

Chapter 2

Evaluation of Empirical Design Studies and Metrics

Mahmoud Dinar, Joshua D. Summers, Jami Shah and Yong-Seok Park

Abstract Engineering design is a complex multifaceted and knowledge-intensive process. No single theory or model can capture all aspects of such an activity. Various empirical methods have been used by researchers to study particular aspects of design thinking and cognition, design processes, design artefacts, and design strategies. Research methods include think-aloud protocol analysis and its many variants, case studies, controlled experiments of design cognition, and fMRI. The field has gradually progressed from subjective to objective analyses, requiring well-defined metrics since design of experiments (DOE) involves controlling or blocking particular variables. DOE also requires setting experiment variables at particular levels, which means that each variable needs to be characterized and quantified. Without such quantification, statistical analyses cannot be carried out. This chapter focuses on quantifiable characteristics of designers, targeted users, artefacts, and processes.

Keywords Design thinking • Design metrics • Empirical studies

J. Shah (✉)

Mechanical and Aerospace Engineering, Ohio State University,
Scott Lab E343, 201 W. 19th Avenue, Columbus, OH 43210, USA
e-mail: shah.493@osu.edu

M. Dinar

George W. Woodruff School of Mechanical Engineering,
Georgia Institute of Technology, 813 Ferst Drive, Atlanta, GA 30332, USA

J.D. Summers

Mechanical Engineering, Clemson University, Clemson, South Carolina, USA
e-mail: jsummer@clemson.edu

Y.-S. Park

Mechanical and Aerospace Eng Arizona State University, Tempe,
Arizona 85287-6016, USA

2.1 Systems View of Design

The aim of most design studies has been to discover strategies and processes that could potentially result in better products, lower development time, and lower cost than the competition. A simplistic model of design is that a designer (or design team) applies design knowledge (internal and external) to a design problem, following a suitable process to obtain design solutions. A systems-level view of design is shown in Fig. 2.1; it contains most major aspects of product design from an engineering point of view. Over the past 50 years, design researchers have conducted empirical studies of virtually all of the aspects of design shown in Fig. 2.1. The objectives of these studies vary from the development of design methods and tools, to enhancing design education and the derivation of design models and theories.

An overwhelming number of design studies have targeted designers: their cognitive processes and search strategies, role of expertise and domain knowledge and characterization of design skills. Studies of design teams have included methods

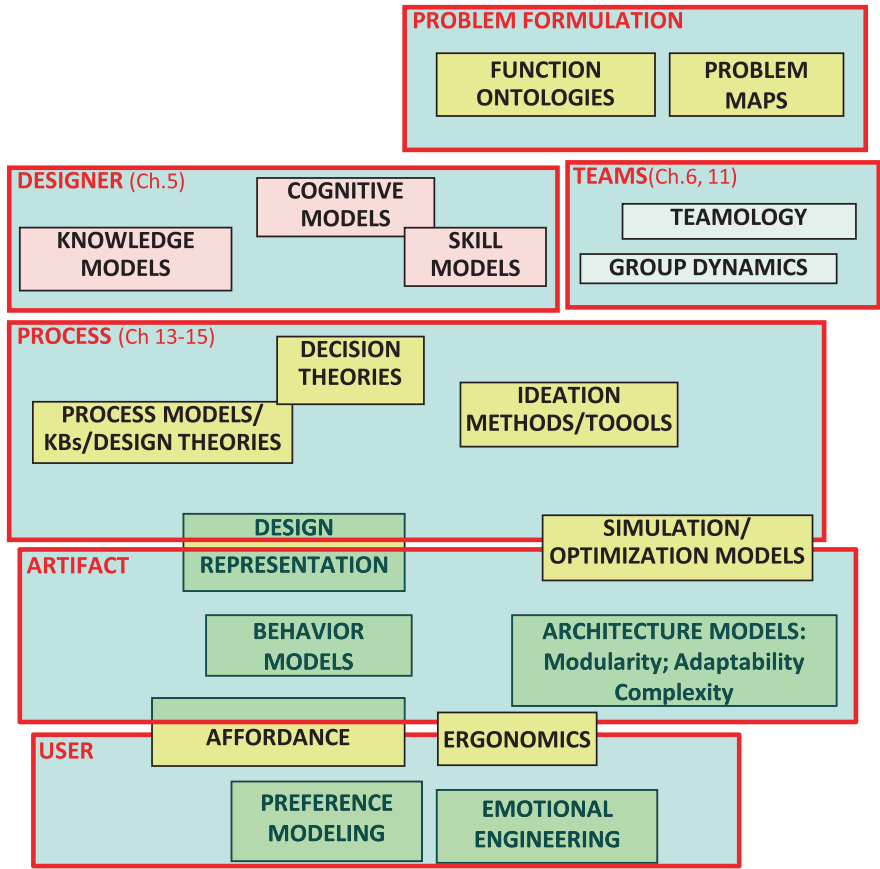


Fig. 2.1 Models of design (later chapters give more details)

for composing effective teams (teamology) and interaction of personalities and communications between team members (group dynamics). More recently, there have been studies in design problem formulation and its impact on quality and efficiency of finding good solutions. Development of function ontologies has been a major effort in this regard, with a few studies looking at broader aspects of problem formulation.

The effectiveness of various methods and tools has also been the subject of studies, from conception generation/evaluation to refinement and optimization. In the USA, there has been a heavy emphasis on utility and decision theory, largely due to heavy personal bias in NSF's design program leadership. Simulation and behaviour models tend to be domain specific and are usually not considered part of design research.

The US government and defence agencies have long been concerned by major cost overruns and schedule delays in the development of complex systems, such as military aircraft and assault vehicles. There is a belief that these systems have become overly complex due to single-minded emphasis on performance factors. There are also some in the government who believe that continuous changes in system requirements and addition of features, unintentionally rewards complexity. This has led to new research in developing metrics for complexity and adaptability, which could potentially be used in system selection process.

A key consideration in product design is an understanding of the user, his/her capabilities (ergonomics), the environment in which the product will be used, and ways in which it can be used or misused (positive and negative affordances). Ergonomics, human factors, and human-machine interfaces have long been disciplines of study in their own right, and we will not attempt to discuss them here.

Driven by mathematicians and design theorists, some popular methods, such as QFD house of quality, Kano model, and popular concept selection methods, have all come under severe criticism. One particular criticism is that these methods implicitly use linear utility, which does not account for user preferences. Another objection is that QFD violates Arrow's impossibility theorem (groups do not have transitive preferences). Yet another issue is that customer preferences collected based on individual attributes could result in products that have attribute combinations for which there may be little demand. Instead, researchers have proposed the use of conjoint analyses in developing product requirements.

One other point of clarification is necessary here. Many of the areas mentioned go across multiple boundaries than depicted in Fig. 2.1. For example, preference modelling and emotional engineering can be just as much part of problem formulation, as they are of artefact behaviour. Similarly, functional ontologies are needed in artefact modelling, as well. To show all these linkages would make Fig. 2.1 much too complicated. Also, in this article, we are leaving out another important aspect: the role of market studies and competitive benchmarking and price point targets.

2.1.1 Research Methods Used in Empirical Studies of Design

The most common method used in design studies is the so-called think-aloud protocol analysis and its many variants. This method is based on the direct observation of designers engaged in design activities. We can classify methods employed in these experiments based on *what* data are collected (verbalized actions, sketches, calculations), *how* it is collected (audio/video recording, computer tool), and *when* it is collected (during or after the design exercise). When viewed in the context of the systems view depicted in Fig. 2.1, we see that protocol analysis (PA) involves a very narrow slice, the study of cognitive processes of designers. Progressive ideation methods, such as C-Sketch and 6-3-5, do not allow direct communication between group members, so this method would not be useful. Instead, we may use an outcome-based method, such as snapshots of sketches/text progression through different key stages of these methods. Another limitation of PA is the short duration of sessions.

In contrast to PA, case studies can be used to collect data from large complex projects and can cover long periods of time. One can analyse an ongoing or past project from project documentation, interviews, meeting minutes, computer simulations, PLM/PDM data, etc. This can give a very comprehensive view of the entire system. Case studies are well suited to collecting and disseminating experiential knowledge, which is a crucial element of engineering design.

While PA is designer centric and case studies largely process centric, an artefact centric method of study is what is termed “product teardown” or reverse engineering. This method can be used for many different objectives such as, students learning how “stuff” works, or companies studying how a competitor’s product achieves a particular function, or businesses in developing countries “copying” products from well-established manufacturers. In design research, product teardown by students in design classes led to the development of a function ontology (Tilstra et al. 2009).

It is nearly impossible to simulate real-world design in an academic setting even practicing designers are used as subjects, because we can neither create the motivation, nor rewards or risks, nor the size and complexity of most real engineering design problems. Typically, studies use subjects with limited designer expertise, fictitious problems, and “play” environment with no penalty for failure. Nevertheless, such simulated design experiments have better ecological validity than controlled laboratory experiments at the microscopic level, such as those done by cognitive psychologists on perception, memory, and cognition. However, the latter have higher intrinsic validity due to the smaller number of uncontrolled factors. This leads one in the direction of multilevel, aligned experiments (Vargas-Hernandez et al. 2010) to combine the best of both.

In recent years, several studies have been examining design thinking through physiological phenomenon, such as brain imaging using fMRI apparatus and sensing other internal behaviours, such as pulse rate. They seek to determine the physiological basis for cognitive actions and emotions. This is even lower on the ecological validity scale.

2.1.2 Measurable Characteristics

To put design studies on scientific foundations, it is essential that we clearly identify all variables relevant to the subject of the study, since design of experiments (DOE) involves controlling or blocking particular variables. DOE also requires setting experiment variables at particular levels, which means that each variable needs to be characterized and quantified. Without such quantification, statistical analyses cannot be carried out. Variables may relate to designers (skill levels, creativity), artefacts (complexity, adaptability, modularity), methods (efficiency, effectiveness), design teams (composite personality, skill profile), design ideas, and so on. In the next sections, we review various characterization and quantification methods used in empirical studies.

2.2 Variable Quantification Examples

In this section, we will present examples of characterization, quantification, and measurement methods used in empirical studies in a number of areas related to design. The basis for selecting these studies is that they all involve experiments that use objective measures.

2.2.1 Ideation Metrics

Ideation metrics are needed either to assess the outcome of ideation methods in order to assess their relative effectiveness, or to assess the productivity or creativity of individuals. How should one determine how good a design idea, or a set of ideas, is? One general approach to evaluating ideation is the consensual assessment method of Amabile (1996). It suggests that a subjective assessment by a panel of judges is appropriate as long as each judge is an expert in the domain and the judges evaluate ideas independently of each other. This method has rarely been used with some modifications in ideation assessment. Kudrowitz and Wallace (2013) have defined a set of measures that assigns one of the five labels (creative, clear, novel, useful, and product-worthy) on a three-point scale (2 = yes, 1 = somewhat, and 0 = no) to an idea. An aggregate of scores of 12 random raters per idea from an online crowd is used to score ideas. The authors state that their approach is useful as a first-pass evaluation of a large pool in early ideation stages. Green et al. (2014) have conducted a similar study by crowd-sourcing novice raters. However, they have compared the novices' assessments with experts and devised strategies for selecting a subset of novice raters who have a high agreement with experts. These subjective methods can be difficult to reproduce or validate.

On the other hand, the ideation metrics of Shah et al. (2003) are well established in design research and are objective. They consist of four metrics: quantity, variety, novelty, and quality. Quantity is measured by the total number of generated ideas. Variety is a measure of total unique ideas, taking into account similarity of generated ideas. Novelty is a measure of how rare generated ideas are. It is measured in comparison with ideas generated by a set of participants in a sample or in a historic population. Quality measures the feasibility of an idea and whether it meets the design requirements. All scores are normalized on the same scale (often 1–10).

To calculate these measures, the design is decomposed into its desired key functions. Weights can be assigned to each function. Every generated idea is evaluated with respect to the key functions, and the solution for each function is described. Quantity will be the total number of ideas found by a participant. Variety will be the total number of unique ideas. Quantity and variety can be either the total number of complete solutions or the total number of subsolutions per function. A novelty score for each function is found by determining how rare the idea is, i.e. if all participants have the idea, the novelty score for that idea is the lowest; if only one participant has the idea, the novelty score for that idea is the highest. The novelty score is the sum or weighted sum of the novelty scores of all functions for all solutions. Quality can be assessed by a panel of expert judges who assign a score to each idea generated for each function. The quality score for a design is the sum or weighted sum of the quality scores of all functions.

Modifications on Shah et al.'s metrics have been proposed by others. Oman et al. (2014) propose the expanded creativity assessment method (ECAM) where weights for novelty and quality are not assigned a priori, rather they are assigned based on the rarity or frequency of the ideas in a function; the more the ideas for a function, the lower the assigned weight for it. Oman et al. (2012) conducted a survey of other creativity assessment methods where they also present an earlier version of ECAM called comparative creativity assessment.

2.2.2 Evaluating Fitness of Conceptual Designs with Requirements

Concept selection is a convergent process to evaluate alternative design concepts with respect to customer needs. To conduct concept selection, quantification methods most frequently used are as follows: Pugh matrix (Pugh 1991); quality function deployment (QFD) score (Kogure and Akao 1983); weighted sums (WSM) (Fishburn 1967); and analytic hierarchy process (AHP) score (Saaty 1980). All, except Pugh, use some form of Likert scale (5 or 9 point). The Pugh matrix compares alternative design concepts against customer needs (Pugh 1991). It not only provides quantitative results, but also allows decision makers to generate hybrid candidates. The main drawback to it is in low rating resolution, since only “–”, “s”, and “+” coding scheme is employed to ratings of each comparison.

Compared to other concept selection methods, however, its strength lies in handling a large number of decision criteria (Pugh 1991; Pugh and Clausing 1996). On the other hand, QFD is a consensus-driven analysis by showing the transformation of customer needs into appropriate technical requirements using house of quality (HoQ) (Kogure and Akao 1983). An advantage of QFD over Pugh matrix is to set weights for these technical parameters. The data from HoQ often combine with Pugh matrix to select a design concept. The weighted-sum model (WSM), presented by Ulrich and Eppinger (1988, 2004), is often applied when decision makers need high resolution for better differentiation among alternative design concepts. After allocating weights to each of the criteria, a decision maker evaluates all of the alternative concepts with respect to one criterion at a time. The total score for each concept can be determined by the summation of the weighted scores. AHP is also a multicriteria decision-making method where decision makers evaluate multiple alternative design concepts by comparing one to another by assigning weights at each level independently in the hierarchical structure. A nine-point Likert scale is used in AHP with cardinal rating via pairwise comparison, spanning from 1 to 9 and their corresponding reciprocals.

Wassenaar and Chen's (2003) study on decision-based design summarized drawbacks of concept selection using multicriteria decision making. First, normalization is inappropriate when attributes have different dimensions. As an alternative, however, the weighted-sum method (WS) and AHP account for assigning weights rather than normalization. Yet it is still quite subjective due to choices of weights and ranks. Hoyle and Chen (2007) highlight that based on Arrow's impossibility theorem (AIT) (Arrow 1950), Hazelrigg's (1996) study shows that QFD utility exists only at the individual level. Consequently, there is a need to overcome current concept selection methods.

2.2.3 Complexity Metrics

Modern products are complex cyber-physical systems; the increasing complexity impacts development time, effort, and cost. According to the US Government Accountability Office (GAO), a major system in the last decade, on average, costs 26 % more than its initial estimated cost (projected to increase and the average delay in delivering the final product was 21 months (United States Government Accountability Office 2008). Aspects of complexity include the product structure, development process, and manufacturing. Many different complexity metrics have been proposed, but few have been verified experimentally.

Complexity is defined as a quality of an object with many interwoven elements and attributes that make the whole object difficult to understand collectively (El-Haik and Yang 1999). Complexity, long studied in computer science, biology, organizational science, and information theory (Du and Ko 2000), has yielded many metrics. In engineering design, these metrics are used to evaluate the complexity of design *problem*, *product*, and *process*. As the complexity of a product

increases, the life cycle costs of the product also increase, while a simple product leads to enhanced reliability and quality at lower costs (Braha and Maimon 1998a). Others have used complexity metrics for surrogate modelling to predict assembly time and market price of products (Ameri et al. 2008; Summers and Ameri 2008; Mathieson and Summers 2009, 2010; Summers and Shah 2010). Thus, it is rarely the property of complexity that is of interest, but the property that can be predicted when considering complexity that is truly of interest.

Two views of complexity in design are that it is *the difficulty in solving a problem*, be it manufacturing or design (Braha and Maimon 1998a, b; Holtta and Otto 2005; Hamade 2009), or that *the whole exceeds the sum of the parts* (Boothroyd et al. 2002; Weber 2005). Complexity should include how the parts are assembled; it is not a simple additive property of the components, but rather an emergent property found only collectively in the assembly. This view is predominantly for studying the complexity of the designed product. Of the several developed perspectives on measuring this complexity, some propose that *complexity measures the minimum amount of information (bits) required to describe the object in a given representation* (Suh 1999, 2001). Such a paradigm ignores the possible interconnectedness of the information and the difficulty of parsing this minimal representation, however. A related perspective entails the concept of *complexity used to measure the phase change between order and randomness (entropy)* (El-Haik and Yang 1999). Similarly, through the algorithmic or computational perspective, *complexity is a measure of the tasks required to achieve some function (or components)* (Bashir and Thomson 2004) or *a measure of the number of operations required for solving a problem* (Ahn and Crawford 1994). A survey of engineering design complexity metrics (Summers and Shah 2010) classifies complexity into **size** (count of particular elements) (Kolmogorov 1983; Sedgewick 1990; Varma and Trachterberg 1990; Ahn and Crawford 1994; Fitzhorn 1994; Braha and Maimon 1998a; Simon 1998; El-Haik and Yang 1999; Balazs and Brown 2002; Bashir and Thomson 2004; Pahl et al. 2007; Shah and Runger 2011), **coupling** between elements (Dixon et al. 1988; Sedgewick 1990; Ahn and Crawford 1994; Simon 1998; Balazs and Brown 2002; Bashir and Thomson 2004; Pahl et al. 2007; Singh et al. 2012), and **solvability** (if it is possible to predict the design product to satisfy the design problem) (Fitzhorn 1994; El-Haik and Yang 1999; Suh 1999; Sen et al. 2010).

Measuring complexity in engineering design is based upon work from different domains and perspectives, including information modelling, software analysis, and traditional manufacturing and design. From an information perspective, Independence and Information axioms can be used to either reduce or manage the complexity of the design product (Suh 1999, 2001). Similarly, information theory has also been used as a baseline for measuring complexity (Braha and Maimon 1998a, b; El-Haik and Yang 1999). For example, researchers in software development have used complexity measures to determine the “Big-O” difficulty of a problem based on the best possible solution at hand, either implemented or theoretical. Engineers have adapted such complexity measures to model engineering design processes (Harrison and Magel 1981; Varma and Trachterberg 1990; Zuse

1991; Ahn and Crawford 1994; Phukan et al. 2005). Design researchers have long argued that a less complex design is preferable for many reasons (Dixon et al. 1988; Fitzhorn 1994; Simon 1998; Bashir and Thomson 2001; Balazs and Brown 2002; Pahl et al. 2007). For instance, Simon argued that engineering design is related to decomposable systems and that assessing the hierarchical interconnectedness of an engineered artefact enhances the management of such design complexities (Simon 1998). Similarly, others have shown the suitability of complexity measures for predicting assembly times, for elucidating mechanical engineering metrics for DSM and representational directional node link systems, and explored how product complexity varies based on representation (Mathieson et al. 2013; Ameri et al. 2008; Summers and Ameri 2008; Mathieson and Summers 2009, 2010; Summers and Shah 2010; Owensby et al. 2012). Much of the work on measuring complexity has been focused on developing a single holistic value or complexity function (Bashir and Thomson 2001; Shah and Runger 2011; Singh et al. 2012; Sinha and de Weck 2013a, b). Others have attempted to keep the metrics distinct, proposing instead a complexity vector (Namouz and Summers 2014; Owensby and Summers 2014; Summers et al. 2014).

While many metrics of complexity have been proposed in the literature and demonstrated on various examples, few have been experimentally compared for their utility or appropriateness in different application domains. For example, complexity metrics have been correlated with small satellite cost using single representations (Bearden 2003). The function–structure-based metric has been evaluated against large construction projects (Bashir and Thomson 2004). The complexity metric of the level of personnel cross-links in a cross-functional organization has been studied against the project cost and duration (Shafiei-Monfared and Jenab 2012). In each of these, historical data have been fit to develop single, unique complexity metrics for each application. A different series of studies have been conducted to compare different representations and complexity metrics for simple products (sprinkler, seed spreader, and table fan) (Ameri et al. 2008). It was shown that the complexity metrics are not rank-ordered consistently across different representations when comparing products. A similar study explored three types of metrics applied against different representations of products at different scales (simple gearbox and hybrid powertrain) (Singh et al. 2012).

2.2.4 Characterizing and Measuring User Preferences

A part of the design process is modelling preferences, i.e. to define what set of attributes are desired and at what level. Preference models can be a basis for concept selection in later stages. Therefore, developing mathematical models that characterize preferences in a quantifiable way is a key in an efficient design process. An example of such efficiency is the automatic or large-scale comparison of different designs or variants. Absent a mathematical preference model, comparisons are not only resource-consuming but often purely subjective. Yet, even

with mathematical models, evaluating preferences exhaustively either can be computationally expensive, or can ignore appropriate suboptimal designs due to some simplified assumptions in building the models. Hunt et al. (2007) noted that in multicriteria design optimization, Pareto efficient designs reduce the problem into a single-criterion problem and often omit unquantifiable criteria. They generalized the Pareto front to a preference cone, whereby the directional trade-off between two criteria is zero on the cone, is infinite in the first quadrant, and is a positive value otherwise. They showed that their method considered the relative importance of criteria in the optimization process and allowed designers to freely explore a set of feasible designs even when they were unfamiliar with their preferences a priori.

In another approach to reducing cost of preference modelling, Moore et al. (2014) proposed value-based global optimization (VGO), which takes into account the cost of analysis and explicitly includes it in the design utility function. They used value of information as a metric for determining the cost of optimization process. If the expected value of information is negative, analyses are terminated. VGO fits a surrogate Gaussian model into a set of existing models, and based on their cost, accuracy, and predictions, another model is selected that maximizes the value of information. Using a case study of a hydraulic hybrid passenger car (with randomly generated test data), they showed that their VGO algorithm converges fast and the cost of analysis is lower compared to the efficient global optimization (EGO) (Jones et al. 1998).

Wassenaar et al. (2005) and Wassenaar and Chen (2003), implemented discrete choice analysis in modelling consumer demands to facilitate decision making in engineering design. They studied a case using the JD Power Consumer survey on passenger vehicles where they identified five customer choice attributes such as engine-to-performance ratio and comfort level, collected data from 2552 consumers, created a choice model, and estimated demand. The model of choice probability was estimated using a binary multinomial logit function (grouped logit) on a Kano utility shape function. The result was the ability to predict change in market share based on changing a design attribute.

Wan and Krishnamurty (2001) proposed a method for learning preferences with dynamic interactive modelling. The method features devise marginal utility functions, dynamic preference information gain, and checking for inconsistencies in preferences among trade-offs. They conducted a case study solving the design of a four-bar mechanism. The design space was populated with each attribute divided into unequal intervals with a finer mesh around values where designer expected the optimum solutions. The advantages were shown to be working with locally optimal sets rather than a globally optimal Pareto front in addition to leading to more accurate and consistent preference models at a lower cognitive load on the designer.

Tovares et al. (2014) conducted a factorial experiment to examine the effect of fidelity in user experience on product preferences. They compared preference models based on virtual reality to 2D sketches and physical prototypes in the design of a long-haul truck. They found that the additional information provided

by the experience does not have a negative impact on the predictability of the preference models and that the VR experience is more similar to physical prototypes than 2D sketches.

On the other hand, Orbay et al. (2015) study the relation between 3D shape models and consumer preferences. Deconstructing the shape of a few cars, they generated a hierarchy of volumetric shape abstractions where the final shape of each car is a leaf node. Surveying about 30 participants, they found an abstraction level that made a brand recognizable. The implication is finding a point of debranding in the product shape prior to which designers can make decisions that do not endanger brand recognition. In addition, they also found relations between shape and consumer judgements in terms of attributes (adjectives) such as fast and sophisticated.

Other researches in preference modelling include a few machine learning approaches. Ren and Papalambros (2011) used support vector machines and an EGO algorithm to learn to optimize preferences iteratively based on answers from humans to queries of an interactive computer tool. Tucker and Kim (2011) proposed implementing emerging change mining techniques (e.g., very fast decision trees, or association rule mining while considering several interestingness measures such as the Gini index) to capture trends in emerging customer preferences and facilitate comparison of gain ratios of different attributes over time.

One of the early applications of mathematical modelling in describing preferences is the application of Von Neumann and Morgenstern's utility theory. Alternatively, Dym et al. (2002) propose pairwise comparison charts (PCCs) for ranking designs by designers' votes (or that of consumers), since "comparisons are cheap and require little detailed knowledge". They state that PCC should be used as a discussion tool and not a group decision tool. However, Barzilai (2006) argues that neither utility theory nor voting systems such as PCC encompass multiplication and addition which are pertinent to preference modelling in engineering design; he provides a theoretical foundation using set theory with strong scales in groups and fields.

2.2.5 Characterizing Design Problem Formulation

Not many studies focus on measuring problem formulation characteristics. The problem map (P-maps) ontological framework (Dinar et al. 2015a) is a computational framework which facilitates the representation and quantification of designers' problem formulation. The ontology allows assigning data fragments about problem formulation to one of the six entities: requirements, use scenarios, functions, artefacts, behaviours, and issues. The fragments can be related to each other within each category (entity type) with a hierarchical structure or between categories with links. Different variables can be extracted from P-maps. There are two different ways to define characteristics of problem definition expressed in

P-maps. One is to define characteristics of a state, and the other is to define that of changes across states obeying certain conditions. Both types of characteristics are numerical.

State characteristics can be defined as characteristics of accumulated data fragments over a time period up to a point, the state. An example of a state characteristic is the simple count of requirements. Another example called isolated entities is the count of entities that are not a part of a hierarchy. This characteristic can show how much of the problem is not further decomposed. On the other hand, the number of disconnected entities, i.e. entities without link to other types, can show the inability to recognize relationships among different aspects of the problem. A designer may consider different environmental or usability factors that affect a design problem but fail to identify how these factors situate the requirements.

The second type of characteristic is temporal and process-based, measuring the occurrences of adopting certain strategies. There are characteristics that relate to temporal changes but are not representing a strategy. Consider a sequence of different entity types such as “requirement, function, requirement, artefact, function, function” and a time stamp assigned to them based on their order (1 through 6). A variable can be defined as the median of occurrences of an entity. In the given sequence, requirements are added at times 1 and 3, and functions are added at times 2, 5, and 6, and thus, the median of occurrences of requirements and functions is 2 and 5, respectively. Problem formulation strategies can be formalized in P-maps. A strategy is formalized by a set of conditions that occur across states during the development of P-maps. One strategy is entity depth prevalence. When defining a problem, a designer can add more detail to a fragment or entity before linking it to other categories or link entities at a high level before decomposing each type of entity (Ho 2001). For this strategy, the conditions can be stated as if (a) entity parent of type A added at time t_1 , (b) entity child of type A added at time t_2 , (c) entity of type B added at time t_3 , (d) entity of type B is linked to the type A parent entity at time t_4 , and (e) $t_4 > t_3 > t_2$.

The P-maps framework has facilitated a few empirical studies of problem formulation. One study investigates the relation between problem formulation characteristics as independent variables and creativity (Dinar et al. 2015c). Creativity is assessed by the ideation metrics of Shah et al. (2003). Results of linear regression analysis show that: *quantity* and *variety* increase if designers do more abstraction and specify key issues without decomposing them; *novelty* increases if designers specify fewer requirements and use scenarios but more functions, have more functions in hierarchies, and explore each entity in depth rather than in breadth across entity types; *quality* increases if designers specify more behaviours and fewer artefacts, identify more conflicts, and follow a breadth exploration strategy. The quantified problem formulation characteristics and ideation metrics enable determining the statistical significance of inferences made based on the data.

The regression models based on one problem are used to predict the ideation scores of another problem. Compared to scores by an independent panel of judges, the predictions of variety and quality are more accurate. Other studies based on the P-maps framework include the development of a test of problem formulation skills

(Dinar et al. 2015d) and objective assessment of students learning conceptual design through multiple assignments (Dinar and Shah 2014; Dinar et al. 2015b). In both studies, a quantified scoring scheme is suggested by normalizing the number of appropriate responses with respect to data collected from a sample of participants for a specific problem.

2.2.6 *Decision-Based Design*

Decision theory uses “utility” to quantify the value of an alternative, often expressed in monetary terms. To overcome limitations of multicriteria decision making, various approaches have been proposed (Callaghan and Lewis 2000; Roser 2000; Gu et al. 2002). Chen’s analytical techniques include discrete choice analysis (DCA) (Wassenaar and Chen 2003); the product attribute function deployment (Hoyle and Chen 2009) method; and integrated Bayesian hierarchical choice modelling (IBHCM) (Hoyle et al. 2010) approach with quantification aspects.

Various analytical techniques such as multiple discriminant analysis (Johnson 1970), factor analysis (Green and Tull 1970), multidimensional scaling (Green and Carmone 1970), conjoint analysis (Green and Srinivasan 1978, 1990), and discrete choice analysis (DCA) (Wassenaar and Chen 2003; Chen et al. 2012) have been developed to provide a model of customer preference and choice. Among these, discrete choice analysis (DCA) uses individual customers’ data represented by a rating scale, in order to model customer choice and ordered logit (OL) (Chen et al. 2012). As the single criterion in alternative selections, in other words, DCA utilizes the economic benefit method to evaluate economic benefit (Wassenaar and Chen 2003; Chen et al. 2012).

The product attribute function deployment (PAFD) method (Hoyle and Chen 2009) is a design tool to guide the product planning phase of a product development. Beyond the framework of quality function deployment (QFD), PAFD method is the quantitative decision-making processes of DBD by removing the need for the user weights and rankings associated with the QFD method (Hoyle and Chen 2009). Additionally, single-objective utility maximization supports decision making under uncertainty and mitigates the difficulties related to weight factors and multicriteria decision making (MCDM) in QFD. This can be feasible by identifying attributes, selecting concepts, and setting targets in the DBD framework. Consequently, quantitative assessments of the PAFD provide better design decisions among alternative concepts.

There is a need to make the connection between quantitative attributes used in engineering design and qualitative attributes that customers might consider. Integrated Bayesian hierarchical choice modelling (IBHCM) approach is a hierarchical demand modelling that addresses this need and captures heterogeneous customer preferences (Hoyle et al. 2010; Chen et al. 2013). The Bayesian estimation methodology is employed to integrate multiple data sources for model

estimation and updating. An integrated estimation procedure is applied to alleviate error propagations in hierarchical structure. IBHCM also applies the mixed logit choice and the random-effects ordered logit model for predicting stochastic consumer preferences and modelling consumer evaluations of multilevel design artefacts, respectively (Chen et al. 2013). As a result, IBHCM offers a comprehensive solution procedure and a highly flexible choice modelling for complex design features.

2.2.7 Quantification of Team Dynamics

Prior research on team dynamics has shown that there is a correlation between a variety of factors and team performance. In order to study these correlations, researchers adopted various analytical techniques to get a better understanding of team dynamics (Eris 2002; Wood et al. 2012; Sonalkar et al. 2014). Few have employed quantification methods to form effective teams and globally distributed teams (Wilde 2008; Park 2014). To form creative and effective teams, two studies focused on specific characterizations of designers. Wilde (2008, 2011) developed his teamology formulas by devising a simplified set of 20 questions based on the Myers–Briggs-type indicator (MBTI) personality test. The teamology score is mapped onto two different role maps which are associated with Belbin's role theory (Wilde 2008, 2011). This team role map allows allocating responsibilities, resolving role duplications, and covering low consciousness roles.

To extend the use of teamology in globally distributed and culturally diverse environment, Park (2014) developed a computational method referred to as global design team formation (GDTF) by merging a sociocultural framework (i.e. global leadership and organizational behaviour effectiveness) with the teamology framework. Through the quantitative representation scheme, this method facilitated forming psychologically and culturally cohesive teams from among a diverse population.

On the other hand, to understand the fundamental cognitive mechanism in teams, Eris (2002, 2004) created a taxonomy of questions, i.e. deep reasoning question (DRQ) and generative design question (GDQ). He then measured the ratio of DRQ to GDQ in relation to team performance, indicating that design teams are more likely to ask questions that are divergent in nature in order to produce alternative concepts, over the course (Eris 2002, 2004).

Wood and other colleagues applied latent semantic analysis (LSA) (Deerwester et al. 1990; Landauer et al. 1998) to written descriptions of designers' mental models, in order to quantify team interaction structure and mental model convergence (Fu et al. 2010; Wood et al. 2012). Based on the results from LSA of textual similarity of two documents, they developed a metric that showed differences in individuals' mental models. They identified the relationship between team interaction structure and mental model development.

2.2.8 Characterizing and Measuring Design Skills

A number of cognitive skills relevant to conceptual design have been identified (Shah 2005). They include divergent thinking, visual thinking, spatial reasoning, abstract reasoning, and problem formulation. In order to assess a designer's skill level, a set of standardized tests has been developed for these design skills. This skill evaluation may have potential uses in (1) determination of design strengths/weaknesses of individuals for the purpose of corrective action; (2) matching individuals with complementary strengths on design teams; and (3) continuous improvement and evaluation of course content. Such tests require the characterization and objective measurement of factors relevant to those skills. Divergent thinking skill was characterized in terms of four outcome measures: fluency, flexibility, originality, and quality, and four process measures: abstractability, affixability, detailability, and decomplexability (Shah et al. 2012). Visual thinking was measured using six characteristics: visual comprehension including perceptual speed, visual memory, visual synthesis, mental image manipulation/transformation, spatial reasoning, and graphical expression/elaboration (Shah et al. 2013). Qualitative or abstract reasoning ability was characterized in terms of qualitative deductive reasoning, qualitative inductive reasoning, analogical reasoning, and abductive reasoning (Khorshidi et al. 2014).

2.2.9 Characterizing Patterns and Strategies in Design Processes

With advancements in computing power in recent decades, some empirical studies of design are not only related to quantification but also related to computation. Computational methods, notably machine learning, are used to find patterns from large datasets automatically. Stahovich (2000) created LearnIT, an instance-based learning tool that inducts rules from iterative parametric designs carried out by designers. The goal of the system is to automate documentation and reuse at a low cost.

Some computational approaches focus on text analysis. Dong et al. (2004) used latent semantic analysis (LSA) to understand the relationship of design documentation in teams with successful outcome. LSA is text analysis method that measures the semantic similarity between pieces of documents by creating a high-dimensional word-by-document matrix and drawing patterns by reducing the space with singular value decomposition. A panel of expert faculty and professional designer judges ranked team performance on a set of 13 criteria. Spearman's rank correlation analysis showed significant correlation between semantic coherence in teams' documentation and performance.

Fu et al. (2013a) also used LSA to find semantic similarity in the US patent database and searched for a structure in mapping form to function with a Bayesian

algorithm. The goal is to create a tool that aids designers by providing analogical stimuli from a clustered design repository. Based on the created structure which determined a measure for distances among concepts (form and function), Fu et al. (2013b) conducted an experimental study to understand the effect of the distance of an analogue from a problem on designer creativity. They formed three groups of designers who received near, far, and no external stimuli. They found that there is a sweet spot in how effective an analogue can be on designers' outcome.

Glier et al. (2014) used three different classifiers (Naïve Bayes, support vector machine, and k-nearest neighbours) to determine how biology corpora can inspire design. Participants were given a design problem (corn shucker) and text stimuli (biosentences). Instead of asking the participants to generate ideas, they were asked to respond true or false to the question if the sentence gave them any idea for the problem. The stimuli were a few hundred sentences taken from papers in different biology journals. The true or false responses formed the class variable. Tokenization and stemming was used for feature selection in the text, i.e. to reduce the sentences into a set of words more pertinent to biology. They reported precision, recall, and *F* score of each of the three classifiers for a different problem and concluded that the naïve Bayes classifier though having a slightly lower precision score was superior to SVM because of being a simpler model. They also suggested that each function led to a different classifier and planned to develop different classifiers for a function basis.

Dinar et al. (2015a) also used a few machine learning methods in search for patterns in data collected from novice students in the P-maps ontological framework. They used association rule mining with confidence and lift as the evaluation metrics, representing commonness and high correlation, respectively. The rules with higher confidence and lift indicated that designers who had found more implicit requirements also had a deep function hierarchy and designers who had identified more relations between functions and artefacts failed to find implicit requirements. They also used sequence mining among strings of entity types and relations added successively. The evaluation metric is called support which shows how frequently a partial order of the entities appeared among different designers. The subsequences with the highest support were ("requirement", "requirement", "requirement"), ("requirement", "function"), and ("requirement", "parent_of_requirement", "requirement") implying that the novices are problem-oriented; they structured requirements and functions in a more organized way than they did with artefacts and behaviours.

2.3 Contrasting Quantitative Versus Qualitative

One aspect of engineering design research that has been explored for many years is the study of creativity in early stages of design as supported by idea generation. Studies have been undertaken to understand the role that different representations play in idea generation and evaluation (McKoy et al. 2001; Linsey et al. 2008;

Hannah et al. 2011), the role that analogical mapping plays in design (Linsey and Viswanathan 2014), and the effect that different design methods have on concepts generated (Linsey et al. 2011; Chulvi et al. 2012a). In these studies, an important element of the research method employed is the evaluation of the sketch that is generated by the participants. The evaluation might be objective where the results of the evaluation are independent of evaluators or subjective where the analysis results depend on the individuals evaluating the sketches. Often, the degree of inference required to interpret and evaluate the sketch influences the objectivity. Likewise, metrics that are quantitative such as counting the number of lines, features, or renderings can positively influence the objectivity of the metrics. These characteristics of sketch evaluation metrics can be found in (Joshi and Summers 2012).

A brief comparison of sketching and ideation evaluation metrics from 24 studies is illustrated in Table 2.1 (Cross 1997; McGown et al. 1998; McKoy et al. 2001; Yang 2003; Tovey et al. 2003; Cham and Yang 2005; Linsey et al. 2005b, 2008, 2011; van der Lugt 2005; Yang and Cham 2007; Lau et al. 2009; Yang 2009; Chiu and Salustri 2010; Schmidt et al. 2010; Ramachandran et al. 2011; Westmoreland et al. 2011; Chulvi et al. 2012a, b; White et al. 2012; Worinkeng et al. 2013; Cheng et al. 2014; Arrighi et al. 2015; Lee et al. 2015). The goals or the research questions defined by the researchers are illustrated in addition to the data sources that are used for the study. The type of the study is defined as case study (CS), protocol study (PS), or user study (US) as discussed earlier. Half (twelve) of the studies presented can be identified as controlled user studies. Four were protocol studies that captured behaviour or thought explanations while sketching. Finally, eight are classified as case studies with the primary mechanism of study being document analysis. The metric type is coded from four points of view: objective/subjective/subjective with inter-rater reliability testing (O/S/R); explicit/implicit (E/I); qualitative/quantitative (L/N); and manual/automated (M/A). There are no metrics that were automatically coded in the papers reviewed.

The controlled user studies are highlighted in the table. Of the thirty metrics defined for the controlled user studies, twelve (40 %) are objective or were subjective but tested for inter-rater reliability. The others (60 %) were subjective without a clear test for rater objectivity. However, when considering the study overall, half of the studies included objective or inter-rater-tested metrics. Only one study employed both objective (quantity) and non-tested subjective (novelty, variety, and quality) metrics (Schmidt et al. 2010). The three subjective metrics were developed as part of a previous effort (Shah et al. 2000, 2003). Employing previously established metrics is one approach to addressing the objectivity of research as it establishes a distance between the investigator and the object of study (Le Dain et al. 2013). In an attempt to create some objectivity in the evaluation, several researchers have used panels of evaluating judges.

A final observation of the metrics used in the studies is that most of the researchers have chosen to use multiple different metrics in their research. In this way, the researchers have distributed the subjectivity of their analysis and evaluation of the concepts or sketches generated across multiple different dimensions.

Table 2.1 Comparison of research on sketching and ideation based on metrics of evaluation [adapted from Joshi and Summers (2012)]

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Westmoreland et al. (2011)	Understand the sketching roles in student projects	Visual representation such as sketches, CAD, line drawings, and photographs from senior design reports	CS	Subject matter—system, subsystem, artefact	O-E-L-M
				Part of multiple objects—in same grouping on page but different from one another in type or subject	S-I-L-M
				Motion indicator	O-E-L-M
				Applied forces	O-E-L-M
				Part of set—multiple visuals related to each other	S-I-L-M
				Views—isometric, orthogonal, multiple	O-E-L-M
Linsey et al. (2011)	Understand the relationship between method, representation, and creativity	Sketches from user study	US	Variety	R-I-L-M
				Novelty	R-I-L-M
				Quantity (based on function count)	R-I-N-M
				Quality	R-I-L-M
Schmidt et al. (2010)	Does emphasizing sketching affect ideation?	Design ideas and sketches	US	Novelty	S-I-N-M
				Variety	S-I-N-M
				Quantity	O-E-N-M
				Quality	S-I-N-M
McKoy et al. (2001)	Understand the representation influence on communication	Sketches and textual descriptions of data	US	Quality based on the satisfaction of identified functions	S-I-L-M
				Novelty—using function and sub-function breakdown	S-I-Q-M
				Accuracy of communication	S-I-L-M

(continued)

Table 2.1 (continued)

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Linsey et al. (2005a)	Understand the role that group ideation plays on ideation	Sketches and textual descriptions, post-session survey	US	Quantity	S-I-L-M
				Quality	S-I-L-M
Linsey et al. (2008)	Understand the influence of analogy on sketched solutions	Sketches	US	Quantity	S-I-L-M
Yang (2003)	Understand the relationship of sketching with project outcome	Student design log books, data from morph charts	CS	Quantity—sketch count, dimensioned sketch counted separately	O-E-N-M
Lau et al. (2009)	Understand the role of sketching in design	Sketches in design journals	CS	Representation—2D or 3D	O-E-L-M
				Annotations	O-E-L-M
				Media—tangible, digital, or mixed	O-E-L-M
Cham and Yang (2005)	Understand the relationship between sketching ability and design outcomes	Data from survey and student design logbooks	CS	Demonstration of grasp of concept	S-I-L-M
				Accuracy of proportions	S-I-L-M
				Correctness of proportions, 3D perspective	S-I-L-M
Yang and Cham (2007)	Understand the relationship of sketch ability on outcome	Data from survey and student design logbooks	CS	Quantity—sketch count	O-E-N-M
				Demonstration of grasp of concept	S-I-L-M
				Accuracy of proportions	S-I-L-M
				Correctness of proportions, 3D perspective	S-I-L-M
Yang (2009)	Understand the quality of sketch correlation with design outcome	Data from survey and student design logbooks	CS	Quantity—sketch count	O-E-N-M
				Quantity—sketch count	O-E-N-M

(continued)

Table 2.1 (continued)

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Ramachandran et al. (2011)	Understand the relationship between early design seed models and creativity	Sketches from user study	US	Quantity—sketch count Quality—high, medium, and low based on solutions for requirements	O-E-N-M R-I-L-M
Worinkeng et al. (2013)	Understand the effect of presketching on ideation	Sketches	US	Quantity Novelty	O-E-N-M R-I-N-M
White et al. (2012)	Understand the influence of ideation method on quantity and student self-efficacy	Sketches and questionnaires	US	Quantity Change in self-efficacy	O-E-N-M O-E-N-M
McGown et al. (1998)	Understand the sketching behaviour	Sketches from design notebook, observer notes	CS	Complexity based on line shading and annotation Size scale Drawing media Information content Linkography	S-I-L-M O-E-N-M O-E-L-M S-I-L-M R-I-N-M
van der Lugt (2005)	Understand the sketching through design thinking	Sketches from user study	US		
Chulvi et al. (2012a)	Understand the relationship between logical and intuitive methods and creativity	Sketches	US	Novelty Quality	S-I-L-M S-I-L-M
Cross (1997)	Understand the problem–solution shift in design	Think-aloud transcripts and sketches	PS	Frequency/time	S-I-L-M
Tovey et al. (2003)	Understand the role that different line styles play in concept sketching	Videos of sketching activities	PS	Feature sequence	S-I-L-M

(continued)

Table 2.1 (continued)

Ref.	Research goal/questions	Data source	Type of study	Metric	Type of metric
Chiu and Salustri (2010)	Compare peer evaluation and expert panel assessment of creativity	Project final review presentations	CS	Novelty	S-I-L-M
				Quality	S-I-L-M
				Creativity	S-I-L-M
Chulvi et al. (2012b)	Compare academic creativity methods with expert intuition	Sketches	US	Moss (quality * novelty)	S-I-L-M
				Sarkar (quality * novelty)	S-I-L-M
				EPI (quality * novelty)	S-I-L-M
				Expert (novelty)	S-I-L-M
				Expert (quality)	S-I-L-M
Lee et al. (2015)	Understand the relationship between sketching activities and creativity	Videos of sketching activities	PS	Expert (creativity)	S-I-L-M
				Creativity	S-I-L-M
Arrighi et al. (2015)	Understand how different CAD tools influence quality and creativity of solutions	CAD models	PS	Robustness	S-I-L-M
				Generativeness	S-I-L-M
Cheng et al. (2014)	Understand the influence that partial analogies have on ideation	Sketches	US	Creativity (experts)	S-I-L-M
				Creativity (self)	S-I-L-M

By doing so, the researchers have addressed the subjectivity of the research by segmenting it in much the same way that faculty might use a rubric to increase the objectivity of grading project reports.

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