neither a classical mechanical device, which may constrain concept generation, nor one as novel as a robotic lunar explorer, which is too complicated to complete in a few hours. The selected task in the present study had both advantages and disadvantages. On the one hand, participants are familiar with teaching podiums on campus and are able to generate some design concepts even if they have no experience in design. On the other hand, the selection of a familiar object as a design task may restrict task-specific motivation to some extent, and may therefore have some effect on cognitive efficiency.

Participants in the present study were randomly recruited from engineering staff and students. Some of them had no design knowledge and experience at all, and some of them had work experience in engineering design before they came back to school. However, most of the mechanical group members were not real experts, those who should have more than 10 years design experience (Ericsson, Krampe et al., 1993) as industry professionals. The expertise levels for the mechanical and non-mechanical groups were 3 and 0 years respectively on average. Although the quantitative measures and the relations between these measures demonstrated significant differences between the two groups, the results need to be re-examined with a wider range of participants who have higher expertise levels.

In the present study, mental effort (cognitive load) was self-reported by participants at the end of design sessions, and cognitive efficiency was evaluated at the performance level. The dynamic details of mental effort and cognitive efficiency in a design session were unknown. If cognitive efficiency can be observed in real time during a design session, more details on cognitive actions will reveal how to improve cognitive efficiency. Physiological methods, such as eye-tracking and EEG (Cai & Lin, 2012; Sun, Xiang, Chai, Wang, & Huang, 2014), can be a supplement to subjective methods because the former methods can analyze objective observations of behavior, physiological conditions, brain activity, or performance. However, there are some limitations to applying physiological measures in design processes. For example, EEG signals are very sensitive to fluctuating mental and emotional states, so they should be re-calibrated as frequently as every few minutes. It is not convenient to apply EEG technology in the whole design process which may take a few hours or even several days/months. In addition, designers' sketching activities, which are critical for visual thinking and concept development, will be constrained when EEG signals are collected. In future, technical developments may allow the objective measures to be unobtrusively and reliably applied during the design process.

8.4 Further Studies

The present study suggests future work should examine the results in a wider population, extending the methods to a wider research area, and applying the identified strategies to practical education and training.

The methods proposed in the current paper help to explain design behavior that can also be used for problem-solving in other fields. The design strategies, for example, generating as many ideas as possible or focusing on the initial idea, are used to structure the design process. In engineering design, designers use three types of knowledge: knowledge to generate ideas, knowledge to evaluate ideas, and knowledge to structure the design process (Ullman, 2009). The first two types of knowledge are domain-specific. Idea generation comes from natural ability and experience; idea evaluation comes from experience and formal training. However, knowledge about the design process is largely independent of domain-specific knowledge (Ullman, 2009). Additional studies using domain-specific design problems across different fields such as electrical and software engineering will definitely increase generalization and should be considered in future work.

Cognitive efficiency describes how individuals efficiently solve problems under cognitive load. Cognitive load represents the load imposed on the cognitive system by a particular task. Therefore, cognitive efficiency can be further studied by considering the properties of tasks (for example, task difficulty) and problem solvers (for example, cognitive capacity and cognitive style) and the relation between tasks and problem solvers (for example, motivation, interest, and expectation).

In the present study, cognitive efficiency described the relation between cognitive cost and cognitive benefit. Cognitive cost was represented by designers' mental effort, and cognitive benefit was quantified by the creativity levels of design outcomes. The cost and benefit can also be described by other properties according to the research goals. For example, time can be the cost, and esthetic appeal (instead of functional requirements in the present study) can be used as a criterion for the benefit. In addition, in face-to-face or net meeting collaborative design processes, both individual cognitive efficiency and group cognitive efficiency can be evaluated. The encoding scheme of cognitive actions and linkograph can also be used for analyzing interactions between designers (Cai et al., 2010; Kan & Gero, 2008; van der Lugt, 2000).

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Appendix A: Consent Form

I have read the information presented in the information letter about a study entitled "Modeling and Quantification of Sketch Changes during the Conceptual Design" being conducted by Dr. Sophie Yao and Ms Ganyun Sun in the Department of Mechanical Engineering, at the University of New Brunswick. I have had the opportunity to ask questions about my involvement in this study and to receive additional details I requested. I understand I have been given a copy of this form. I agree to participate in the study.

SECTION 1. PURPOSE

I have been informed that the purpose of the research is to understand how design information changes during the sketching process in order to develop more natural sketching tools to assist designers to generate creative design concepts.

SECTION 2. PROCEDURES

This research will be conducted in our research lab, located in HE44, Head Hall, the University of New Brunswick. I understand that my participation will require me to:

1) in the first session, solve a design problem on a Tablet PC monitor for no more than one hour;
2) in the second session, verbally describe my thoughts during the design process and answer questions regarding the design from the experimenter for about one hour;

SECTION 3. POTENTIAL HARMS, RISKS OR DISCOMFORTS

The risks involved in participating in this study are minimal. You can discontinue the participation at any time if any potential risk or discomfort is identified during the experiment.

SECTION 4. CONDITIONS OF PARTICIPATION

- I understand that my participation in this study is voluntary and I am free to withdraw my consent and discontinue my participation at anytime without negative consequences.

- I consent to be video- and audio- taped as I participate in this study. Yes☐ No☐

SECTION 5. INFORMATION ABOUT THE STUDY RESULTS

- I understand that the data from this study may be published.
- I understand that my participation in this study is CONFIDENTIAL, that is, the researcher will know but will not disclose my identity, and that my name will not appear in any published data.
- I would like to receive a summary of the study's results.

Yes,☐ please send them to this email address

____

or to this mailing address

____

No,☐ I do not want to receive a summary of the study's results.

I HAVE CAREFULLY STUDIED THE ABOVE AND UNDERSTAND THIS AGREEMENT. I FREELY CONSENT AND VOLUNTARILY AGREE TO PARTICIPATE IN THIS STUDY.

NAME (please print) ____

SIGNATURE ____

WITNESS SIGNATURE ____

DATE ____

If at any time you have questions about your rights as a research participant, please contact Bernd Kurz, Chair of the Research Ethics Board, University of New Brunswick, at (506) 453-5189 or by email: ethics@unb.ca

Appendix B: Survey Form

Thank you for taking part in this research project. This survey form will help us better understand your background in engineering design and analyze the experiment data. The subject number is arranged in the sequence of experimental date. Your name will never be used in the presentation or publication of the results unless you specifically hope so. Any information related with this research we get from you is confidential and will only be accessed by the member of the research team.

Subject No. ________________________

Degree: __________________________

(If working) Field: ________________

(If working) No. of Years: __________

(If studying) Program: _____________

(If studying) No. of Years: __________

Gender: ___________________________

Age:
25 and below ( ) 26-30 ( ) 31-35 ( )
36-40 ( ) 41-45 ( ) 46- 50 ( )
50 and above ( )

Mother language:
____

Date: __________________________________

Questions:

1. Do you like design? If yes, which kind of design do you like best, e.g. architecture, mechanical, structural, furniture, costume, fashion, et al.?

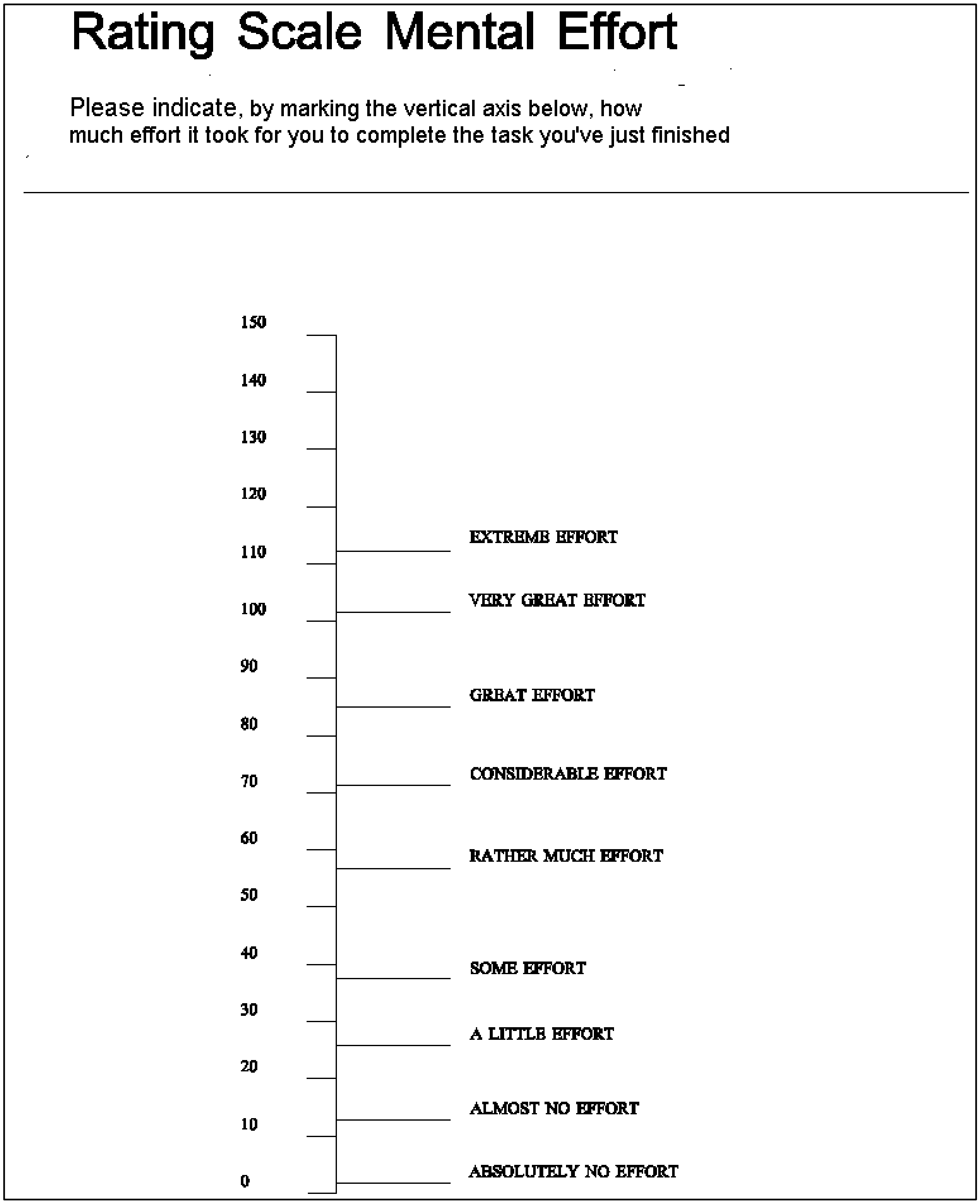
2. Have you designed something or tried to design something in mind before? If yes, what did you design?

3. Have you studied any courses about any design theory or methodology? If so, what did you learn from them?

4. Do you have any work experience in design of mechanical, electrical, or structural, architecture, etc.? If so, how many years?

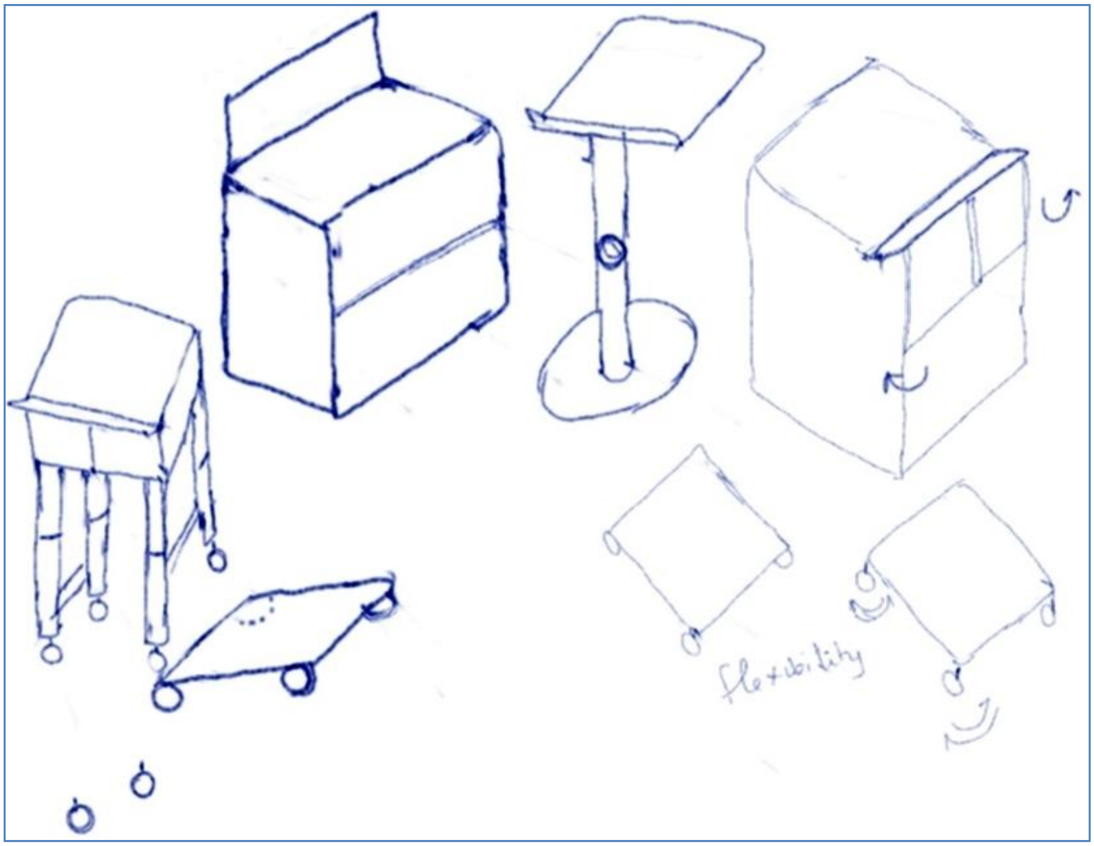
If at any time you have questions about your rights as a research participant, please contact Bernd Kurz, Chair of the Research Ethics Board, University of New Brunswick, at (506) 453-5189 or by email: ethics@unb.ca

Appendix C: Rating Scale Mental Effort (RSME)

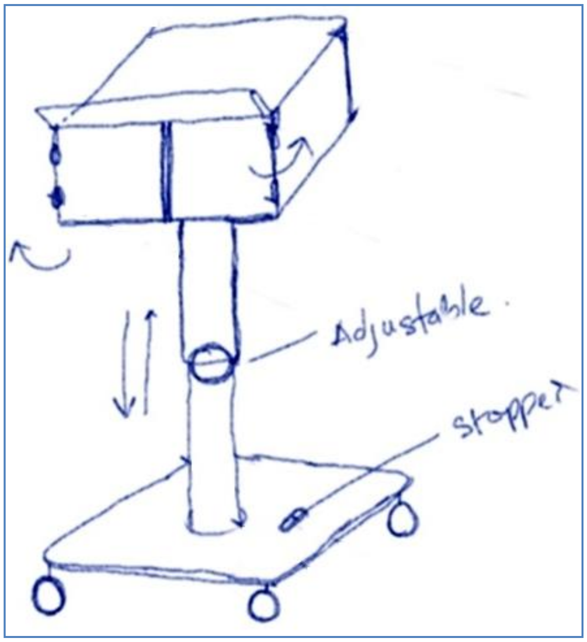


Appendix D: An Example of Data Analysis

D.1 Original Sketches by Participant 3

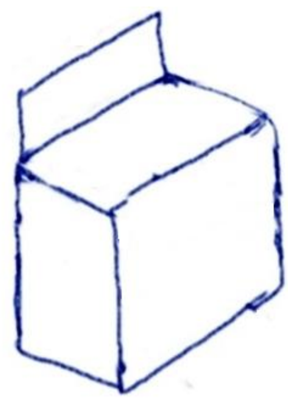


Page 1 by Participant 3

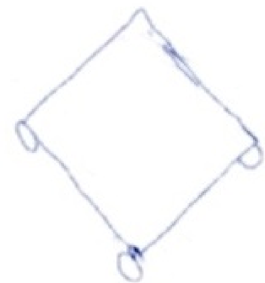


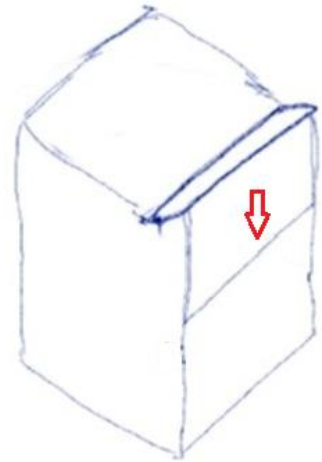
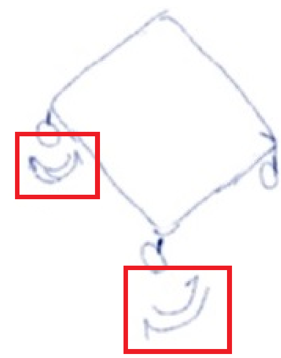
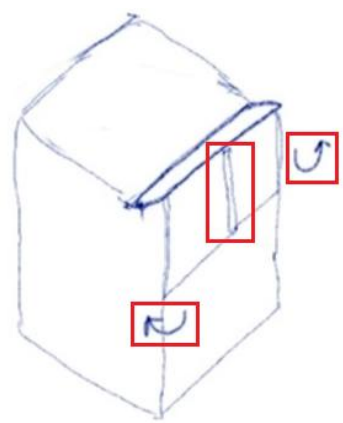
Page 2 by Participant 3

D.2 Segment and Transcript

Segment	Transcript	Sketch
#1	I was trying to figure out the look of the (podium), how it is going to look like, how will the podium look like. And now, this is like a box, like a podium I was thinking about. This is the podium I thought. This is one of the concepts. I was thinking that could satisfy this, the requirements.	

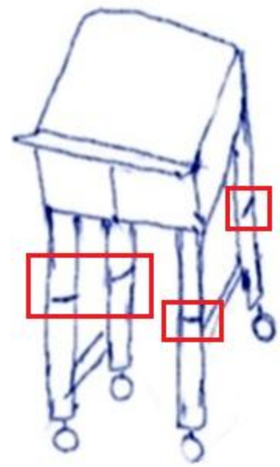
Segment	Transcript	Sketch
#2	Initially, I was in mind that the podium would be stationary. From the knowledge I've known before because I have looked podiums. The podiums I normally knew is, they are stationary. We can't move them. I am going to the requirements. I saw that the podium needs to be moved. It is adjustable. It doesn't block the students' view to see the chalkboard. So I am thought of trying to look the concepts on how to move the podium based on the requirements. So that is why I thought of this (gesture: wheels). This is a wheel, wheel to move the podium (gesture: move hands), make the podium to move. They have four wheels. This, the podium will be put, initially I thought of put, place it (box) on the top of this wheel. So it could move.	
#3	I was trying to draw my concepts; another podium concepts. This was the top of the podium, where the laptop, lecture materials will be placed. So I am trying to, it is similar to this (the box), I was trying to reshape, thinking in mind, there is no space, based on the requirement, yes, there is no space, between the students' desk and chalkboard. So, another thing, this concept, I thought of, here (the box) I didn't think of, maybe the laptop fall or something. So here I try to add a groove on this, to prevent the laptop from falling off.	

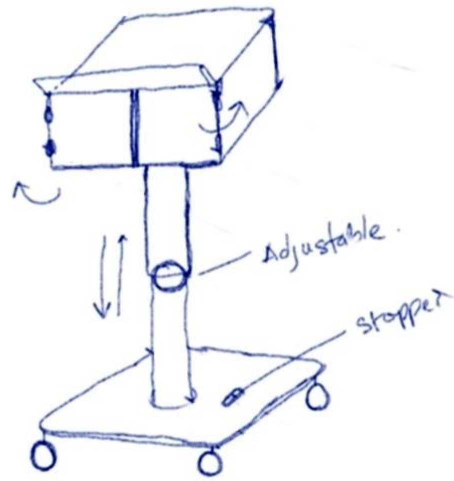
Segment	Transcript	Sketch
#4	This is still another concept for the podium. I was thinking another function of the podium, which is movement. It could move. So I was trying to develop different way. The movement function can be, look like, this was I was trying to, I was trying to decomposing the function of the podium, this is the, trying to draw the wheel. How the wheel could look like, it could be different from I've drawn this one. So I was trying to develop different, different ideas, or how the wheels could look like, based on what is written here (gesture: the design problem), based on the requirements of the podium. So this was actually what I was trying to...	
#5	Here the wheel doesn't, it wasn't flexible (12:00). It cannot be twisted. It is rigid. It cannot go forward and back. So I thought of that. This one, I was trying to make it a little bit flexible, so that it can move in any direction. Like this one, the previous one I was talking about. This detail, I thought of this concept, the movement function, I thought of making the front view. One or two of the wheels are flexible. But it was rigid. So it can move the, help move the podium in different directions. This was the concept. Then this one, I was trying to draw, trying to make the four wheels flexible, so that each of them can move in any direction.	

Segment	Transcript	Sketch
#6	I was thinking another function of the podium, because I read the requirements "for instructors to put laptop, lecture notes, and other teaching materials". I was thinking to put something like a groove in here, so the lecturer is presenting with the laptop, maybe another lecture notes can be put inside the groove. It just came into my mind. I was trying to develop the concepts based on the requirements of the... So this groove is like another function of the podium, like sub function of the podium.	
#7	(add arrows to show the direction of movable wheels) I was trying to show, like this, the wheels can move any directions. It is just a symbol to show that.	
#8	I was thinking so many things, like how do I, is it OK to put a door. Like this, still the same function, about, I was trying to put a door, so the lecturer, if he want to take something, he just open like that, take it off or put it back, whatever, it just like protect the content of groove. The two arrows just show the door could be open (gesture: open the door) in that direction.	

Segment	Transcript	Sketch
#9	Something again came to my mind, as I said, as I go through the requirements, I was trying to develop as many concepts as I could, based on this requirements, here, I was trying to develop another concepts, that this one (on the right) and this one (on the left) are too big, because it said, the requirement says “it doesn’t block the students’ view to chalkboard”. I was trying to make it as simple as I can. This is the base, and then this is like a stand, a single stand, not having a big box, like this... I thought of OK, why not...let me... maybe this concept might be OK. I was just thinking how to make it a good representation of the requirements, because the customer has requirements, right? So I was trying to develop as many concepts as I could to fit the requirements. I was trying to develop the top of the podium, where the laptop put... so I was trying to, how will the top looks like? This is like a stopper, to prevent the lecture notes or laptop from falling off. I really have what I have in mind, so I was trying to represent it on paper.	

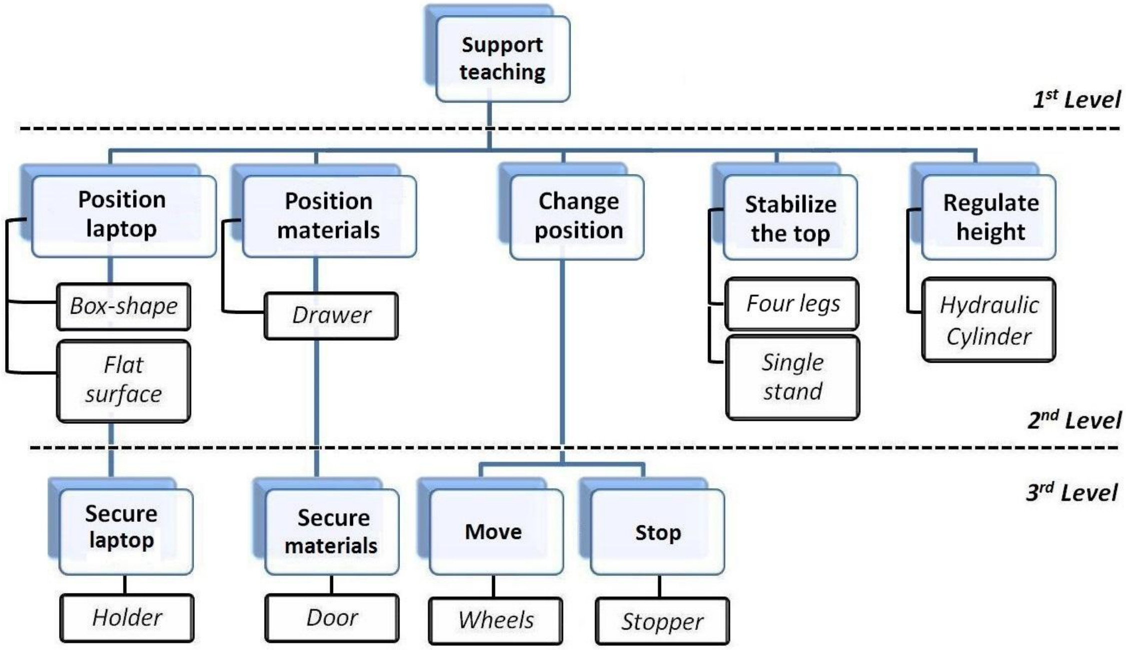
<table>
<tr><th>Segment</th><th>Transcript</th><th>Sketch</th></tr>
<tr><td>#10</td><td>I was thinking of how to put this groove, the sub function of holding all the materials, I was trying to develop another concept that could co-operate that requirement (gesture: on the left of sketch). It is similar to this (gesture: on the top of the sketch), but I was trying to add, something like a groove to this concept. I was trying to develop the groove. When I say the groove, I mean this, something like a drawer. This was another concept. This has four legs. It has the same top with this (on the top of the sketch), but this has a groove and four legs. It is like a link between two legs, just make it a little bit stronger, like a stabilizer. This concept has legs. It is smaller. One wheel on each of the legs. Wheel to make it move. Initially I thought of stability. This might not be stable. So I thought of feet, that is OK. Probably I will use four legs on this, just make it stable. That is why I decided four legs. Initially when I was drawing the box, this concept is just a plate of, is just a layer, but this (gesture: at the bottom) is a little bigger, I know it is going to contain in here, in the drawer, it will contain materials, on the top it will contain the laptop, so I was thinking that the weights here (gesture: on the left of sketch) is going be much more than the weights here (gesture: on the top of the sketch). I was thinking how to make it stable. Using four legs? Here I was trying to make the legs flexible (add wheels). It can move in any direction. Just change the legs. I used this leg, the concept here (gesture: on the right), to do this (gesture: on the left).</td><td></td></tr>
</table>

Segment	Transcript	Sketch
#11	Oh, my god, how do I get another sub function here, which I just noticed that "it needs to be moved or adjusted". So I was thinking, probably making the concept, adjust the height, in case maybe the student cannot see, can be lower, moved like that, or maybe the lecturer is too tall or too short, so I was thinking what could happen. How do I satisfy that function/requirements.	

Segment	Transcript	Sketch
#12	I was thinking the adjust. I couldn't think of any idea ... so I try to, can I use the stand of this concept, the top of the concept, the door, I try to pick up some of the (gesture: put together) sub concepts... try to mix concepts, to make a main concept, how it will look like. I was trying to borrow some features, different concepts. So I try to make up to provide the, like prototype...Four legs, it won't more work, for the structure, four legs, adjust, no, no, no, I think this (gesture: in the middle of the sketch, a stand) might be a good one. Let me use this, the one stand here, use the top from here, use this movement concept, to combine them together to form the whole prototype. Four legs, it won't more work, for the structure, four legs, adjust, no, no, no, I think this (gesture: in the middle of the sketch, a stand) might be a good one. Let me use this, the one stand here, use the top from here, use this movement concept, to combine them together to form the whole prototype. I was trying to pick up different idea from different concepts, mix them together. This idea, to my old idea, to my old assessment, is the best based on the requirements. So that is why I try to draw it in a page. The top... the door... the stand. I don't want something too big. I was trying to make it as simple as I can. I prefer the single stand. I think the lecturer can adjust, up and down. This is a door... this is a hinge, door hinge, just to permit (gesture: open a door), like a hinge. Arrows, it can be adjusted. The four wheels can be moved in any direction. I think this is the best, subjectively, this is the best.	

Note: The red rectangles and arrows mark the part added by the participant in the design segment.

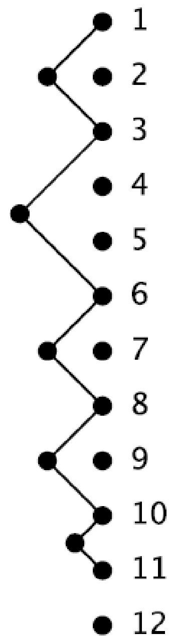
D.3 Tree-structure Function Decomposition



D.4 Encoding of Cognitive Actions

Segment	Physical Actions	Perceptual Actions	Functional Actions	Conceptual Actions	Transitions	Links	Linked Nodes	Kolmogorov Complexity
#1	5	3	3	1	7			53.34
#2	3	2	1	2	5			39.00
#3	9	4	3	2	9	1	#3-#1	75.80
#4	14	7	1	1	9	1		89.84
#5	5	3	1	2	6	1		51.00
#6	2	1	1	1	3	1	#6-#3	22.46
#7	1	1	0	0	1	1		4.75
#8	6	2	2	1	5	1	#8-#6	44.92
#9	5	3	3	1	7			53.34
#10	10	7	7	2	16	2	#10-#8	117.91
#11	3	1	0	1	2	1	#11-#10	16.25
#12	18	14	14	5	33	4		252.00

D.5 Linkograph Measures



Link index = The number of links / The number of segments = 5/12 = 0.42;

$node_i$ (1)	$node_i$ (2)	x_i	y_i
1	3	2	2
3	6	4.5	3
6	8	7	2
8	10	9	2
10	11	10.5	1

Link distance $x = \sum_{i=1}^{5} x_i = 6.6$;

Link distance $y = \sum_{i=1}^{5} y_i = 2.0$;

Entropy measures

Whole-link entropy $H_l = -p(ON) \times \log_2(p(ON)) - p(OFF) \times \log_2(p(OFF))$,

where $p(ON)$ = The number of links / Total possible links;

Total possible links = $n(n-1)/2$ = $12 \times 11/2$ = 66;

$p(ON)$ = 5/66 = 0.061 and $p(OFF)$ = 1 − $p(ON)$ = 0.939;

$H_l = -0.061 \times \log_2(0.061) - 0.939 \times \log_2(0.939)$ = 0.33.

Fore-link entropy $H_{fi} = -p_i(ON) \times \log_2(p_i(ON)) - p_i(OFF) \times \log_2(p_i(OFF))$

Serial number of segments	Fore-links	Total possible links	$p_i(ON)$	$p_i(OFF)$ $= 1 - p_i(ON)$	Fore-link entropy H_{fi}
1	1	11	1/11	0.909	0.439
2	0	10	0/10	1	0
3	1	9	1/9	0.889	0.503
4	0	8	0/8	1	0
5	0	7	0/7	1	0
6	1	6	1/6	0.833	0.650
7	0	5	0/5	1	0
8	1	4	1/4	0.75	0.811
9	0	3	0/3	1	0
10	1	2	1/2	0.5	1
11	0	1	0/1	1	0
12	0	0	0	0	0

Fore-link entropy $H_f = \sum_{i=1}^{12} H_{fi} = 3.40$

Back-link entropy $H_{bi} = -p_i(ON) \times \log_2(p_i(ON)) - p_i(OFF) \times \log_2(p_i(OFF))$

Serial number of segments	Back-links	Total possible links	$p_i(ON)$	$p_i(OFF) = 1 - p_i(ON)$	Back-link entropy H_{bi}
1	0	0	0	1	0
2	0	1	0/1	1	0
3	1	2	1/2	0.5	1
4	0	3	0/3	1	0
5	0	4	0/4	1	0
6	1	5	1/5	0.8	0.722
7	0	6	0/6	1	0
8	1	7	1/7	0.857	0.592
9	0	8	0/8	1	0
10	1	9	1/9	0.889	0.503
11	1	10	1/10	0.9	0.469
12	0	11	0/11	1	0

Back-link entropy $H_b = \sum_{i=1}^{12} H_{bi} = 3.29$

Curriculum Vitae

Candidate's Full Name: Ganyun Sun

Educational Institutions Attended:

D Sc	Institute of Mechanics, Chinese Academy of Sciences, China	2003~2008
M Sc	Dalian University of Technology, China	2000~2003
B Eng	Dalian Jiaotong University, China	1996~2000

Publications:

Peer Reviewed Journals

1. **Sun, G.**, Yao, S., & Carretero, J. A. (submitted for review). An information based approach to studying designers' cognitive processes.

2. **Sun, G.**, Yao, S., & Carretero, J. A. (in press). An experimental approach to understanding design problem structuring strategies. *Journal of Design Research*, http://www.inderscience.com/info/ingeneral/forthcoming.php?jcode=jdr

3. **Sun, G.**, Yao, S., & Carretero, J. A. (2014). Comparing cognitive efficiency between experienced and inexperienced designers. *Journal of Cognitive Engineering and Decision Making,* 8(4), 330-351. doi: 10.1177/1555343414540172.

4. Liu, X., Wang L., Wang, C., **Sun, G.**, Liu, S., & Fan,Y. (2013) Mechanism of traumatic retinal detachment in blunt impact: A finite element study. *Journal of Biomechanics*, 46(7), 1321-1327. doi: 10.1016/j.jbiomech.2013.02.006.

5. **Sun, G.**, Zhang, Y., Huo, B., & Long, M. (2009). Parametric analysis for monitoring 2D kinetics of receptor-ligand binding. *Cellular and Molecular Bioengineering*,

2(4), 495-503. doi: 10.1007/s12195-009-0079-1.

6. **Sun, G.**, Zhang, Y., Huo, B., & Long, M. (2009). Surface-bound selectin-ligand binding is regulated by carrier diffusion. *European Biophysics Journal with Biophysics Letters*, 38(5), 701-711. doi: 10.1007/s00249-009-0428-y.

7. Zhang, Y., **Sun, G.**, Lu, S., Li, N., & Long, M. (2008). Low spring constant regulates P-selectin-PSGL-1 bond rupture. *Biophysical Journal*, 95(11), 5439-5448. doi: 10.1529/biophysj.108.137141.

8. Long, M., Lu, S., & **Sun, G.** (2006). Kinetics of receptor-ligand interactions in immune responses. *Cellular & Molecular Immunology*, 3(2), 79-86.

9. **Sun, G.**, & Wang, Y. (2005). Dynamic sensitivity analysis for acoustics-structure coupled systems with sealed cavities. *Chinese Journal of Computational Mechanics*, 22(5), 550-554. (In Chinese)

Peer Reviewed Conference Proceedings (and Presentations)

1. **Sun, G.**, Yao, S., & Carretero, J. A. (2015). A pilot study for investigating factors that affect cognitive load in the conceptual design process. *Proceedings of the Human Factors and Ergonomics Society 59th Annual Meeting*, vol. 59(1), pp. 180-184. doi: 10.1177/1541931215591037 (15 min lecture presentation)

2. **Sun, G.**, Yao, S., & Carretero, J. A. (2013). An investigation of the relation between the complexity of problem structure and mental effort in ill-structured problem solving. *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, vol. 57, pp. 260-264. doi: 10.1177/1541931213571057. (15 min lecture presentation)

3. **Sun, G.**, Yao, S., & Carretero, J. A. (2013). Evaluating cognitive efficiency by

measuring information contained in designers' cognitive processes. *Proceedings of ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2013)*, vol. 5: 25th International Conference on Design Theory and Methodology, p.V005T06A029; 10 pages. doi: 10.1115/DETC2013-13628. (15 min lecture presentation)

4. **Sun, G.**, & Yao, S. (2012). Investigating the relation between cognitive load and creativity in the conceptual design process. *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 308-312. doi: 10.1177/1071181312561072. (15 min lecture presentation)

5. **Sun, G.**, & Yao, S. (2012). A framework for an evolutionary computation approach to supporting concept generation. *Proceedings of Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 1972-1976. doi: 10.1177/1071181312561292. (15 min lecture presentation)

6. **Sun, G.**, & Yao, S. (2011). A new framework of studying the cognitive model of creative design. *DS68-7: Proceedings of 18th International Conference on Engineering Design (ICED11)*, vol. 7: Human Behaviour in Design, pp. 501-510.

Conference Presentations:

1. **Sun, G.** (2015). An information based approach to studying designers' cognitive processes. Presented at the Graduate Research Conference of the University of New Brunswick, Fredericton, Canada, 23 April 2015.

2. **Sun, G.** (2013). Measuring the complexity of design problem structuring based on

function decomposition. Presented at the 9th Mechanical Engineering Graduate Students Conference, University of New Brunswick, Fredericton, Canada, 10 October 2013.

3. **Sun, G.**, Zhang, Y., & Long, M. (2006). Two-dimensional kinetics of selectin-ligand association. Presented at the 8th National Conference of Biomechanics, Hong Kong, China, 19~24 December 2006.

4. **Sun, G.**, Zhang, Y., & Long, M. (2006). Measuring interactions between biological proteins using optical tweezers assay. Presented at the 5th International Conference on Photonics and Imaging in Biology and Medicine, Wuhan, China, 1~3 September, 2006.

5. **Sun, G.**, Zhang, Y., & Long, M. (2005). Measuring receptor-ligand interactions by thermal fluctuation. Presented at the Congress of Chinese Society of Theoretical and Applied Mechanics, Beijing, China, 25~28 August 2005.