TOWARD CONSTRUCTING A THEORETICAL MODEL FOR FUTURE DESIGN EDUCATION

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ABSTRACT

The globalization of economies, along with the rapid development of information technologies, has seen the transition of societies from industrial economies towards creative knowledge economies that emphasize knowledge and skills. However, there are challenges for design education to meet the demands of the knowledge economy. Designers are facing more “wicked problems” and poorly-understood phenomena in a world characterized by volatility, uncertainty, complexity and ambiguity (VUCA). Some design educators have pointed out that traditional education programs are not up to the challenges faced in a complex world. For industrial design educators, this phenomenon raises provocative questions, such as: What are the trends in design education? How can we cultivate design students to prepare for the demands of future designers in a complex and rapidly-changing world?

This thesis aims to investigate the state of art and future vision of design education and construct a theoretical model for future design education. The thesis firstly reviews different literatures describing important elements of design education including learning theories, definition of design education and theoretical models of design education (Chapter 2). General research methods in the field of design education are introduced including interview, systematic review, questionnaire, theory, case study and data analysis (Chapter 3). The thesis conducts three studies to collect data about the influencing factors of future design education including expert interviews (Chapter 4), Top 50 design institute analysis (Chapter 5) and a questionnaire on design education (Chapter 6). A structural equation model about future design education is developed based on these studies. This model has several features, which are: (1) holistic and comprehensive; (2) reflecting the changes of industrial design; (3) based on empirical data in the real world; (4) provides operable teaching strategies for educators; and (5) indicates the gap between current situation and future vision of design education. In addition to this theoretical contribution to design education community, this thesis applies AI-supported collaborative learning strategy in educational practice, that aims to facilitate design education based

on the proposed model (Chapter 7). An AI-supported design tool was developed that is innovative and efficient to help designers for idea generation and fast prototyping. A case study in the form of design workshop is implemented and discussed to evaluate the reliability and validity of the proposed learning strategy and the design education model (Chapter 8). In conclusion, the specific contributions to cultural studies, AI-supported strategy and collaborative learning are discussed (Chapter 9). The implications of future work are highlighted (Chapter 10).

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1. INTRODUCTION

1.1 Background

The globalization of economies, along with the rapid development of information technologies, has seen the transition of societies from industrial economies towards creative knowledge economies that emphasize knowledge and skills (Teixeira, 2010). According to a report from the World Economic Forum (WEF, 2018), 42% of the required skills in today's workforce will change and 75 million jobs will be displaced during the 2018-2022 period. The report also states that creativity and flexibility are important 2022 skills (WEF, 2018). This trend challenges the education domain to prepare students for jobs and markets that do not yet exist. Finegold and Notabartolo (2010) identified 15 competencies that are important for the workforce of the 21st century including creativity, problem solving, flexibility and adaptability etc. Some researchers consider design as a key indicator with which to understand the process of change (Kimbell, 2001). Design thinking is defined as the "design practice and competence used beyond the design context" (Johansson Sköldberg, Woodilla, & Çetinkaya, 2013) that leads to creative problem solving. Norman and Klemmer (2014) believed that design thinking skills will be a key success factor for future creative leaders in technology, business and education. (Wright & Davis, 2014) proposed using design education as a framework to deliver 21st century competences (Larson & Miller, 2011). Furthermore, Ringvold and Digranes (2017) proposed that design education plays an important role in educating future citizens for the sustainable development of societies. The World Design Organization (WDO) encourages industrial designers to solve global problems and achieve the UN 2030 Sustainable Development Goals (SDGs) (WDO, 2020), and WDO members have identified seven SDGs that are particularly relevant to the industrial design community (WDO, 2020). These examples suggest promising opportunities for design education to play an important role in cultivating the future workforce.

However, there are challenges for design education to meet the demands of the knowledge economy. Designers are facing more "wicked problems" (Buchanan, 1992) and poorly-understood phenomena in a world characterized by volatility, uncertainty, complexity and ambiguity (VUCA) (Bennett & Lemoine, 2014). Sheldon (1988) emphasized the challenging tasks faced by design educators in developing design courses to meet the needs from industry and society. He said "design the right product for the market is a long way towards corporate success, thus good design is the hardest task in industry and the hardest to teach in education" (Sheldon, 1988). Some design educators have pointed out that traditional education programs are not up to the challenges faced in a complex world (Collina, Galluzzo, Maffei, & Monna, 2017; Fleischmann & Hutchison, 2012), and there is a gap between the learning that students acquire at university and the skills they need to put into practice after graduation (Ball, 2002). Donald Norman suggested that modern designers face increasingly complex problems and that change is needed in design education (Norman, 2010; Norman & Klemmer, 2014). Noting the multi-disciplinarity of design education, he pointed out that much of the traditional theory in the design profession comes from other disciplines which are no longer suitable for today's complex systems and therefore a more systematic approach is required (Norman & Klemmer, 2014). For industrial design educators, this phenomenon raises provocative questions, such as: What are the trends in design education？ How can we cultivate design students to prepare for the demands of future designers in a complex and rapidly-changing world?

1.2 Research Questions

From an instructional point of view, theoretical models or paradigms of learning process can represent ways of thinking and patterns of research, which can lead to the development of educational theory and practice (Husén, 1988). A well-developed model can simplify and minimize the phenomena that cannot be easily or directly observed. The aim of this research is to identify the current trend of design education and propose a theoretical model to facilitate the design-learning process for future design education. This thesis tries to answer the following research questions:

Research Question 1: What are the current theoretical models of design education?

To address this research question, background knowledge of design education is collected to inform the research carried out. This includes literature review of the components of design education, as well as current theoretical models of design education (see Chapter 2). This objective also includes exploring the general methodological approach undertaken in the area of design education (see Chapter 3).

Research Question 2: What are the influencing factors in shaping a theoretical model for future design education?

To address this research question, interviews with senior experts in design communities are conducted to understand the current trends and influencing factors in industrial design and design education, taking account of the impacts of social change and technology advancement in the knowledge economy (see Chapter 4). The next chapter describes an analysis of the curriculum content and methods of delivery of the world's top 50 design institutes. From this, a theoretical and holistic model is developed describing the key elements of future design education (see Chapter 5). With operable strategies, this model provides educators with clear directions for the future of design education requirements in an authentic context. This model is further evaluated and refined based on a questionnaire of educators working on the front line. And the implications of the model on design education practice are discussed (see Chapter 6).

Research Question 3: How to enhance design education based on the proposed theoretical model?

To address this research question, an AI-supported collaborative learning strategy is developed to facilitate design education (see Chapter 7). User experiments are conducted to evaluate the learning experience and educational effectiveness of the strategy so as to evaluate the reliability and validity of the proposed theoretical education model (see Chapter 8). The final chapter ends with the discussion about the research (see Chapter 9) and a summary (see Chapter 10).

1.3 Thesis Overview

The structure of the thesis is illustrated in Figure 1.1, showing how individual chapters correspond to the research questions. The first research question tries to understand the research base of design education including literature review and introduction of general methodology. Three studies were conducted to develop a theoretical education model by exploring the influencing factors for future design education. The third research question is answered by applying the strategy of the proposed theoretical education model in educational practice. This thesis tries to explore the future design education both from the theoretical and practical perspectives.

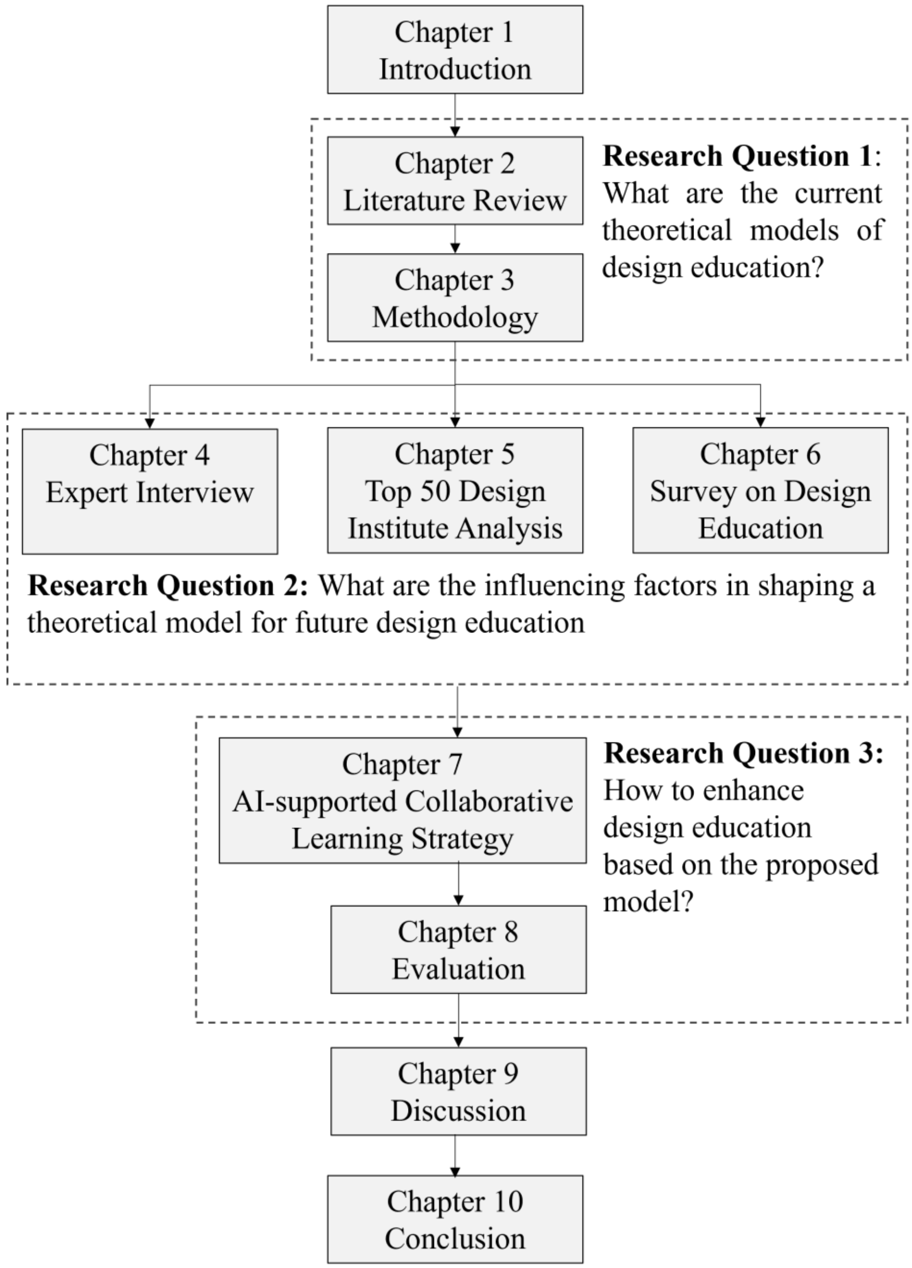


Figure 1.1 Thesis Structure

2. LITERATURE REVIEW

2.1 Chapter Overview

The literature review covers three areas: industrial design, learning theories and theoretical models of design education. For learning theories' part, this chapter reviews the classical learning theories to summarize the trend in education community. For industrial design part, this chapter looks at the changing descriptions and scopes of industrial design from its first definition in 1980 until the latest definition launched in 2015. The last part is to discuss the current theoretical models of design education and develop a preliminary model as a base for the following studies.

2.2 Evolution of Learning Theories

There are several main perspectives and approaches of learning theories, including behaviorism, cognitivism, constructivism, humanism, and others. The evolution of learning theories shows a trend in education, that is moving from passive learning to active learning, from teacher-centered to student-centered.

2.2.1 Behaviorism

Behaviorism is a worldview that assumes a learner is essentially passive, responding to environmental stimuli. Skinner (1974) believes all behavior can be explained without the need to consider internal mental states or consciousness. The learner's behavior is shaped through positive reinforcement or negative reinforcement. Both positive reinforcement and negative reinforcement increase the probability that the antecedent behavior will happen again. In contrast, punishment decreases the likelihood that the antecedent behavior will happen again. Positive indicates the application of a stimulus; Negative indicates the withholding of a stimulus. Learning is therefore defined as a change in behavior in the learner.

2.2.2 Cognitivism

The cognitivist revolution replaced behaviorism in 1960s as the dominant paradigm. Cognitivism focuses on the inner mental activities – opening the “black box" of the human mind is valuable and necessary for understanding how people learn (Ertmer & Newby, 2008). Mental processes such as thinking, memory, knowing, and problem-solving need to be explored. Knowledge can be seen as schema or symbolic mental constructions. Learning is defined as change in a learner's schemata (P. A. Cooper, 1993). A response to behaviorism, people are not “programmed animals" that merely respond to environmental stimuli; people are rational beings that require active participation in order to learn, and whose actions are a consequence of thinking. Changes in behavior are observed, but only as an indication of what is occurring in the learner’s head.

2.2.3 Constructivism

Constructivism as a paradigm or worldview posits that learning is an active, constructive process. The learner is an information constructor. People actively construct or create their own subjective representations of objective reality. New information is linked to prior knowledge, thus mental representations are subjective. A reaction to didactic approaches such as behaviorism, constructivism states that learning is an active, contextualized process of constructing knowledge rather than acquiring it. Knowledge is constructed based on personal experiences and hypotheses of the environment. Each person has a different interpretation and construction of knowledge process (Ertmer & Newby, 2008). The learner is not a blank slate but brings past experiences and cultural factors to a situation (Ertmer & Newby, 2008). What students learn is influenced by the tools and signs of their socio-cultural environment, as well as the established communities of practice which their academic discipline represents (Finegold & Notabartolo, 2010). Rooted in constructivism and concept mapping, Oxman (2004) presented a conceptual understanding of the knowledge domain and proposed an education model termed Think-map, rooted.

2.2.4 Humanism

Humanism, a paradigm that emerged in the 1960s, focuses on the human freedom, dignity, and potential. A central assumption of humanism is that people act with intentionality and values (Decarvalho, 1991). This contrasts with the behaviorist notion of operant conditioning and the cognitive psychologist belief that the discovering knowledge or constructing meaning is central to learning. Humanists also believe that it is necessary to study the person, especially as an individual grows and develops over the lifespan. It follows that the study of the self, motivation, and goals are areas of particular interest. A primary purpose of humanism could be described as the development of self-actualized, autonomous people (Rogers, 1971). In humanism, learning is student centered and personalized, and the educator’s role is that of a facilitator. Affective and cognitive needs are key, and the goal is to develop self-actualized people in a cooperative, supportive environment (Decarvalho, 1991).

Rooted in humanism, experiential learning theory (ELT) (Kolb et al., 1999) regards that learning is a holistic adaptive process that merges experience, perception, cognition and behavior. There are four phases of learning cycle in ELT including (1) concrete experience, (2) reflective observation, (3) abstract conceptualization and (4) active experimentation, namely learning by experiencing, reflecting, thinking, and doing. ELT has been widely accepted as a useful framework for student-centered educational innovation, that can take a variety of forms, such as undergraduate projects, case studies, role playing and community debates etc.

2.2.5 Summary

These four basic learning theories are evolving from passive learning to active learning, from teacher-centered to student-centered. In Behaviorism, the learner is essentially passive and responds to environment. Then the theory is replaced by Cognitivism that emphasis learner's active participation although it treats all the mental activities as in "black box". While Constructivism points out that learning is a constructive and contextualized process. Learners construct meaning by relating new information to what they already know. In doing so, they are influenced by their motivation as well as by their social-cultural environment. The latest learning theory Humanism agrees that the educators' role is a facilitator and emphasis the student is learning in a cooperative environment to reach self-actualized. This perspective puts learner's attitude, motivation, and ability to learn in the central role.

2.2.6 Implications on Education Models

Based on the review of classical learning theories, the implications on new education models are discussed. Firstly, the evolvement of learning theories reflects the shift from passive learning to active learning, and from teacher-centered to students-centered. Various studies have shown student-centered learning approaches, specifically those including peer learning, offer advantages over traditional teacher-dominated methods (Love, Dietrich, Fitzgerald, & Gordon, 2014; Rubin & Hebert, 1998). In employing peer learning, students take responsibility for their educational experience, rather than being dependent on the educator (Arrighi & Mougenot, 2016). A constructivist perspective on learning has implications for the role of the student, for the design of the curriculum and assessment, and for the role of the teacher. The curriculum should allow for active student participation and control, offer ample opportunity for interaction, and provide an authentic context for students' learning. Educators need to make a shift from teacher-focused to learning-focused, and their role needs to change from being an authoritative source of knowledge to facilitating students' learning (Birenbaum, 2006).

Secondly, Constructivism demonstrate that students can acquire knowledge, skills, and attitudes in particular contexts. This demonstrates their potential: to analyze new and different contexts and to act accordingly. As a result, the curriculum should stress the relevance of authentic learning activities that reflect students' future work as a designer. As technology evolves, the goal of design educators is to teach students to be adaptable lifelong learners, ready for the changing demands of the profession.

2.3 Scope of Design Education

According to the Cambridge Dictionary of American English, design is "the creation of a plan or convention for the construction of an object or a system". There are various design disciplines such as interior design, visual design, product design, design has different connotations in different fields, while this research focus on industrial design. Design education in this thesis is defined as the learning of theory and application in the design of products and services. It is learning how to apply practical methods, prior knowledge, and natural talent to solve problems in the field of industrial design (Casakin & Goldschmidt, 1999). The subjects of this research are the educators who are teaching the undergraduate and graduate students in the disciplines of industrial design or product design (sometimes overlaps).

2.4 Evolution of Industrial Design

Societal, scientific and technological developments are expanding the field of industrial design towards designing products, systems and related services (Hummels & Frens, 2008; Stappers, Giaccardi, Mooij, & van Boeijen, 2020). The growth of industrialization and mechanization which began with the second industrial revolution led to the emergence of industrial design, which was originally defined as "a creative activity whose aims is to determine the formal qualities of objects produced by industry. The formal qualities are not only the external features but are principally those structural and functional relationships which covert a system to a coherent unity both from the point of view of the producer and the users" by Tomas Maldonado in 1969

(Maldonado, 1979). At that time, an industrial designer is one who is qualified by training, technical knowledge, experience and visual sensibility to determine the materials, mechanisms, shape, color, surface finishes and decoration of objects which are reproduced in quantity by industrial processes (WDO, 2015). Another famous definition of industrial design is “a process of design applied to products that are to be manufactured through techniques of mass production” (Heskett & Giorgetta, 1980). This process distinguishes industrial design from craft-based design. The third industrial revolution spawned the development of electronics and information technology, and the fourth industrial revolution developed smart manufacturing (Collina et al., 2017). Similar to other discipline, industrial design evolves in response to the industrial revolution (Budd & Wang, 2017). In 2015 the professional practice committee of The World Design Organization (WDO) unveiled a new definition of industrial design, asserting that “industrial design is a strategic problem-solving process that drives innovation, builds business success, and leads to a better quality of life through innovative products, systems, services and experiences” (WDO, 2015). WDO further emphasized industrial design as an integrated profession that links several domains including engineering, ergonomics, business and aesthetics, and involves social, environmental and cultural issues, providing a more optimistic way of looking at the future (WDO, 2015). This change has led to the need for new kinds of industrial designers. Table 2.1 compares the definitions of industrial design and industrial designer between the periods of the second and the fourth industrial revolution.

Table 2.1 Evolution of Industrial Design

Industrial revolution	The second industrial revolution	The fourth industrial revolution
Industries	Mechanization	Information technology
Definition of industrial design	a creative activity whose aims is to determine the formal qualities of objects produced by industry (Maldonado, 1979)	a strategic problem-solving process that drives innovation, builds business success, and leads to a better quality of life through innovative products, systems, services and experiences (WDO, 2015)
Definition of industrial designer	who is qualified by training, technical knowledge, experience and visual sensibility to determine the materials, mechanisms, shape, color, surface finishes and decoration of objects which are reproduced in quantity by	who have a comprehensive understanding of advances in technology, changes in business type and operations, user needs and requirements and appropriate scientific methodology to inform and evaluate design (Collina et al., 2017; Nae, 2017; Valtonen, 2016)

	industrial processes (WDO, 2015)	
Design subjects	Objects	Products, systems, services, and experiences

2.5 Theoretical Models of Design Education

Theories of design education are not new and there are models depicting different aspects of design education including education aims, design-learning process and learning resources. This section presents and discusses the theoretical models that satisfy certain criteria, namely: (1) a model can apply generally to an aspect or whole of design education, and (2) a model can act as a descriptive analogy helping educators to visualize complex variable and the relationships simply.

2.5.1 Education Aims

Regarding the aims of design education, some researchers have emphasized competency-centered learning. For example, Lewis and Bonollo (2002) invited professional designers and company executives to participate in an undergraduate program as clients to evaluate design student's works. They identified five main design skills based on participants' comments, namely: (1) problem solving skills, such as skills in task clarification and concept generation; (2) social competence and interpersonal skills; (3) project management skills; (4) professional and career skills, such as self-presentation and entrepreneurial skills; and (5) responsibility for outcomes. Hummels, Vinke, Frens, and Hu (2011) introduced a competency-centered education model, where a competency is defined as "an individual's ability to select, acquire, and use the knowledge, skills and attitudes that are required for effective behavior in a specific professional, social or learning context". This model gives equal weight to knowledge, skills, and attitudes. It includes ten specific competency areas that are involved during design process (Hummels et al., 2011): (1) self-directed and continuous learning, (2) descriptive and mathematical modeling, (3) integrating technology, (4) ideas and concepts, (5) form and senses, (6) user focus and perspective, (7) social cultural awareness, (8) designing business processes, (9) design and research processes and (10) teamwork and communication. Similarly, Dominici (2017) summarized six important skills for design graduates, that are: (1) critical thinking, (2) eco literacy, (3) collaboration, (4) active role, (5) leadership and (6) divergent thinking. However, he has not emphasized the design thinking skills rather focus on general literacy.

Some research has focused on the students' development as an education aim. For example, Curry (2014) synthesized the Dreyfus developmental model (Dreyfus, 2004) (novice, advanced, beginner, competency, proficiency, expertise) and the design methodology model proposed by Lawson and Dorst (2013) (problem solving, learning, evolution) to produce an integrated model to facilitate the acquisition of design expertise. As shown in Figure 2.1, this model distinguishes between "seven levels of design expertise" which correspond with seven different ways of design thinking. This model is helpful for design educators to apply appropriate teaching strategies at incremental stages of student development. In this model, the aim of design education is to facilitate students to develop to be an expert. This model follows Humanism, that regards designer's individual growth as the aim of design education.

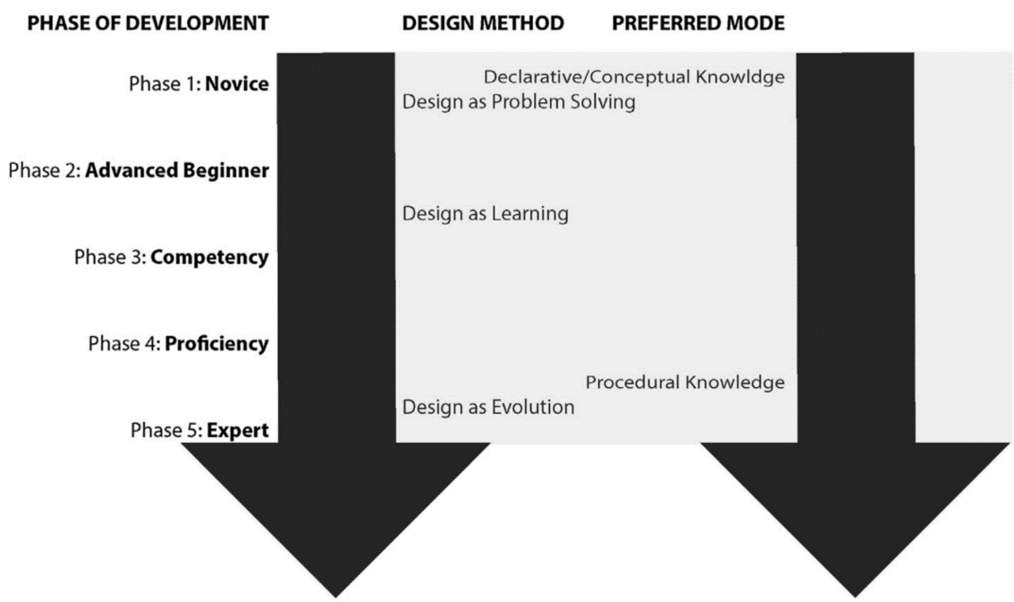


Figure 2.1 Integrated Model of Dreyfus Model and Design Methods (Curry, 2014)

2.5.2 Design-learning Process

In design education and especially in the design studios, constructing a formal model of the design process can assist student learning by providing a structured approach to industrial design problem solving and a tool for the planning and management of design projects by breaking down the whole process into subordinate processes (Lewis & Bonollo, 2002). And while following a formal model of a design process makes it easier for students to understand and internalize the process (Rauth, Köppen, Jobst, & Meinel, 2010). Classical design paradigms explain the design process from different perspectives. But in general, there are two main streams of design paradigms: designing as rational problem-solving and designing as reflective practice (Dorst & Dijkhuis, 1995).

Simon (Michalos & Simon, 1970) took design as a rational problem-solving process. It assumes there is a "problem" to be solved, and the descriptions of the problem can be comprehensively and accurately produce, if possible in the form of a structured requirements specification (Löwgren, 1995). Designers follow a prescriptive design process, from the input of an objective analysis of design problems to the outcome with an objective design solution. There is more emphasis on the analysis of design processes, objective observation, and direct generalizability of the findings. According to this paradigm, design is the search for a solution through a vast maze of possibilities. The designer undertakes basic design cycles of four design activities: analyzing, synthesizing, simulating, evaluating. Rooted in the problem-solving paradigm, the phases of solving a design problem are organized in a linear, recursive, or iterative process. This paradigm focuses on the process-component of design activities which is good at revealing the reasons behind the designers' actions. It helps designers to understand the whole design process in a logical way (Dorst & Dijkhuis, 1995). Figure 2.2 shows an example of problem-solving design process (Polya, 2004) with four phases including (1) understanding the problem, (2) devising a plan, (3) carrying out the plan and (4) looking back.

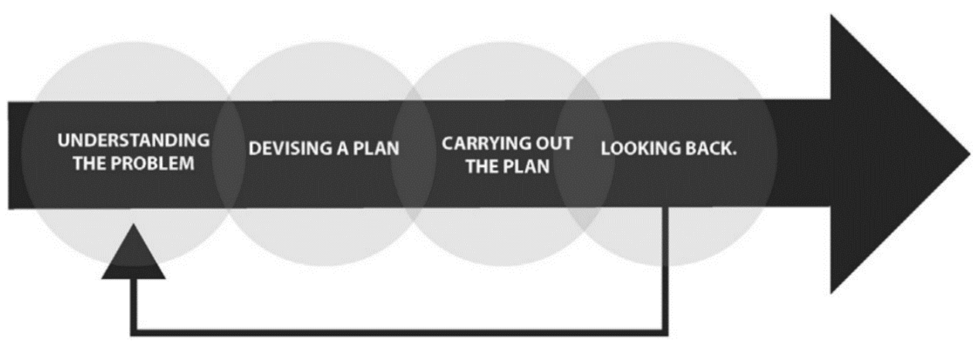


Figure 2.2 Problem-solving Design Process (Polya, 2004)

However, the real situation is that designers do not work in this way, since the problems are often unknown when a design project begins, and the requirements and constraints are changing continually (Mccracken & Jackson, 1982). Rittel and Webber (1973) observed that design problems by nature are "wicked problems", which are problems only understood during the process of trying to solve them. Thus, it is difficult to apply systematic theory and scientific methods for understanding the design process (Curry, 2014). Different from the classical problem-solving design paradigm, industrial design is now providing a more optimistic way of looking at the future by reframing problems as opportunities (Hummels & Frens, 2008). Wormald (2011) emphasized that "problem finding" is more important than "problem solving" in strategic innovation. The designers of the future are expected to apply new technologies in ways that are both new and daring, and they need to explore opportunities rather than solve problems.

A radically different design paradigm has been developed based on two theories: the idea of reflective practice (Schwartz & Schon, 1987) and the notion of situated cognition (Bardram, 1997). Reflection is a mental process that facilitates this creation of meaning and knowledge. The focus of the reflective practice paradigm is the interaction between the designer and the environment of design. This design paradigm links the design process, the tasks, and the designers in a more organic way. Research and knowledge are brought into the design process through the intuition and common sense of the designers. Schön (1992) described design as a process of framing a problem, performing moves toward a solution, and the evaluation of these moves, that leads to a deeper understanding of seeing of the problem, leading to new frames and new moves, as shown in Figure 2.3.

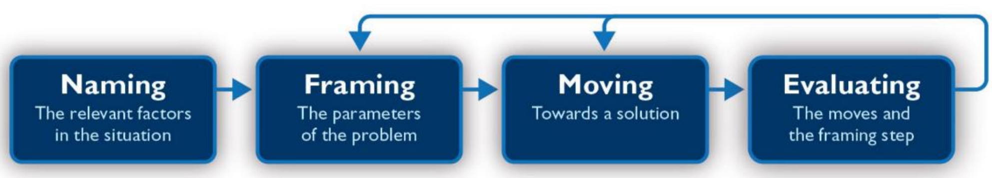


Figure 2.3 Reflective Practice Design Process (Schön, 1992)

The reflective practice paradigm also has shortcomings such as the lack of a clear frame and the difficulty of developing methods based on its underlying theory. The implicit "knowing-in-action" is important, but this hard-to-formalize knowledge is difficult to teach.

The two design paradigms have their rationale of describing the design process, though both have been criticized. Dorst and Dijkhuis (1995) claimed that the design activities that involve more "objective interpretation" would be described well by the rational problem-solving paradigm, while those ones that are more involved with "subjective interpretation" are better described by the reflective paradigm.

Other researchers tried to use different terminology to describe the design paradigms. For example, Fallman (2003) distinguishes three design paradigms: a conservative, a romantic and a pragmatic approach. The conservative approach has its philosophical base in rationalism and has similarities with Simon's problem-solving process. Design is seen as a scientific or engineering endeavor. The design process is supposed to advance gradually through a series of structured steps from the abstract (requirements specifications) to the concrete (resulting artifacts) (Löwgren, 1995). The romantic approach gives prominence to the role of the designer who is seen as an imaginative mastermind, a creative genius or an artist equipped with almost magical abilities of creation. The process itself is guided by the designer's values and taste with respect to quality and aesthetics (Stolterman, 1994). Romanticism has close relationship with humanism learning theory, both of which emphasize individual human abilities. Romanticism suggests creativity and imagination as core human abilities for designers. The pragmatic approach gives importance to the position of the design project. This approach sees design as a process of interpretation and creating meaning. It is closely related to reflective practice paradigm and sees designing as a reflective conversation with the materials of the design process (Schön, 1992). Fallman (2003) discussed these three paradigms and summarized their differences in terms of the involved elements such as designer, problem, product, process, knowledge, and role model, as shown in Figure 2.4.

	Conservative Account	Pragmatic Account	Romantic Account
Designer	An information processor; a *'glass box'*	A reflective, know-how bricoleur; a *'self-organizing system'*	A creative, imaginative genius; an artist; a *'black box'*
Problem	Ill defined and unstructured; to be defined	Unique to the situation; to be set by the designer	Subordinate to the final product
Product	A result of the process	An outcome of the dialogue; integrated in the world	A functional piece of art
Process	A rational search process; fully transparent	A reflective conversation; a dialogue	Largely opaque; mystical
Knowledge	Guidelines; design methods; scientific laws	How each problem should be tackled; compound seeing; experience	Creativity; imagination; craft; drawing
Role model	Natural sciences; engineering; optimization theory	Bricolage; human sciences; sociology	Art; music; poetry; drama

Figure 2.4 Summarizing Table of Three Design Paradigms (Fallman, 2003)

Besides the main design paradigms, some researchers in design field have proposed models of design process from new perspectives. For example, Takeda, Veerkamp, and Yoshikawa (1990) argued that the representation of design process should be computable for realizing intelligent computer-aided design systems, by which a computer can perform a design task. They proposed a computable model of design process, which is a logical process realized by abduction, deduction, and circumscription (Takeda et al., 1990). In this model, abduction is used to expand the designer's ideas; deduction is used to get all facts from available design knowledge; and circumscription is applied to solve an inconsistency found during deductive reasoning. Figure 2.5 shows the process of the computable model. This model is an evolutionary refinement of traditional design process to adapt to intelligent computer-aided design systems. However, this model relies much on knowledge base of design resources and design principles. And it deemphasizes human designers' creativity and oversimplified designer's cognitive activities as tasks operated by computers.

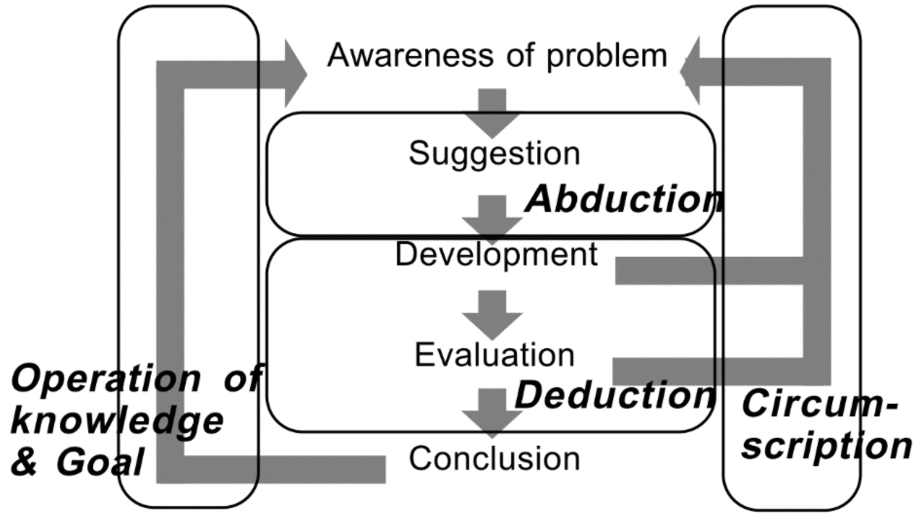


Figure 2.5 Design Process of the Computable Model (Takeda et al., 1990)

Based on the design paradigms and models of design process, there is an extensive literature and theoretical education models. Rooted in problem-solving paradigm, education models generally identify five or six phases of solving a design problem, organized in a lineal, recursive, and iterative process. For example, Bonollo and Lewis (1996) adopted the research from Hales (1987) that five phases were used to describe the design process: (1) briefing and task clarification; (2) concept generation; (3) evaluation and refinement of concepts; (4) detailed design of preferred concept; (5) presentation of results. This model is very operational, which also explains the output from each phase, as shown in Figure 2.6. Taking the phase of concept generation as an example, students are required provide “a folio of concept sketches, supported by simple models or mockups, visual representation of design ideas”.

Subordinate process	Nature of process	Output from process
1. Task clarification	A set of tasks including negotiating a design brief with the client, setting objectives, planning and scheduling subsequent tasks, preparing time and cost estimates	Design brief, including design specification, project plan with time-line and cost estimates
2. Concept generation	A set of creative tasks aimed at generating a wide range of concepts as potential solutions to the design problem specified in the brief	A folio of concept sketches, supported by simple models or mock ups, providing a visual representation of design ideas
3. Evaluation and refinement	A set of analytical tasks in which the concepts in (2) are evaluated and reduced to a small number of refined solutions, usually only one or two candidate solutions	A folio of refined concept sketches, supported by models and technical information as required and illustrating the preferred concepts
4. Detailed design of preferred concept	A set of tasks aimed at developing and validating the preferred concept, including layout drawings, dimensional specifications, selection of materials, finishes, indicative tolerances	A folio of layout and detailed component drawings, supported by a technical report giving preliminary manufacturing information
5. Communication of results	A set of tasks whereby the concept detailed in (4) is communicated to the client via appropriate two- and three-dimensional media and written report	A folio of presentation drawings, including technical drawings from (4) and supported by a refined three-dimensional model and/or prototype

Figure 2.6 Operational Model of the Design Process (Lewis & Bonollo, 2002)

D.school in Stanford University (Rauth et al., 2010) presented five basic stages: (1) empathise; (2) define the problem; (3) ideate; (4) prototype and (5) test. The five stages can often occur in parallel and be repeated iteratively, though the university pointed that the certain steps in the process are only stages within a flexible process. Hummels and Frens (2008) from Technology University of Eindhoven argued that traditional design paradigms share a sequential approach to gather information that does not allow for flexibility and personal freedom. Rooted in reflective practice, they introduced a reflective transformative design process that values design action as a generator of knowledge and is driven by student's vision on the design opportunities. It is composed of five activities, as shown in Figure 2.7: (1) ideating, integrating, and realizing interaction solutions between users and systems; (2) envisioning design opportunities aims to transform society; (3) validating quality in context; (4) making, synthesizing and concretizing; (5) thinking, analyzing and abstracting. Depend on the context and people, the students are free to determine the order of these activities and reflection (the blue lines linking the activities) occurs during the design process. This model of design process supports flexibility and individuality, and emphasizes reflections are an integral part of learning itself (J. L. Cooper & Robinson, 2014).

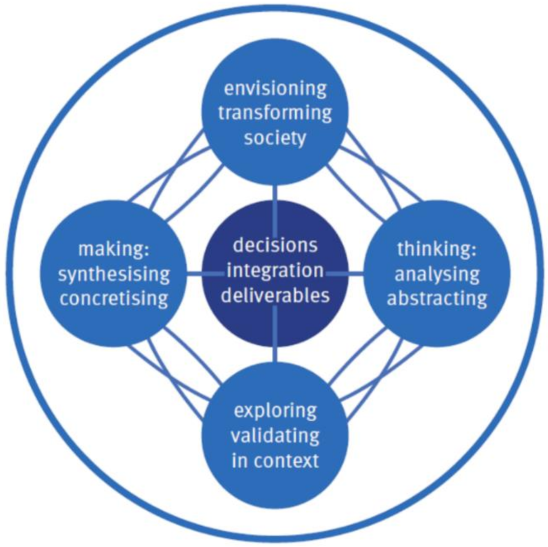


Figure 2.7 Reflective Transformative Design Process (Hummels & Frens, 2008)

W. Chen (2015) summarized five main design tasks based on literature review, that are (1) design research, (2) concept generation, (3) design decision, (4) design presentation and (5) design documentation. This model links design process with learning tasks well. It is interesting to find that the experiential learning process is similar to the above-mentioned design processes. As shown in Figure 2.8, The four-stage learning model includes concrete experience (experiencing), abstract conceptualization (thinking), reflective observation (reflecting) and active experimentation (doing).

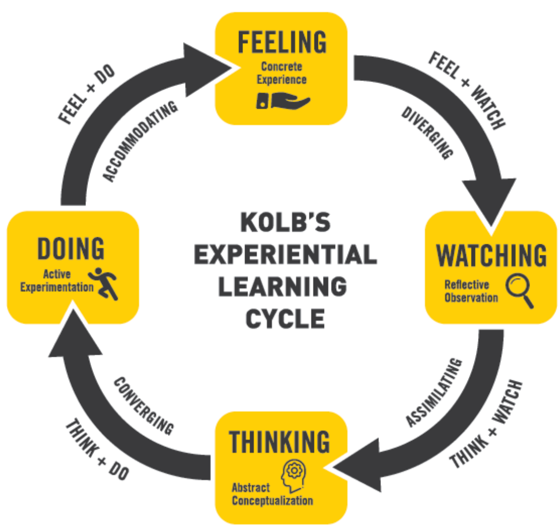


Figure 2.8 Experiential Learning Process (Kolb et al., 1999)

Reflective observation can support the design research phase, and abstract conceptualization coincides with the idea generation phase, while active experimentation and concrete experience coincide with the iterative process between prototyping and evaluation. Telenko et al. (2016) presented a Designette framework integrating Kolb et al. (1999)'s experiential learning process with product traditional design-learning process, as shown in Figure 2.9.

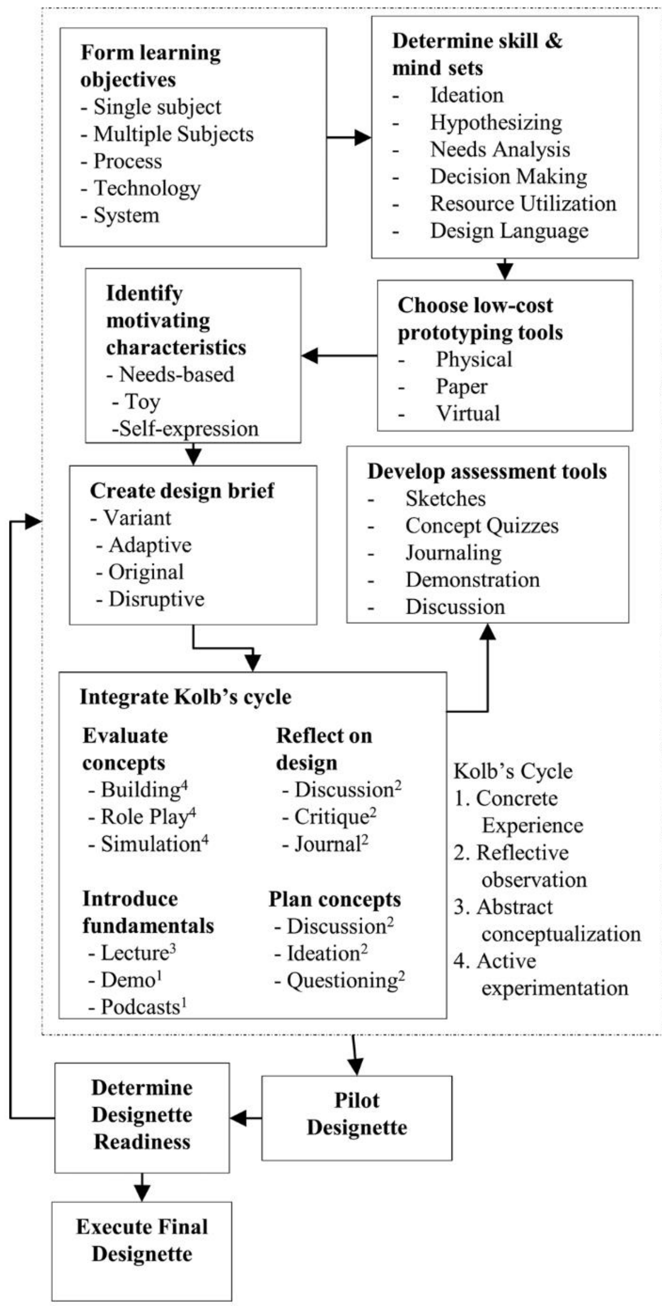


Figure 2.9 Flowchart for Designette Development (Telenko et al., 2016)

Similarly, Ollenburg (2018) also integrated the experiential learning process with the generic design process of analysis (what is today), projection (what could be), and synthesis (what is tomorrow), as shown in Figure 2.10. This model helps design students to deal with uncertainty and conduct foresight design practices.

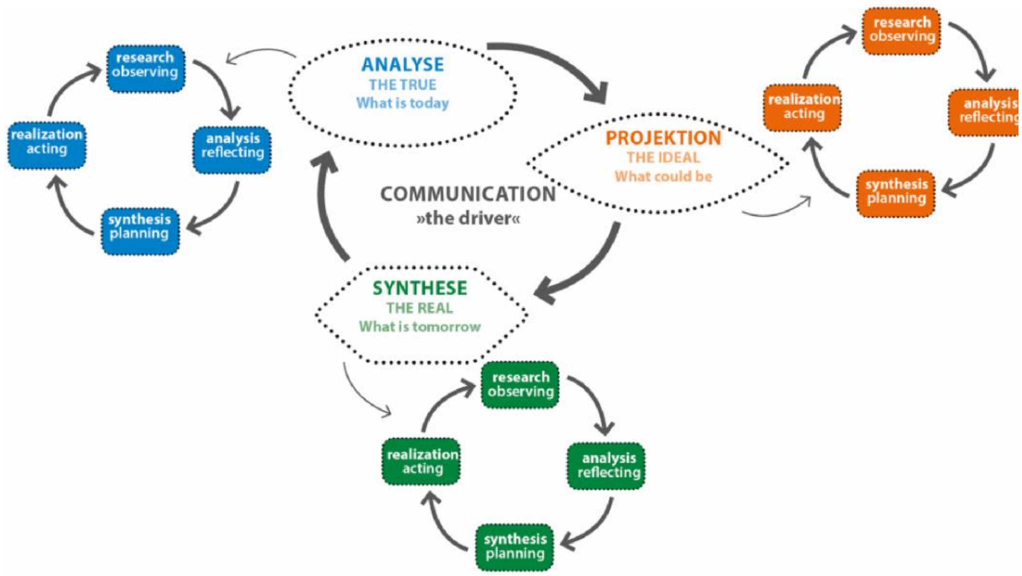


Figure 2.10 Design Process Model (Ollenburg, 2018)

There are some other researchers have discussed about learning processes and learning strategies for design education. For example, Sims (2014) proposed "design alchemy" as a model incorporating the learning theories of social learning, situated cognition, experiential learning, constructivism and connectivism. Dominici (2017) developed a systemic framework in design education with a list of learning methods: teamwork learning and community-based learning, learning by doing, situated learning, project-based learning, problem-based learning, self-organizing learning, peer learning and boss-less education. However, they did not provide an operable model to help design educators to arrange the learning activities.

In summary, design process and learning process are intertwined, both of which emphasize students' activities like researching, ideating, prototyping and reflecting. This thesis treats them as a whole, that is design-learning process.

2.5.3 Learning Resources

Learning resources are defined as sets of information represented and stored in a variety of media and formats that assist student learning. They are key elements to support the implementation of the design process. Salomon (1992) argued that the whole learning environment includes curriculum, teacher's behaviors, collaborative tasks, mode of peer collaboration and the like. Brown, Doughty, Draper, Henderson, and McAteer (1996) regarded learning resources including lectures, tutorials, courseware, books, handout and teaching staff as important elements for the students by ensuring their effective integration into a course. S. H. Chiu (2010) identified top four knowledge sources requested by design students were books, the Internet, studio mates and auditing critiques. To facilitate multidisciplinary collaborative learning, Fleischmann and Hutchison (2012) proposed the concept of creative exchange and developed the Pool model. As shown in Figure 2.11, this model is based on a "pool" idea that the education resources and people can be used when needed. Pool model embraces industry and community partners as an integral part of learning resources and allows the participants to become co-creators to stimulate innovation.

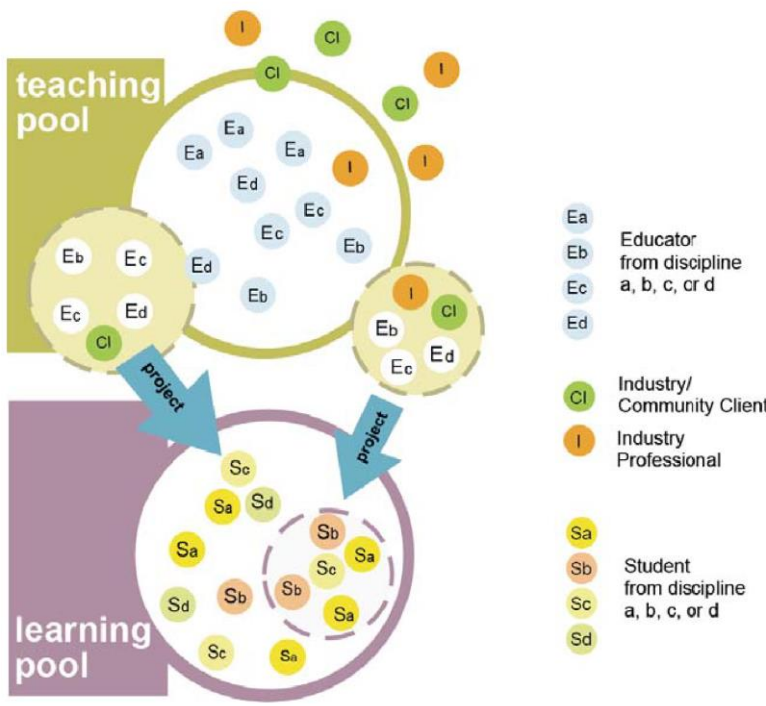


Figure 2.11 Pool Model (Fleischmann & Hutchison, 2012)

Wright and Davis (2014) developed a flexible and inclusive learning environment model including three key qualities, as shown in Figure 2.12: (1) innovation (curriculum, program, technology); (2) network (industry, academia, and community); and (3) transdisciplinary (skills, disciplines, stakeholders). This model highlights the interactions between education sectors, industry and community required to expand knowledge creation.

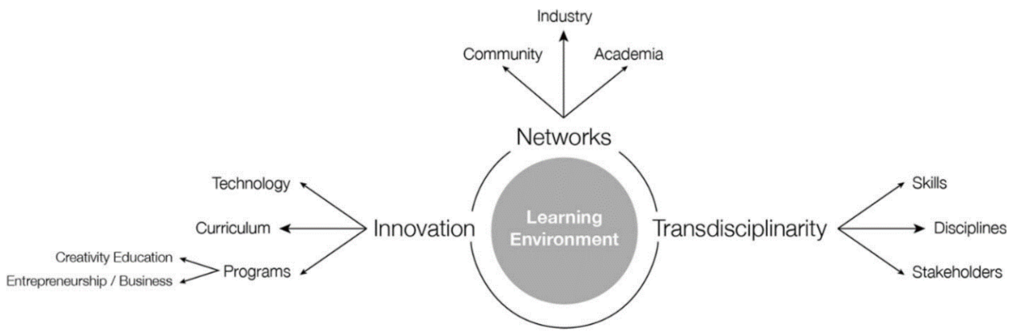


Figure 2.12 Learning Environment Model (Wright & Davis, 2014)

Renda and Kuys (2015) discussed the media of learning resources including traditional sources, professionals, social media, and blogs, as shown in Figure 2.13. This model enumerates the learning resources from a connectivism perspective, though it cannot represent the whole picture of learning resources.

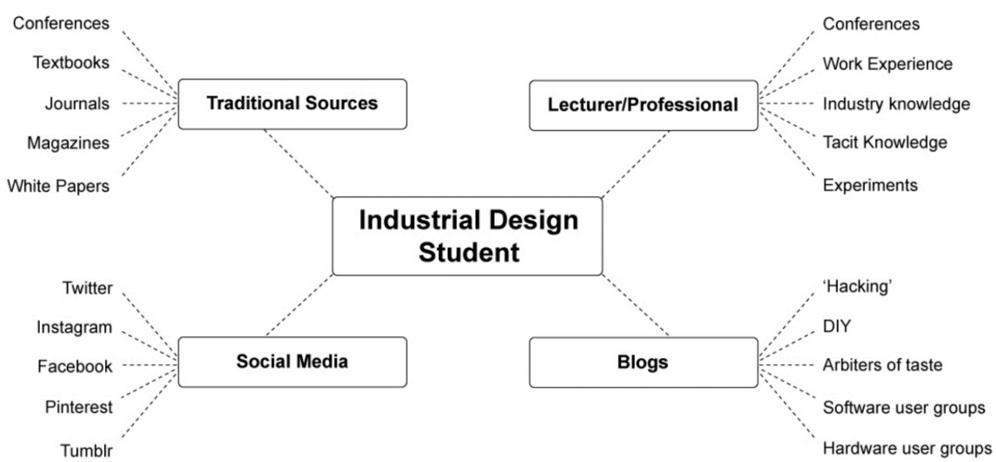


Figure 2.13 Context of Industrial Design Student (Gianni Renda & Blair Kuys, 2015)

W. Chen (2015) has proposed a more inclusive model. He conducted a survey with 189 industrial design students and divided the learning resources into four categories based on the data: people, object, method, and environment, as shown in Figure 2.14. The people category includes instructors, peers, technicians, experts, family, and others. The object category includes the Internet, books and magazines, products, equipment, and others. The method category includes brainstorming, discussion, observation, interview and survey, practice, computer aided, and others. The environment category includes the libraries, workshops, processing factories, department stores and malls, and others. This study explored the weight of different learning resources from a student-centered viewpoint.

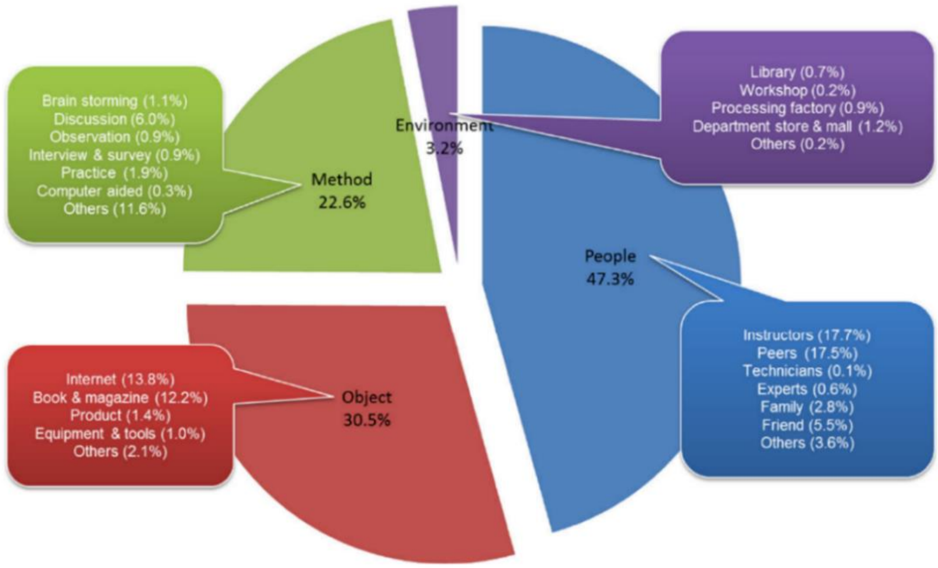


Figure 2.14 Categories of Design Learning Resources (W Chen, 2015)

2.5.4 Integrated Education Models

There are some integrated models that describe design education in a holistic way. Rooted in constructivism, Van Merriënboer and Kirschner (2001) shared a causal view of the "world of knowledge" where a learning environment is designed to support the acquisition of specific skills (learning goals), as shown in Figure 2.15. The model oversimplifies the design-learning process and ignores the individual differences that affect the learning goals such as intellectual capacities and social skills.

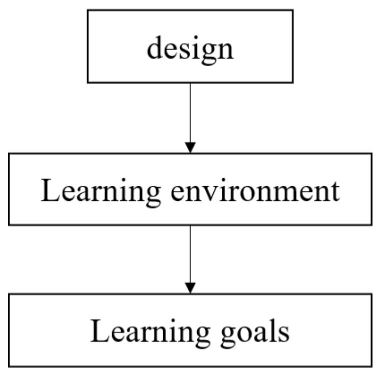


Figure 2.15 Causal View of Design Education (Van Merriënboer & Kirschner, 2001)

Based on the reflection practice paradigm (Schwartz & Schon, 1987), D. Smith, Hedley, and Molloy (2009) developed a reflective learning model with three interactive strands: environment, process and communication, as shown in Figure 2.16. Each strand focuses on a particular aspect of design education to assist the students to engage deeply with the core material. However, this model is student-oriented and works within the scope of a design course rather than the whole education program.

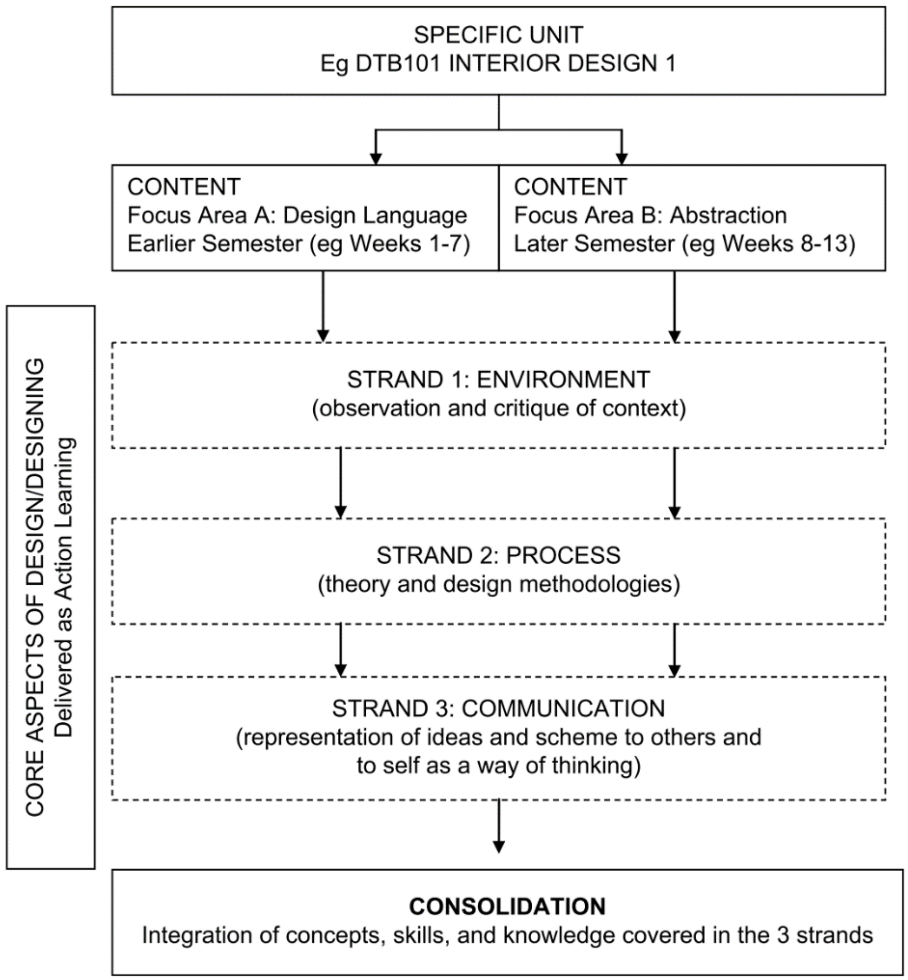


Figure 2.16 Reflective Learning Model (D Smith et al., 2009)

Wrigley and Straker (2017) developed Educational Design Ladder that places key curriculum elements into a structured and cohesive system including education aims, learning activities and assessment tasks. It depicts the cumulative nature of learning and the nature of some major transitions in the learning process. As shown in Figure 2.17, the five stages of ladders represent five themes of design thinking. The units within the ladder increase in complexity as the students' understanding increase with each stage. With this framework, students' work can be assessed for higher order design skills, rather than for knowledge retention alone. This module evaluates designers based on the sophistication of final outcomes. However, some other researchers thought students' design skills should be the education aims.

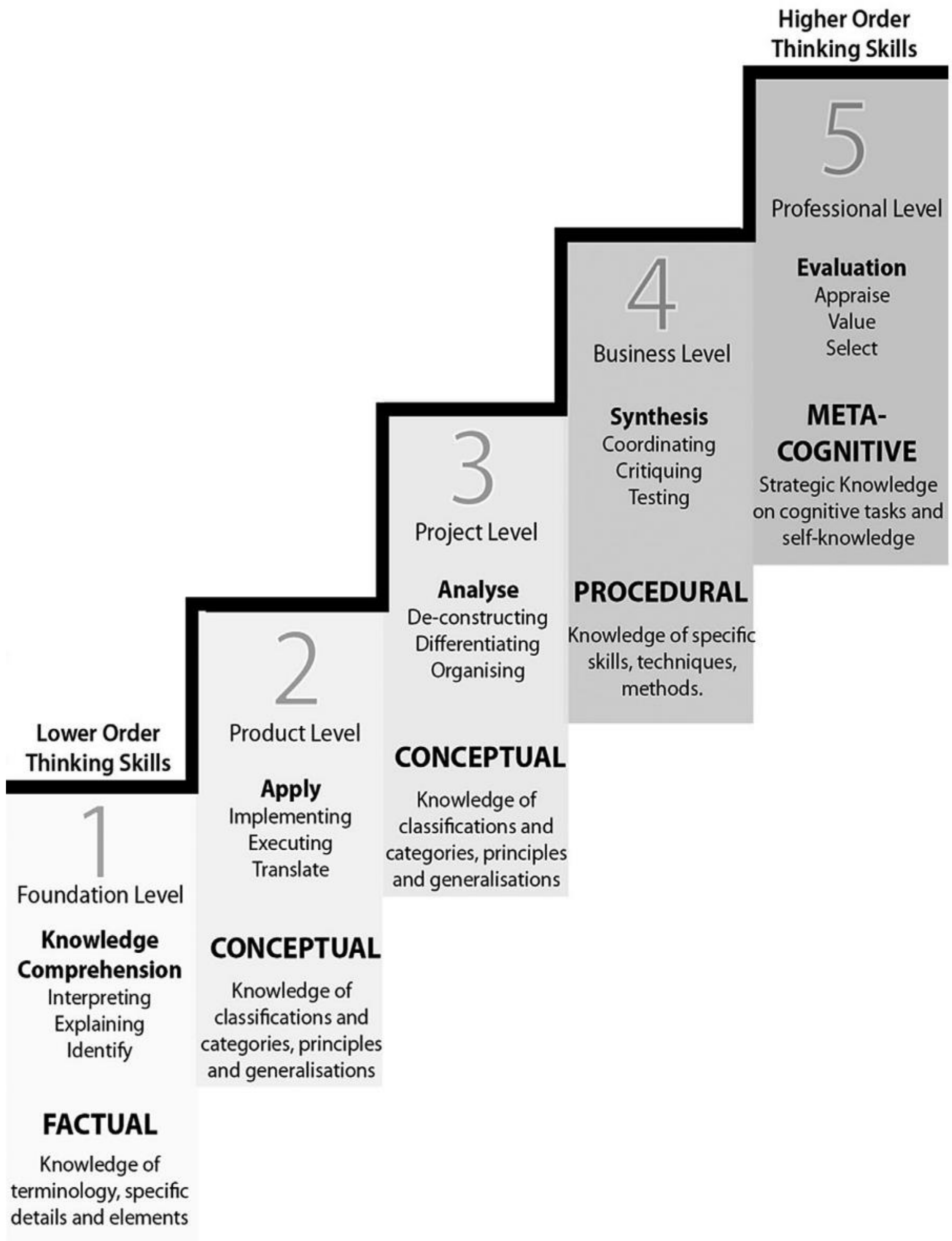


Figure 2.17 Educational Design Ladder Pedagogy (Wrigley & Straker, 2017)

T. Zhang, Lu, and Wu (2017) proposed a "Christmas Tree" model to facilitate inclusive design education including six layers, namely: (1) education aims; (2) educational standards that determine the graduates' qualities requirement; (3) course system; (4)

syllabus that is basic guideline for educators; (5) teaching methods and (6) core courses. From top to bottom of the "tree", the key education elements are arranged hierarchically, as shown in Figure 2.18. This model discusses the main architecture for implementing design education. However, it is too general and lacks consideration about design process, which is regarded as important factor by other researchers. What is more, this model is at a strategic level, which lacks details of course content and teaching methods for educators to follow.

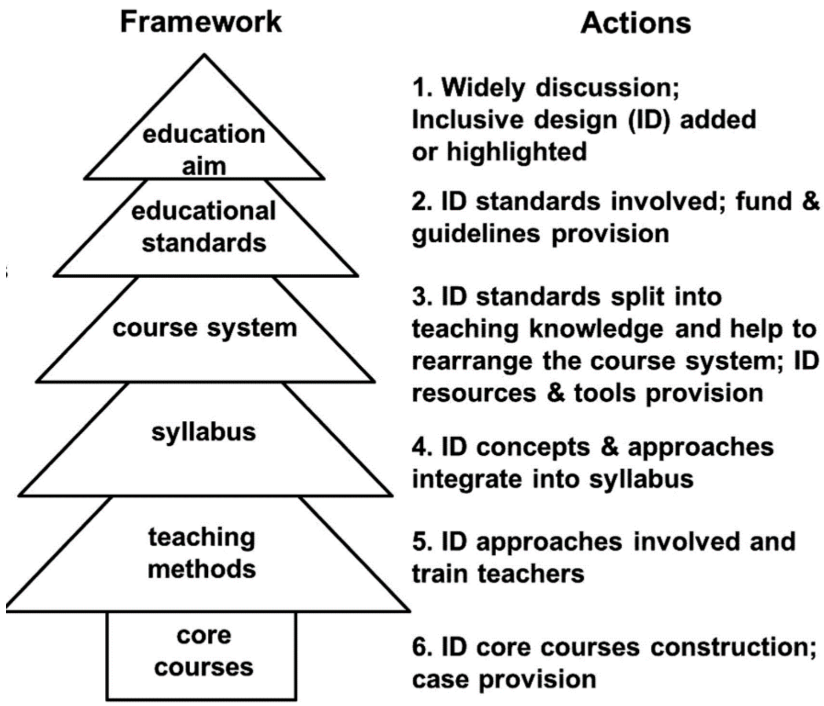


Figure 2.18 "Christmas Tree" Model (T Zhang et al., 2017)

The teaching experts from d.school considered design education as a progressive movement of repetitively applying the design process and tools to build mindsets which together develop creative competencies (Jobst et al., 2012; Kelley & Kelley, 2013). They proposed a learning model to support the development of creative confidence, consisting of four layers: methods, process, mindsets and creative confidence (Rauth et al., 2010), as shown in Figure 2.19. Here creative confidence was defined as a development of trust in one's own creative knowledge, creative skills and creative mindsets (Rauth et al., 2010). This model is useful to consider the relationships between design methods, tools, design process and design mindsets, but the model over-simplifies the resulting intention for design education and more details of each layer are required.

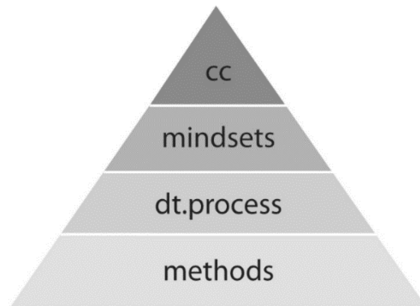


Figure 2.19 Education Model towards Creative Confidence (Rauth et al., 2010)

Adapting the creative confidence model, Wright and Wrigley (2019) proposed the Design-led Education Innovation Matrix to assist educators in developing students' understanding of the design process, skills and mindsets. As shown in Figure 2.20, this model applies three horizons to represent the "growth staircase" of design expertise. "Design as exploring" is categorized as the horizon one, that involves understanding the design process while mastering foundational tools and technology. Horizon two "design as connecting" involves preparing students for more complex life and work environments with innovation skills (critical thinking, creativity, communication, and collaboration). And the highest horizon "design as intersecting" consists of developing adequate life and career skills. This model integrates the education aims and design thinking principles, allows students to embrace learning opportunities beyond the classroom. However, this model lacks operational teaching agendas and strategies.

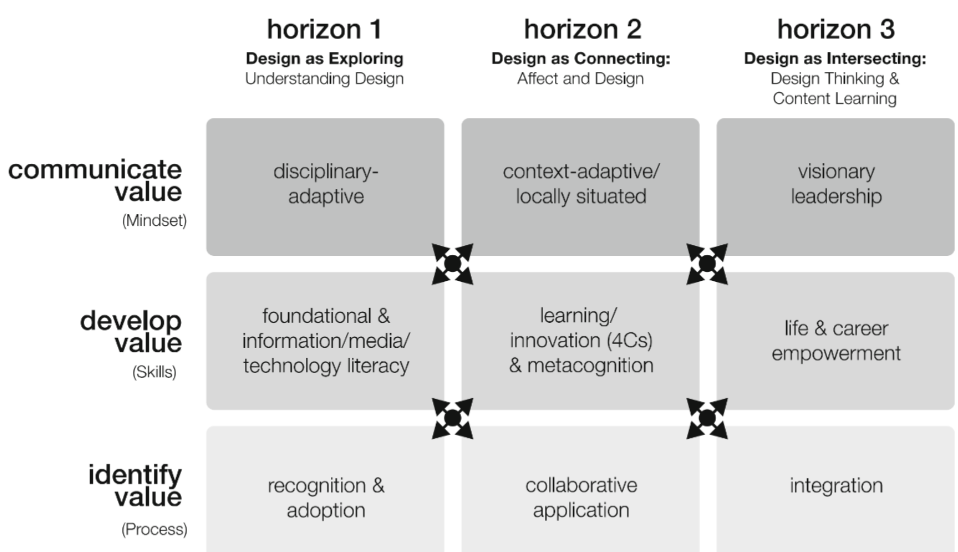


Figure 2.20 Design-led Education Innovation Matrix (Wright & Wrigley, 2019)

2.6 Conclusion

In conclusion, a review of the literature has made it clear that there are many theories involving all the elements of design education including education aims, design-learning process, and learning resources, as shown in Table 2.2.

Table 2.2 Components of Design Education

Education aims	Personal development	development model (Curry, 2014)
	Competency	design competency (Hummels et al., 2011), creative confidence (Jobst et al., 2012; Kelley & Kelley, 2013; Rauth et al., 2010), creative self-efficacy (Tierney & Farmer, 2002) and design mindsets (Rauth et al., 2010; Wright & Wrigley, 2019)
Design-learning process	Design process	Rational problem-solving (Michalos & Simon, 1970) and reflective practice (Schwartz & Schon, 1987)
	Learning process	Experiencing, conceptualization, reflecting and experimentation (Kolb et al., 1999)
Learning resources	Stakeholders	Educator, industry professional, student, family, friends (Fleischmann & Hutchison, 2012)
	Methods	Interview, surveys, discussion, computer aided, technology (W. Chen, 2015; Wright & Davis, 2014)
	Tools	Social media, blogs, internet, workshop, books, magazines (W. Chen, 2015)
	Environment	Library, community, academia, industry (W. Chen, 2015)

According to the integrated education models such as Van Merriënboer and Kirschner (2001)’s causal view of design education, reflective learning model (D. Smith et al., 2009), d.school’s creative confidence model (Rauth et al., 2010), and “Christmas Tree” Model (T. Zhang et al., 2017). Students must go through the design-learning process, supported by learning resources provided by the educators, to achieve the education aims.

Given the above brief overview of the literature, we propose that there is a means by which to integrate these insights into a theoretical and systematic model to facilitate educators. A simple model consists of three categories, as shown in Figure 2.21.

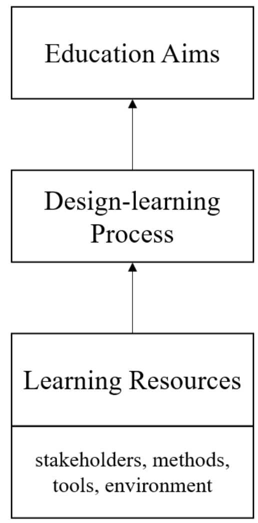


Figure 2.21 Preliminary Model of Design Education

In this model, the education aims category refers to the design expertise or competency that students need to acquire to face the challenges in the rapidly-changing world. Previous research used different terms to describe the aims of design education, such as students' development (Dreyfus, 2004), design competency (Hummels et al., 2011), design expertise (Curry, 2014), creative confidence (Jobst et al., 2012; Kelley & Kelley, 2013; Rauth et al., 2010), creative self-efficacy (Tierney & Farmer, 2002) and design mindsets (Rauth et al., 2010; Wright & Wrigley, 2019), etc. The design-learning process category (Dominici, 2017; D. Smith et al., 2009) refers to the iterative cycles of learning construction (P. A. Cooper, 1993; Dorst & Dijkhuis, 1995) and reflection (Schwartz & Schon, 1987). The learning resources category refers to the stakeholders in education programs (W. Chen, 2015), design methods (Rauth et al., 2010), design tools (W. Chen, 2015; Dominici, 2017; Rauth et al., 2010) and the learning environment (W. Chen, 2015) to support the design-learning process. All these elements function as a whole to foster creative thinking and creative acting in design education. This model is a synthesis of current theories of design education. However, it has not reflected the impact on design education of social change and technology development. Previous research has revealed that there is currently no satisfactory and comprehensive model for future design education. Demand for new models of design education has never been greater, and it is evident that methods and strategies of teaching must be rethought and redesigned.

3. METHODOLOGY

3.1 Chapter Overview

The aim of this thesis is to study the current situation of design education and develop a theoretical model to envision the future design education. The previous chapter reviewed the literature which provides a relevant theoretical perspective that can be used to inform the research process. The overall aim of this chapter is to provide a methodological perspective which can be applied in this research.

Constructing a theoretical model of future design education arises a series of research questions, including: what are important elements of design education in theory? How is future design education like? etc. In order to answer these questions, rich information about design education and relevant stakeholders should be collected and analyzed. This information includes qualitative data and quantitative data. The debate over qualitative data and quantitative data has been an issue since the very beginning of educational research. Cohen, Manion, and Morrison (2002) clarified the differences between qualitative data and quantitative data. Qualitative data are normally used to understand the context of research and the participants in it; to understand participants' views of the research; to explain the cause and effects etc. On the other hand, quantitative data are used for generalizing the results of studies; measuring effects of an intervention; gaining an overall picture and patterns of response; modelling correlations and relationships etc.

There are different methods examining and interpreting the data of a same educational phenomena. Although each method can be used alone, there is not a single all-purpose method (Kuniavsky, 2003). Each one has its strengths and weakness, providing a different insight of a same phenomenon. For example, questionnaire broadly paint participants' desires and hopes, while interviews help to understand the full environment in which the experience happens. Various methods work at specific times and in different situations. Applying mixed methods research helps to balance and complement each other. In this thesis, mixed methods research is applied for mixing data types.

3.2 Mixed Methods Research

Mixed methods research combines various elements of both quantitative and qualitative approaches for the purpose of providing a richer and more reliable understanding of a phenomenon than a single approach would yield (Cohen et al., 2002). Leech and Onwuegbuzie (2009) stated that conducting mixed methods research involves data collection, analysis and interpretation of studies that address a particular phenomenon. Denscombe (2017) argued that mixed methods research increases the accuracy of data and reliability, reduces bias and provides a more complete picture of the phenomenon. In mixed methods research, the specific methods are chosen based on the research questions, with "fitness for purpose" as a guiding principle (Cohen et al., 2002).

Tashakkori, Johnson, and Teddlie (2020) suggested several different designs of mixed methods research including parallel mixed designs, sequential mixed designs, quasi-mixed designs, conversion mixed designs, multilevel mixed designs and fully integrated mixed designs. Similarly, Creswell and Clark (2017) identified six mixed methods research designs according to different timing and sequence of methods which are described below.

(1) Convergent parallel design: both quantitative and qualitative data are collected independently and in parallel with each other, and then converge to offer complementary data.

(2) Explanatory sequential design: quantitative data are collected first, followed by qualitative data to explain the quantitative data.

(3) Exploratory sequential design: qualitative data are collected first typically with a small sample, and then quantitative data from a larger sample are used to generalize the findings.

(4) Embedded design: the research question required both quantitative and qualitative data, and the qualitative data may be embedded in quantitative data or vice versa.

(5) Transformative design: an explicitly political or social intention advances the social justice for the participants under study. In this design, it is less the data types and sequence that are important as the political agenda of the research.

(6) Multi-phase design: the qualitative and quantitative data can be concurrent or sequential, depending on the phase of the research in which they are being used. In this

design, the progress of the research in incremental and cumulative, i.e., one phase is informed by the preceding phase in addressing the overall research question. Creswell and Clark (2017) emphasized that this kind of research is often characterized as a series of “mini-studies” leading towards the overall solution to the research problem. Hesse-Biber and Johnson (2013) stated that there is no single methodological approach in mixed methods research, and each research study can plan its own design.

3.3 Methods Used in the Research

To address the research question, the thesis follows the exploratory design and multi-phase design of mixed methods research by conducting several mini studies. This research aims to develop a theoretical model to envision the future design education and conduct a case study to evaluate the educational effects and learning experience. A diagram is built up identifying this educational research as a holistic concept, depicting the research activities of educational theories, design institutes and design educators. Figure 3.1 gives an overview of the research methods, applied to develop a methodology for this study. The detailed methods are explained for each chapter accordingly.

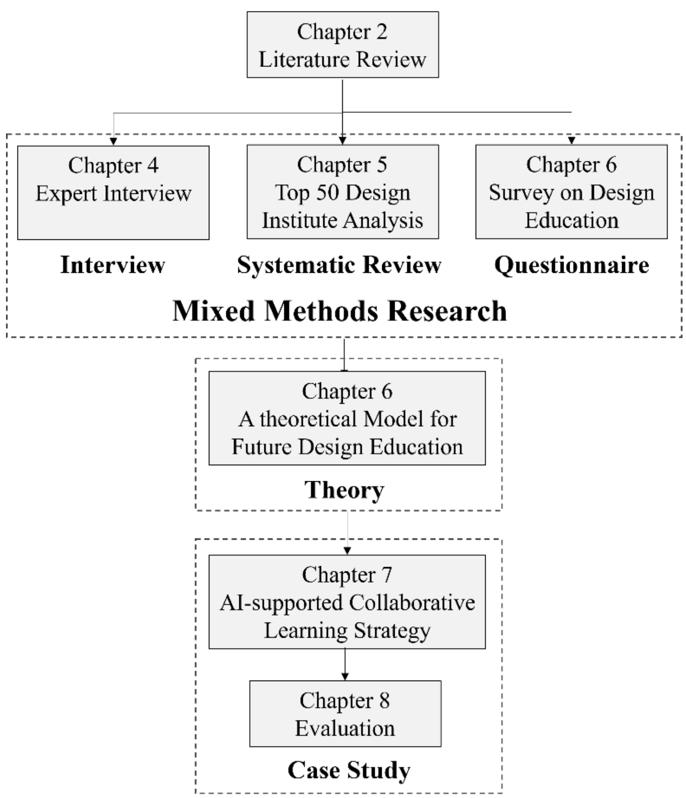


Figure 3.1 Methods Used in the Research

3.3.1 Interview

Interview is powerful tool for researchers. Kuniavsky (2003) defined an interview as a method of asking participants about their experiences. It is an easy approach to collect information about the user's background including their profile, prior experiences, expectations and visions etc. Hochschild (2009) noted that the interview can explore issues in depth, to see how and why people frame their ideas. However, Kuniavsky (2003) also indicated this method is open to interviewer bias, which requires the interviewer to stay neutral throughout the whole process. Kuniavsky (2003) suggested that the questions should be open-ended so as to keep the process of eliciting information non-directly. And the questions of interview need to be composed carefully to avoid potential bias.

In this thesis, an expert interview (see Chapter 4) is conducted to understand the role of social and technological change on industrial design and inform the future direction and development of design education programs. The opinions of experts from academia and industry are important, as such experts understand current methods and limitations of design education, as well as the kind of designer needed by industry. In addition, experts from national and international design organizations can provide visionary perspectives. The senior representatives of companies, universities, and organizations during the 2nd World Industrial Design Conference were invited to participate the expert interview.

3.3.2 Systematic Review

Since the mide-1990s, there has been a growing interest in systematic reviews of qualitative studies. With the trend of evidence-based education, systematic review is increasing used method of investigation bringing together different studies (Tod, 2019). Some systematic reviewers recommend purposeful sampling for selecting studies, while others recommend comprehensive searches and inclusion criteria (Cohen et al., 2002). Heyvaert, Maes, and Onghena (2013) argued that mixed methods research syntheses are more suitable for providing more complete, concrete and nuanced answers to complex synthesis questions.

Pawson (2006) proposed a method of synthesis that seeks to explain different aspects of a phenomena: the reviewers begin by identifying the key theories underlying the specific phenomenon to construct a more refined theory. Then the reviewer applies this theory successively to explain a number of cases. With each application, the reviewer refines the theory. This method includes purposeful sampling, studies with qualitative and quantitative designs, involvement of stakeholders, and the tentative findings that inform decision makers of the likely implications of different decisions (Pawson, 2006). In this thesis, the Top 50 design institutes according to the 2020 QS World University Rankings were systematically analyzed to obtain detailed information of design education (see Chapter 5). There are 40 effective sample design institutes from 14 countries, providing 259 education programs for analysis. The data was collected from third-party resources, such as websites and online publications. To ensure the reliability of online course material, information was only gathered from reputable sources, such as the universities' websites, and only from documents that carried the university logo or name.

3.3.3 Questionnaire

Questionnaire is a widely used and useful methods for collecting survey information, providing structured and numerical data (Cohen et al., 2002). It includes a series of structured questions asking participants to describe their needs, interests and preferences (Kuniavsky, 2003). It investigates participants' profile and opinions, while it is easy to conduct. However, the researcher may ask wrong participants the wrong questions, producing inaccurate results. Internet questionnaire is becoming commonplace in many educational research (Denscombe, 2017). It reduces costs and reduces the time taken to distribute and gather data. It also allows to access large populations easily. However, it may suffer spam and low response rates. Thus, it needs careful design and construction to fit specific participants.

This thesis describes an internet questionnaire (see Chapter 6) that involves further investigation of educators in the front-line of design education in China to gain firsthand information. The questionnaire was sent to 415 design educators from 63 universities in China, which were chosen based on the rankings of top design institutes of China by a professional website for university rankings in China. In total, there are 126 effective samples collected from 21 provinces in China. The main objective of the questionnaire was to determine the influencing factors of design education in current situation and future vision from the educators' perspectives for the purpose of refining the proposed education model. This includes gaining an understanding of today's design education, then to compare with the future vision. The experimental data obtained for the study consists mainly of responses to survey questionnaires and a related quantitative analysis.

3.3.4 Theory

Kerlinger (1966) defined theory as "a set of interrelated concepts, definitions that presents a systematic view of phenomena by specifying relations among variables, with the purpose of explaining and predicting the phenomena". Bacharach (1989) argued that theories serve to simplify the complexity of the real world. Huff (2009) stated that theories are explanations of a generalized nature which enable the research to compare and analyze empirical data. Theoretical model or framework clarifies the facts that are relevant and important in the research (Cohen et al., 2002).

In this thesis, a theoretical model was developed by synthesizing the findings of expert interview, Top 50 design institute analysis and questionnaire. It provides educators with clear directions to follow with examples and operable strategies (see Chapter 6).

3.3.5 Case Study

Case study is important source of research data, that focuses on the causes and relationships in greater details, as well as integrate different viewpoints and explanations (Eisenhardt, 1989). It may include experiment, action research, naturalistic research, participatory research etc. (Cohen et al., 2002). Tight (2010) defined case study as a detailed examination of a sample and an in-depth investigation of a specific program from multiple perspectives to catch its complexity and uniqueness. Flyvbjerg (2006) argued that the advantage of the case study is its closeness to real life, which is context-dependent and allows the researcher to meaningfully understand human behavior.

This research applies an AI-supported learning strategy in educational practice, in order to evaluate the proposed theoretical model (see Chapter 7). A relevant experiment was conducted to collect and analyze information about educational effectiveness and students' learning experiences (see Chapter 8). In order to evaluate the learning strategy in design education practice, a case study in real world was conducted. The setting of case study follows the design methodology for computer-supported collaborative learning settings (Strijbos, Martens, & Jochems, 2004). The case study has recruited 11 Dutch design students and 22 Chinese design students to make up cross-cultural design teams as participants of the case study. The evidences about design students' cross-cultural competence were collected and analyzed including learning process, self-reflection and learning performances.

3.3.6 Data Analysis

Qualitative and quantitative analyses were both used to determine the findings. Among the various methods used, statistical analysis was used for the quantitative data from the online survey. Qualitative analysis was applied to analyze the data from the expert interviews, which provided the various aspects of thinking and reflection of the participants. Through the thesis, various data analysis methods were applied in each study.

3.4 Reliability and Validity

Reliability refers to whether a particular research method will yield the same results if applied repeatedly to the same object (Babbie, 2020). Reliability includes a range of elements within quantitative and qualitative approaches, such as respondent validation, credibility of results, replicability, stability, internal consistency and Cronbach alphs etc. Threats to reliability can result from various sources, such as participant bias and observer bias (Robson, 2002). This research tried to enhance reliability by the use of triangulation. Combining quantitative and qualitative data may strengthen the validity of the research and the inferences that can be drawn from it (Cohen et al., 2002).

Validity refers to whether a particular indicator measures what it is intended to measure, rather than some other phenomenon (Robson, 2002). There are multiple aspects of validity including content validity, construct validity, external validity and internal validity. Threats to qualitative research include generating incomplete data and incorrect interpretation. Validity in this thesis was tackled by the use of standard methods and triangulation.

3.5 Conclusion

In summary, the overall aim of this chapter is to provide a methodological perspective which can be applied in this research, and the specific objectives of this chapter are: (1) to outline the mixed methods research; and (2) to describe the research methods to be applied within this research.

The overriding philosophy of the research is mixed methods research which entails a variety of standard research methods. It tried to ensure the scheme of systematic review, interview, questionnaire, and case study by referring to the literature. It also applied triangulation to improve the validity of the findings by using both qualitative and quantitative data generated by different types of research methods. In order to improve the validity of the data, the study interpretate each element in the theoretical model and focuses on research within design education context in real world. This chapter also introduced the research methods that were used in design studies in exploring the theoretical model for future design education. The followings chapters present the studies that were developed on the general methods described here and the specific analyses will be described in the subsequent chapters.

4. EXPERT INTERVIEW

4.1 Chapter Overview

To understand the role of social and technological change on industrial design and inform the future direction and development of design education programs, the opinions of experts from academia and industry are important, as such experts understand current methods and limitations of design education, as well as the kind of designer needed by industry. In addition, experts from national and international design organizations can provide visionary perspectives. To explore future design education, interviews with design experts were conducted to identify their perspectives on current trends in industrial design and design education.

The World Industrial Design Conference (WIDC) is a global event initiated in 2016 (WIDC, 2016), which aims to establish an international cooperation platform to promote the design industry and design education between nations and geographical districts. The participants of the conference are representatives of design organizations, institutions, enterprises, and universities from more than 30 countries and regions around the world. As a member of the organizing committee for the WIDC (2018), I took this opportunity to conduct interviews with the participating experts to identify their views on current trends in industrial design and design education. I organized a design workshop during the 2nd WIDC in 2018, and invited the senior representatives of companies, universities, and organizations to participate an interview, many of them accepted my invitation and were willing to share their ideas.

4.2 Information about the Subjects

37 participants (29 male and 8 female) were recruited representing 36 organizations from 26 countries and international organizations. The participants were from 14 companies, 11 institutes, and 11 design organizations, including the World Design Organization, the Service Design Network, and the Bureau of European Design Associations, among others. Table 4.1 presents the demographic profile of the participants, 89.2% of whom have held a high-level position, such as directors, while the remainder were senior designers or lecturers. Their average age was 52.8 years (SD=10.7). As they comprised a sufficiently high-level and wide-ranging sample of design experts, the results of the interviews are regarded as authoritative and worthy of sharing with the design community at large.

Table 4.1 Demographic Profiles of Expert Interview

	Organization			Position		Gender	
	Design Studio	Design Institute	Design Organization	Director	Employee	Male	Female
Number	14	11	11	33	4	29	8
Percentage	38.9%	30.6%	30.6%	89.2%	10.8%	78.4%	21.6%
Age	AVG=53, SD=10.7						
Participants' Organizations							
Design Studio	Ageinnovatio, Arrowdot, Aws Design Team, De Tao Group, Design United, Studio Heller, FH Joanneum, Freshworks Design, SmallWorld Venture, Studio Baeriswyl, Tata Motors Limited, VanBerlo Design, Sedeen, ABD Design Studio						
Design Institute	Hong Kong Polytechnic University, National University of Singapore, Politecnico di Milano, Queensland University of Technology, Royal Melbourne Institute of Technology University, Sripatum University, Technische Universiteit Eindhoven, University of Cape Town, University of Computer Studies Yangon, University of Mandalay, Victoria University of Wellington						
Design Organization	World Design Organization, Service Design Network, The Bureau of European Design Associations, British Industrial Design Association, Design Denmark, Japan Industrial Designers Association, Swiss Design Association, APCI Promotion Du Design, Hong Kong Design Trade Association, Mongolia Industrial Design Association, Russia Designers Association						

4.3 Data Collection Process

The format of the study was a one-to-one meeting, with each interview lasting approximately 10 to 15 minutes. The interviews began by asking the experts about their background and their involvement in their respective organizations. Subsequently, the interviewees were asked to give their personal understanding of industrial design and design education. A semi-structured interview approach was taken, in which the participants were asked several questions around two main topics:

1. What is your view of the current trends in industrial design?
2. What are the requirements for the future of design education?

Since the participants have different backgrounds and not all the participants are suitable for both two questions. Each participant has answered one or two of the questions based on their background and willingness. The goal was to shed light on the tacit knowledge of design education for the future. The interviewees described not only their opinions but also the reasons behind them, providing contextual information. It was possible to ask further questions and probe more deeply to ensure understanding. Each of the 37 interviews was audio-recorded, and the transcripts were later analyzed. The length of the interviews varied depending on the participants' level of reflection on their education experience and their willingness to spend time with the researcher.

4.4 Data Analysis Process

A qualitative approach was used to analyze the data, seeking significant insights. Based on grounded theory (Strauss & Corbin, 1994), the data were analyzed in Nvivo and key findings were identified. In addition, the findings covered the key insights of each expert while still referring to the original sources, making the structuring process more transparent and closer to the original sources. This process was conducted by two researchers in parallel to avoid personal bias. Finally, the findings were discussed based on the preliminary model.

4.5 Findings

4.5.1 Trends in Industrial Design

18 participants were willing to respond to this question and identified changes in the field of industrial design. Firstly, with the advance of technology and society, the **focus** of industrial design is now centered on digital products (P5 and P31), service design (P4, 5, 7, 17, 30 and 31) and system design (P4, 5, 7, 11, 15 and 17), and less on traditional manufacturing. As director of a national design association, P31 explained how "industrial design is changing into the digital realm. We are designing services and social interactions." Another director of a national design association (P4) used the term "design strategies" to explain the use of design as a strategic approach to develop the business and public sectors. They also pointed out that "industrial design can solve wicked, multilayered and complex systematic problems, such as the UN Sustainable Development Goals". Similarly, P7 gave an example of designing cities, while P17 talked about how design can solve major problems, such as poverty, food security, environmental changes, transportation, education, etc. P11, from a university, said "It's not just designing for products; it's also designing the process". As a senior designer working in a design studio, P27 mentioned that design also becomes an important research tool. From these answers, we found that the boundaries for industrial design are blurred, which is consistent with the latest definition of industrial design as proposed by the WDO (WDO, 2015). Industrial designers need the knowledge and skills to design solutions in manufacturing, as well as experiential, business and supporting services (Wrigley & Bucolo, 2011).

Since designers are facing larger and more complex challenges where design is interacting with engineering, social sciences, and economic sciences etc., the **process** of industrial design is also changing. 10 participants emphasized multidisciplinary design. P17 from academia asserted that “designers have a unique mindset to provide multi-disciplinary solutions for people with feasibility and viability”. 11 participants emphasized the importance of cross-culture design to solve global problems. A manager of a design studio (P3) said “design is very internationally-oriented and problem-solving is everywhere”. As CEO of an international design consultant company, P37 identified that some countries are deindustrializing and the designers in these countries have to design products for users with other cultural backgrounds. They suggested that the cultural barrier is much higher than the language barrier when bringing business abroad.

Thirdly, with the shift of focus and the process of industrial design, the **role** of design is also changing. As a dean of a design school in a university, P13 indicated that “design will be the heart to connect with engineering and business, these kinds of disciplines”. Another dean (P23) said “design is bridging the gaps between engineering, social sciences and economic sciences, and it is acting as a sort of intermediate”. The participants from industry emphasized the importance of design in multidisciplinary teams. For example, P32 used the words “key label”, while P3 used “mediator” to describe the role of design.

Finally, technology both changes what we design and how we design, with the fact that more **intelligent tools** are now integrated in the design process, including artificial intelligence, big data, smart materials, 3D printing, microelectronics, and Virtual Reality to name just a few (P8, 16, 17, 19 and 27). As a creative director of a design studio, P10 believed that technology plays a very important role in design. Participants from both industry (P17) and academia (P27) emphasized the fact that designers will be utilizing tools, techniques, and other things which they have never previously experienced.

4.5.2 The Future of Design Education

In total, 20 participants have accepted to answer the second interview question: “What are the requirements for the future of design education?”, providing a variety of insights on the **aims** of future design education. A dean of a design school (P13) pointed out that design education is not purely skill-based, but rather it is about cultivating students who possess design thinking and design methods. Meanwhile, a dean of a digital media school (P20) thought design education should develop a mindset for solving every kind of problem, so it is important to teach students design thinking. They further explained that “educators must develop students’ creativity and prepare them to be ready for the changing industry and rapidly-moving innovation technology”. Managing a continuous design education program, P16 suggested that curiosity and an open mind are the key factors for the industrial design. As a senior professor in industrial design, P17 said “we have to teach students to manage complex systems, and it’s challenging to prepare students for the unknow future world”. Being both a university professor and a CEO of a design studio (P24) said “young kids that enter design will be entrepreneurs”. As a specialist in brand strategy and management, P21 suggested that the aim of design education is to allow the students to have different perspectives. A director of a national design association, P5 thought “the combination of technology and creative thinking is essential for the future of design education, and creative thinking is something which AI and robotic systems cannot do”. These answers indicate that being a designer is not the only career option for design graduates who are going to have more opportunities in different fields with design thinking and problem-solving skills.

Regarding the **learning process**, 18 participants highlighted the need for multidisciplinary learning in design education. As a director of a national design association, P5 thought the future of design education will bring together design, engineering, and enterprise. With 25 years of experience as an industrial designer in industry, P9 believed that universities should be open to being cross-disciplinary on a global scale. A dean of a design school (P3) maintained that it is important for designers to have different points of view and to work in partnership with others, while another dean (P15) explained that students need to be exposed to more fields, and that they need to understand society. A senior lecturer (P18) shared the similar opinion that students need to gain broader and richer experience and spoke of Australia creating a four-year program in design, replacing the existing three-year program, so that more students may complete a double degree, including design engineering, design business, and design law, among others.

Notably, 7 participants emphasized the **cultural aspect** of design education. P7 stated how “culture, emotions and history-telling are the soft sides of design, that’s where you build in values.” P13, from a university, thought education should allow students to understand the importance of multicultural collaboration, and as president of an international design organization, P29 spoke of how linking cultures can prepare students for a world without borders. P13 and P29 agreed that the best way to gain multicultural experience is to organize collaborative training projects with other universities. As a Dutch designer frequently visiting China for design projects, P27 asserted that international students can help design teams to understand customers and markets from specific countries.

With regard to learning resources, 20 participants suggested that a **collaborative learning environment** can promote design education, while 14 of the experts spoke of the need for cooperation with industry. P23 emphasized the fact that the kind of industrial design taking place in the lab is not in line with what is happening in industry, and they encouraged teachers to look to industry. Running a design studio, P8 proposed that designers should work with government and companies, since more design challenges are in the system or much broader things. 13 experts spoke of their experience of collaborating with other universities in terms of exchange programs and double-degree programs. P25 discussed how collaborative learning is based on teamwork and networks, which are more effective and more efficient.

Some experts expressed their **visions** of future design education. As a vice president of a university, P26 believed that education in the future will be 24 hours, 7 days per week, supported by technology, while a senior professor in industrial design (P17) proposed that students need to be lifelong learners, ready for all potential changes. From these responses, we have concluded that future design education will be more open in terms of the time, space and disciplines involved.

4.5.3 Model for Future Design Education

Changes and trends in the industrial design profession have stimulated transformations in design education (Sethia, 2001). In the future, the aims of design education will need to have a broader scope and additional dimensions, including creative thinking, problem solving, technology integration, entrepreneurship, etc. As a result, design graduates will have more career options across different fields. The process of industrial design and the learning process of design education coincide such that they both emphasize the relevant multidisciplinary and cross-cultural aspects. Technologies have changed how we represent, create and share knowledge (Yeoman & Carvalho, 2019), and as many experts have pointed out, intelligent tools can support students to keep abreast of rapidly-changing technology. Collaborative education programs connecting with industry and other universities will be helpful learning resources. To summarize the findings from the expert interviews, the preliminary model was refined for the future design education, as shown in Figure 4.1.

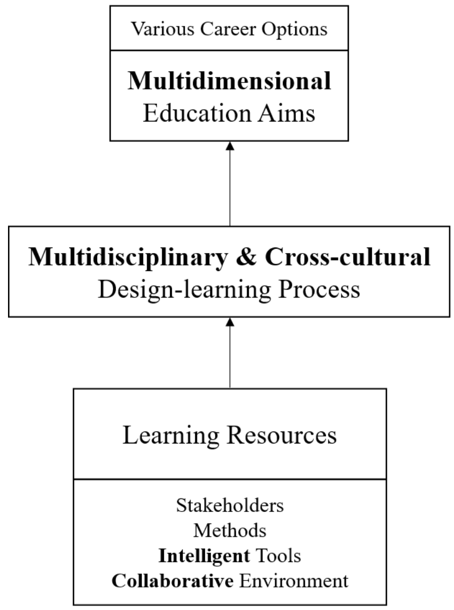


Figure 4.1 Model for Future Design Education

Compared to the preliminary model (see Figure 2.21), this model highlights the main characteristics of education aims, design-learning process and learning resources. This model declares that the education aims are **multidimensional**. Norman and Klemmer (2014) believed that design thinking skills will be a key success factor for future creative leaders in technology, business and education. Ringvold and Digranes (2017) proposed that design education plays an important role in educating future citizens for the sustainable development of societies. These examples suggest that design education plays an important role in cultivating the future workforce with various career opportunities.

The result of expert interview has emphasized multidisciplinary and cross-cultural design-learning process. **Multidisciplinary** learning helps design students to bring different perspectives together and bridge the world of new technology, societal trend, and user needs. The top design institutes are extending their industrial design programs, by promoting multidisciplinary design-learning processes, and by offering hybrid degrees. They are also providing opportunities for new disciplines to emerge, based on the re-structuring of traditional disciplinary boundaries (Teixeira, 2010). Stappers et al. (2020) pointed out that new disciplinary knowledge was brought in design education, that is kind of broadening rather than replacing.

The term **cross-cultural** is used to describe the process of designing for other cultures (McMullen, 2016). With the trend of globalization and fierce competition in the global product market, connections between culture and design have become increasingly close (Shin, Cassidy, & Moore, 2011). Applying culture as design elements in product design enhances products' core value, that makes them be culturally innovative products (Chai, Bao, Sun, & Cao, 2015; R. T. Lin, 2007; Shin et al., 2011). The study has identified two ways to help students gain multicultural experience. One is through organizing global education programs, such as the Master of European Design program, while the other is to take advantage of the ethnic diversity of metropolis and recruit students from different cultural backgrounds. This finding coincides with the research result proposed by Deardorff (2011) that service learning, education abroad and "internationalization at home" (Nilsson, 2003) are three main mechanisms for creating cross-cultural design setting.

With regard to the **collaborative** learning environment, Bullock (2020) argued that a symbiotic relationship between university and industry helps students to take balance of human, technical and manufacturing factors, and develop leadership in collaborative design process. It empowers students to develop responsibility for developing life-long learning skills (Bullock, 2020). Bishop and Mane (2004) found in their analysis that university-business collaboration significantly increase employment and annual earning. University courses with direct links to the society encourage interaction, deeper understanding and "real world" learning (Warburton, 2003). This requires educators work closely with experts in industry.

4.6 Conclusion

This chapter refines the preliminary model based on the result of expert interview. The new model highlights the important features of the development of design education under the influence of social and technological change, so that educators can be given clear directions to follow. However, this is a general theoretical model; and the teaching strategies of each category still need to be explored to allow educators to link theory with teaching practice.

5. TOP 50 DESIGN INSTITUTE ANALYSIS

5.1 Chapter Overview

To obtain detailed information of design education in authentic contexts and to refine the theoretical model, the leading design institutes were investigated. The 2020 QS World University Rankings were used to indicate the rankings of the world's top universities specializing in Art and Design. The rankings were calculated based on both academic reputation and employer reputation (QS, 2020).

5.2 Overview of the Samples

Among the 50 institutes identified, 5 institutes had no English courses, and 5 institutes had no industrial design related courses. They were eliminated from the analysis, leaving a total of 40 effective samples from 14 countries, as shown in Appendix 5A. Among the 40 institutes, 28 (70%) had an independent design school, while in the remaining 12, industrial design was subordinate to the school of art or the school of architecture. The 40 effective samples had 259 education programs including 90 bachelor programs (34.7%), 154 master programs (59.5%) and 15 PhD programs (5.8%). Master and bachelor education seem to be the focus of design education.

Among all the samples, fewer than one quarter of the programs were general industrial design programs with traditional names. There were 26 "Industrial Design" programs (10.0%), 25 "Design" programs (9.7%), 11 "Product Design" programs (4.2%). Meanwhile, a series of programs have a new focus, such as "Interaction Design" (4.2%), "Communication Design" (3.5%) etc. The remaining 177 programs (68.4%) have 147 different program names contributing a wide range of design programs that broaden the boundaries of industrial design. The specialized education programs include service design, creative computing, game design, information design, strategic design, data visualization, virtual reality, transition design, creative entrepreneurship, and transdisciplinary design, among others. The full list of education programs is given in Appendix 5B. Master education tends to have more specialized programs, and the percentage of diversified programs among its samples (78.6%) is much higher than that of bachelor education (55.6%) and that of PhD education (33.3%). Master programs normally recruit students from different educational backgrounds, making it easier to implement collaboration between different disciplines and even to create new design disciplines.

5.3 Data Collection Process

The curriculum contents and methods of the 40 institutes and their 259 design education programs were collated. All data was collected from third-party resources, such as websites and online publications. The availability of online resources differed across institutions: some provided a brief unit synopsis of what and how learning objectives were assessed, while others included the scope of the program and its general learning activities. To ensure the reliability of online course material, information was only gathered from reputable sources, such as the universities' websites, and only from documents that carried the university logo or name.

5.4 Data Analysis Process

Based on grounded theory (Strauss & Corbin, 1994), a qualitative approach was used to analyze the data. The qualitative interviews data were analyzed in Nvivo, divided into three stages: creating notes according to codes, clustering notes and documentation. First, notes were created based on the codes regarding the main three components of design education including the education aims, the design-learning process, and learning resources. Then the notes were clustered, merged and arranged in Nvivo. Finally, in the documentation, relevant keywords were picked to communicate the main findings. The findings covered the curriculum information of each design education program, while still referring to the original sources, making the structuring process more transparent and closer to the original sources. This process was conducted by two researchers in parallel to avoid any personal bias.

5.5 Findings

5.5.1 Multidimensional Education Aims

From the analysis of the samples, the aims of design education differ across design institutes. The Royal College of Art summarized the intended learning outcomes of the education program in three categories (RCA, 2020): (1) Intellectual engagement including idea development, design context awareness, social and economic impact awareness, and design principles awareness; (2) Technical skills, including user engagement, integrating technologies and materials, and presentation techniques; and (3) Professionalism, including time and resource management, collaboration and networks, teamwork, presentation skills, and product marketing. The University of Arts, London, described learning outcomes from several perspectives (UAL, 2020), namely:

(1) research and inspiration; (2) concept and ideation; (3) development and prototyping; (4) production; (5) presentation and storytelling for influence; (6) critical and creative mindsets; (7) employability; and (8) professional identity. Parsons School of Design at The New School shares an institutional vision (Parsons, 2020) that aligns with shifts in the global economy, society, and environment: (1) creativity and (2) social engagement. It orients students' academic experience and encourages them to become engaged citizens dedicated to solving problems and contributing to the public good. Goldsmiths, University of London, described its "Goldsmiths Graduate Attributes" (Goldsmiths, 2020) by introducing four overarching skills: (1) problems solving skills, including critical and analytical skills, adaptability, flexibility, and creativity; (2) business and entrepreneurial skills, including commercial awareness, networking skills, initiative, negotiation skills, teamwork, leadership skills, diplomacy, social skills, and empathy; (3) interpersonal skills, including planning and organization, time management, and self-motivation; and (4) communication skills, including presentation skills, self-marketing, persuasiveness and emotional intelligence. The University of Technology Sydney proposed nine Graduate Qualities (Sydney, 2020) including (1) depth of disciplinary expertise; (2) critical thinking and problem solving; (3) oral and written communication; (4) information and digital literacy; (5) inventiveness; (6) cultural competence; (7) interdisciplinary effectiveness; (8) integrated professional, ethical, and personal identity; and (9) influence. The Glasgow School of Art also highlights professional practices as education aims (GSA, 2020), namely: (1) communication; (2) presentation; and (3) working with others. Aalto University identified several skills that design graduates should have (Aalto, 2020): (1) personal design identity; (2) a comprehensive design toolbox; (3) ideation and prototyping skills; (4) teamwork and co-creation skills; and (5) social consciousness. The Hong Kong Polytechnic University introduces the aims of industrial design (HKPU, 2020) as: (1) user-oriented research skills; (2) market analysis skills and business awareness; (3) engineering knowledge and technology opportunities; (4) cultural appreciation; and (5) social responsibility. Emily Carr University of Art + Design develops six core competencies (Carr, 2020), which are: (1) design processes; (2) self-awareness; (3) time management; (4) articulation; (5) information literacy; and (6) teamwork.

To summarize the education aims of the above design institutes, two categories were identified, namely: generic literacy and design expertise, as shown in Table 5.1. Generic Literacy includes communication skills, teamwork and leadership, and problem-solving skills. A holistic view of Design Expertise covers five aspects, namely: creativity, social and cultural awareness, technology integration, user perspective and commercial awareness.

Table 5.1 Education Aims Based on the Analysis of Top 50 Design Institutes

Generic Literacy
Communication skills: self-marketing (Goldsmiths, 2020), persuasiveness, storytelling (UAL, 2020), negotiation, presentation (GSA, 2020; RCA, 2020), emotional intelligence (Goldsmiths, 2020)
Teamwork and leadership: collaboration (GSA, 2020), time and resource management (Carr, 2020; Goldsmiths, 2020; RCA, 2020)
Problem-solving skills: critical mindset (Sydney, 2020), analytical skills, adaptability, flexibility (Goldsmiths, 2020)
Design Expertise
Creativity: idea development (RCA, 2020), inspiration and ideation (Aalto, 2020; Goldsmiths, 2020; UAL, 2020)
Social and cultural awareness: social and economic impact awareness (RCA, 2020), social engagement (Parsons, 2020), cultural appreciation (HKPU, 2020; Sydney, 2020), social responsibility (GSA, 2020)
User perspective: user engagement (RCA, 2020), empathy, user-oriented research (HKPU, 2020)
Technology integration: integrating technologies and materials (RCA, 2020), prototyping (Aalto, 2020; UAL, 2020), engineering knowledge (HKPU, 2020), technology opportunities (HKPU, 2020), information literacy (Carr, 2020; Sydney, 2020)
Commercial awareness: product marketing (RCA, 2020), initiative (Goldsmiths, 2020), market analysis (HKPU, 2020), networking (Goldsmiths, 2020)

It is found that the aim of industrial design education is not simply to cultivate designers. Rather, the graduates pursue careers as consultants, innovators, entrepreneurs, freelancers, art directors, software developers, cultural producers, ergonomists, researchers, trend analysts, design managers, interaction designers, design strategists, brand managers, service designers, activists, social practitioners, and chief experience officers, etc. The broader boundaries of industrial design provide more career opportunities for students.

5.5.2 Multidisciplinary Design-learning Process

Based on the 259 samples, the multidisciplinary programs integrating industrial design and other disciplines were analyzed. Disciplines were defined according to the International Standard Classification of Education (ISCED) (UNESCO, 2013). As shown in Table 5.2, there are 10 broad fields and 26 narrow fields of education and training. Each broad field is coded with a two-digit number while each narrow field is coded with a three-digit number representing the affiliation.

Table 5.2 Fields of Education and Training (ISCED)

Broad field	Narrow field
01 education	011 education
02 arts and humanities	021 arts 022 humanities 023 languages
03 social sciences, journalism and information	031 social and behavioral sciences 032 journalism and information
04 business, administration and law	041 business and administration 042 law
05 natural sciences, mathematics and statistics	051 biological and related sciences 052 environment 053 physical sciences 054 mathematics and statistics
06 information and communication technologies (ICTs)	061 information and communication technologies (ICTs)
07 engineering, manufacturing and construction	071 engineering and engineering trades 072 manufacturing and processing 073 architecture and construction
08 agriculture, forestry, fisheries and veterinary	081 agriculture 082 forestry 083 fisheries 084 veterinary
09 health and welfare	091 health 092 welfare
10 services	101 personal services 102 hygiene and occupational health services 103 security services 104 transport services

The curriculum content of the programs were coded referring to the detailed descriptions of ISCED (UNESCO, 2013) to avoid ambiguity. From the analysis, several featured examples were identified which include partnerships between 9 of the broad fields and 14 of the narrow fields.

Beyond Art (42.5%): according to ISCED (UNESCO, 2013), industrial design falls under the field of the arts and humanities, so the majority of programs (110, 42.5%) belong to "art programs". However, industrial design reaches far beyond art and develops more subdivision directions, such as interaction design, furniture design, heritage visualization, scientific visualization, design futures etc.

Social Sciences, Journalism, and Information (13.1%): there are 15 programs (5.8%) orienting towards the "social dimension of design". For example, the Master degree program, Creative Sustainability, at Aalto University prepares students to work as sustainability experts in organizations that have a strategic view on transformation towards sustainability. These include the private and public sectors as well as a wide range of NGOs. The Internet Equalities program at the University of the Arts London explores how power relations are organized and embedded in internet technologies, and uses a range of methods including participatory design, feminist human computer interaction, digital ethnography, and design justice. The PhD in Transition Design at Carnegie Mellon University develops future design leaders with the capacity to envision and realize transitions to sustainable futures. To establish mutually beneficial relationships between people, the environment and society, students explore multilevel wicked problems such as climate change, the loss of biodiversity, the depletion of natural resources, the decline of communities, and the widening gap between the rich and the poor, etc. There are 19 programs (7.3%) linking with the field of journalism and information. Communication design and information design focus on film making, map making, graphic design and typography for media and publishers.

Information and Communication Technologies (12.0%): technology has opened the field of design and has transformed the nature of design. A number of the education programs (31, 12.0%) are linked with information and communication technologies. For example, the University of the Arts London has established the Creative Computing Institute to explore the intersection of creativity and computational technologies. This dedicated institute offers innovative new programs, such as the Computing Art program and the Data Science and AI for the Creative Industries program. These programs focus on emergent research areas, such as human computer interaction, artificial intelligence, and machine learning. The Design for Emerging Technologies program at the School of the Art Institute of Chicago offers students resources in interface design, physical interaction design, information architecture, physical computing, software-based optimization and analysis, and design for embedded control and robotic activation.

Business and Administration (10.0%): 26 education programs (10.0%) are linked with business and entrepreneurship education. For example, the Design Strategies program offered by The Hong Kong Polytechnic University has been rated by BusinessWeek as one of the world's best design thinking programs. The program seeks knowledge to facilitate the integration of design and business, and about understanding customers' needs, branding products and services for markets, and creating business values. The program is intended for both design and non-design professionals with working experience. MIT media lab launched the MITdesignX program to promote students and researchers building new business ventures, and they have developed a venture design process including four steps, namely: understanding market needs, engaging with stakeholders to provide value-added solutions, envisioning the business model, and finally, developing a master plan to launch the venture. The Creative Business Leadership program provided by Savannah College of Art and Design emphasizes the knowledge and skills of strategic thinking, financial planning, and effective management. The main education methods employed to facilitate the design-learning process include seminars, market research, and external visits, among others.

Services (8.9%): 23 design programs (8.9%) are concerned with service design and user experience design, while 11 of the programs focus on game design and entertainment design. Students practice their design expertise in the fields of animation, video games, theme park design, film, and television. As an example, the master program Animation, Games, and Interactivity, supported by the Royal Melbourne Institute of Technology University, has strong connections with the creative industry and students exhibit their graduation projects at the Melbourne International Animation Festival.

Engineering, Manufacturing and Construction (7.3%): there are 19 design programs (7.3%) focusing on the engineering field, including transportation systems, materials, and intelligent cities. For example, the Transportation Systems and Design program at the Art Center College of Design combines social science, urban planning and policy with engineering and design to equip students to envision mobility solutions to current and future transportation challenges. The master program in Transport at the University of Sydney is Australia's first interdisciplinary degree focusing on transport, encouraging students to build realistic vehicle concepts around future lifestyles. Some of the programs are looking at future needs, such as the Material Futures program at the University of the Arts London.

Health and Welfare (1.2%): there are 3 design programs linking with the health field. Glasgow School of Art, in collaboration with the School of Life Science and School of Architecture, offers the multidisciplinary degree program, Medical Visualization and Human Anatomy. The students examine human anatomy and construct the same in a real-time 3D environment for simulation and education. Meanwhile, Loughborough University offers a Human Factors and Ergonomics for Patient Safety program, teaching students the theoretical principles, and design methods through which to optimize human well-being and overall health system performance. The program is professionally recognized by the International Ergonomics Association.

Education (1.2%): there are 3 programs (1.2%) linking with the education field. For example, Rhode Island School of Design offers a certificate program "Teaching+ Learning in Art+ Design" that focuses on the development of new practices in art and design teaching across the learning continuum, spanning from kindergarten to college and beyond.

Natural Sciences (0.4%): there is only one specialized design program linking with natural sciences, which provides a very typical example of creating an emerging discipline. The Biodesign program was founded by the University of the Arts London, and it teaches designers to learn from nature and to create sustainable ways of living for a circular economy. Thus far, there is even no universal definition of Biodesign. The program has a strong emphasis on ethical issues related to sustainability and Biodesign practice through making. Students use incubators and microscopes for growing bacteria and yeast, propagating plants or running bioreactors during the design-learning process.

There are still some programs (9, 3.5%) that are difficult to define. For example, Parsons School of Design, Carnegie Mellon University, California Institute of the Arts, Seoul National University, Emily Carr University of Art+ Design, and Zurich University of the Arts, they all provide design programs termed as "interdisciplinary" or “transdisciplinary” for students from different backgrounds. The California College of the Arts even offers an individualized program that provides students with the opportunity to access resources within and across faculties, as they explore topics outside the normal boundaries of existing programs. It give students more freedom to organize their own learning activities and contents.

5.5.3 Cross-cultural Design-learning Process

Two strategies to integrate cross-cultural elements in the design-learning process were identified. One is promoting global education programs. For example, a popular master program Global Innovation Design brings together the complementary expertise and resources of six leading institutions (The Royal College of Art, Imperial College London, Pratt Institute, Keio University, Tsinghua University and Nanyang Technological University) to provide students with a rich and wide spectrum of learning opportunities across design, engineering, technology, culture, commerce, and industry. The students spend two semesters studying abroad in two universities of the alliance. This program aims to cultivate international entrepreneurs of innovation with global vision. Similarly, the Master of European Design features a network of seven leading European design institutes (Aalto University, The Glasgow School of Art, Politecnico Milano, Ecole Nationale Supérieure de Création Industrielle, University of Aveiro, Köln International School of Design, and Konstfack University of Arts, Crafts and Design), where students experience different design education systems and join a strong international community.

The other strategy is taking advantage of the ethnic diversity of metropolis and recruiting educators and students with different cultural backgrounds. For example, the School of Visual Arts Design is in the heart of New York City, and its master program, Design for Social Innovation, has students from 28 countries and counting. Without studying abroad, students can develop their cross-cultural literacy.

5.5.4 Various Stakeholders

The stakeholder category includes instructors, peers, external experts, and others. The analysis of the top design institutes shows that students come from a variety of related backgrounds, such as engineering, architecture, communication, sports science, health, and economics, etc. Many programs are co-taught by professors from design, engineering and business departments, and involve collaboration with different organizations, such as companies, start-ups, schools, non-profit organizations and governments. The leading design institutes have witnessed radical collaboration in design education, bringing together the various stakeholders, including educators, students, users and clients from all disciplines, perspectives, and backgrounds. A range of teaching strategies are used to stimulate and support students' collaborative learning. For example, group critique and peer-evaluation are opportunities to receive peer feedback. Group tutorials, seminars and workshops are used to gather and share information and discuss shared learning.

5.5.5 Multidisciplinary Methods

From the analysis of curriculum content, it is found that the design methods adapt to the multidisciplinary setting of programs. For example, in business design programs, students gain knowledge about system thinking, customer-driven research and entrepreneurial practices. In social design programs, the main design methods are civic participation, social engagement, social observation, ethnographic research, and collaborative design practices. In Entertainment Design programs, students learn relevant courses, such as 3D animation, interactive storytelling, sound design, motion graphics, creative writing, and interaction design.

5.5.6 Intelligent Tools

From the analysis of the top design institutes, it is found that the traditional skills of drawing and sketching, forming, and molding are supplemented and, in many cases, replaced, by skills in computer programming (Processing, Python and Arduino), systems and control (electronics, mechanics), digital fabrication and applied mathematics, etc. As many experts pointed out, intelligent tools can support students to keep abreast of rapidly-changing technology. The top design institutes provide a range of technical resources, and students are encouraged to design through making. The traditional design tools include: (1) Model workshop equipment (machinery for model making with foams and plastics and facilities for plastic vacuum forming, plastic casting, rubber mold making, painting, and finishing. Materials include wood, metal, plastics, foam, clay, wax, and many types of casting materials such as plaster, resin, rubber, latex, and liquid plastic); (2) Metal fabrication tools (machine tools such as lathes, milling machines, MIG, TIG, and ARC welding facilities); (3) Lens-based media equipment (scanner, color laser printing, animation and move making); (4) Computer software and resources (PC workstations, updated software, lens-based media, audio resources). While intelligent industrial design studio tools include: (1) Digital fabrication equipment (laser cutting, CNC milling and lathing, 3D printing, rapid prototyping); (2) Interaction prototyping tools (interaction prototyping, Arduino platform, Particle Photon, Raspberry Pi); (3) Mixed reality tools (VR headsets, Unity, games consoles); (4) AI tools (Natural Language Processing, TensorFlow, deep fakes, GANS, style transfer).

5.5.7 Collaborative Environment

With regard to the collaborative learning environment, different forms were identified in the context of education, including double-degree programs, exchange programs, in-course internships and international platforms.

Double-degree programs create integrated diverse academic spheres for students, with learning resources from either two institutes or two schools. For example, Rhode Island School of Design collaborates with Brown University, and the RCA collaborates with Imperial College London. The University of New South Wales offers a series of double-degree bachelor programs, including the Design+ Education program, the Design+ Media program and the Design+ Commerce program.

Exchange programs involve studying for one or two semesters at an overseas host partner institution. Most universities of the top 50 design institutes allow students to study abroad for a summer school or graduation project.

In-course internships allow students to put theory into practice in an authentic context. For example, The Data Visualization program at the University of the Arts London sends students to undertake internships with the British Red Cross, where they will real-world data-related challenges.

In addition to traditional academic contexts, there are **international platforms** to support collaborative learning such as the Nordic-Baltic network of art and design education (CIRRUS), the International Association of Universities and Colleges of Art, Design and Media (Cumulus), the Master of European Design program, and the International Network of Design for Social Innovation and Sustainability (DESIS), etc.

5.5.8 Refined Model for Future Design Education

The above results contribute to an increased understanding of the state of the art of industrial design education. Based on the analysis of the expert interviews and top 50 design institutes, I constructed a holistic and operational education model that contains three main categories: multidimensional aims, multidisciplinary and cross-cultural design-learning processes, and learning resources. The aims of design education have a broad scope and multiple dimensions, including a list of generic literacy and design expertise. The process of industrial design and the learning process of design education coincide in that they both emphasize their multidisciplinary and cross-cultural aspects. In the learning resources category, students are supported by various stakeholders, multidisciplinary methods, intelligent tools, and collaborative learning environments. They learn from various stakeholders, including their educators, their peers, users, and clients with different backgrounds. Multidisciplinary education programs bring multidisciplinary design methods, and intelligent tools can support students to keep abreast of rapidly-changing technology, including digital fabrication tools, interaction prototyping tools, mixed reality tools and AI tools, among others. Collaborative programs connecting with industry and other universities will be helpful learning environments in the form of double-degree programs, exchange programs, in-course internships, and international platforms. To summarize the findings from the expert interviews, the education model for future design education was refined with more details, as shown in Figure 5.1 With examples and operable strategies, this model provides educators with clear directions to follow, and to link teaching activities in authentic contexts for future design education.

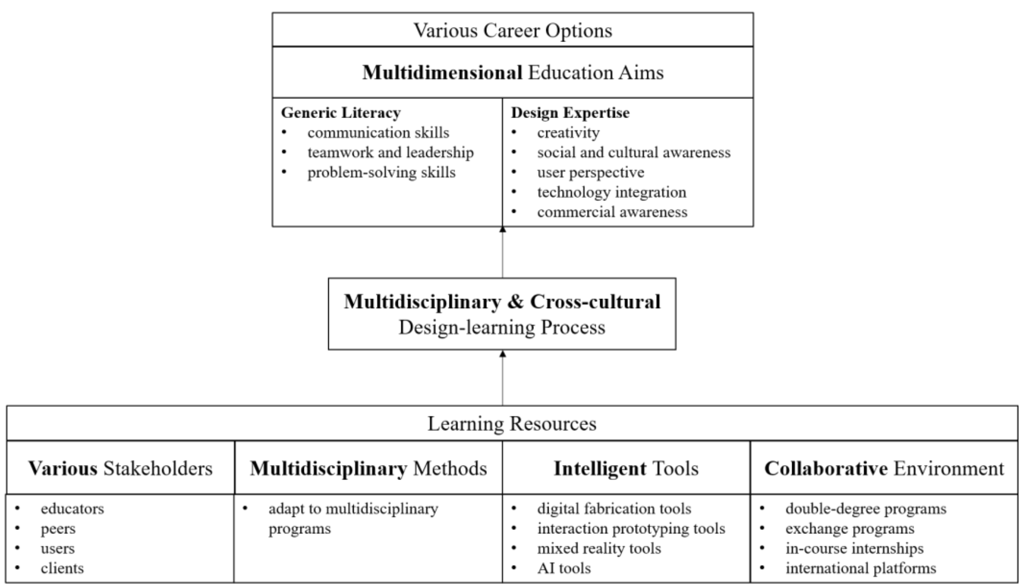


Figure 5.1 Refined Model for Future Design Education

5.6 Discussion and Conclusion

In summary, this refined model has several features, that are: (1) holistic and comprehensive; (2) reflecting the changes of industrial design; (3) based on empirical data in the real world; and (4) provides operable teaching strategies for educators. The refined model for future design education has three main components, namely: multidimensional education aims, multidisciplinary and cross-cultural design-learning processes and learning resources.

5.6.1 Multidimensional Education Aims

Regarding multidimensional education aims, a list of generic literacies and design expertise attributes were identified. They are regarded as important attributes for future.

Communication skills refer to the effective use of spoken and written language skills (OECD, 2005). In this category, there are some subskills. For example, self-marketing is the ability for students to clearly articulate their research and design outcomes, and position their work within the broader context of design fields and society as a whole (Goldsmiths, 2020). Persuasiveness is the ability to present arguments for innovative concepts with clarity and confidence (UAL, 2020). Articulation is the ability to articulate design proposals and outcomes of research, which can be practice in written work, tutorials and oral presentations (Carr, 2020). Communications skills also involve negotiation and emotional intelligences. Developing communication skills requires students' participation in group seminars, peer review and critics. With the transition of societies from industrial economies towards creative knowledge economies, the communication skills are becoming a necessity for success in the future job market (Finegold & Notabartolo, 2010).

Teamwork and leadership refer to the skills of devising, planning, and organizing practice-based learning activities and design outcomes (RCA, 2020). The skills involve time and resource management (Carr, 2020). Educators can provide learning activities for students to develop these skills including group projects, workshop sessions, collaborative works as well as public events (GSA, 2020). Peterson, Mitchell, Thompson, and Burr (2000) stated that teams play a major role in workplace and predicted that it is only likely to increase in the future. The latest definition of industrial design elevates the role of designers in the teams. According to WDO (2015), design is "a strategic problem-solving process that drives innovation and builds business success…", which means it can be adapted to every level of organization and helps creative employees and managers to guide the teams with leadership.

Problem-solving involves goal-directed thinking and action in situations for which no routine solution procedure is available. In this category, there are sub skills such as critical mindset, analytical skills, adaptability, and flexibility. Adaptability refers to the ability to adapt to the complexity of research settings and various challenges (Goldsmiths, 2020). It focuses on students' responsiveness to social, ethical, environmental, and economic conditions as well as the ability to adapt to emerging media and business models. Flexibility involves developing flexible process of research, testing, and conceptual prototyping, that is important skill for entrepreneurism (Goldsmiths, 2020). Learning activities such as debates, reflection, seminars, critiques help students to develop these problem-solving skills. Problem-solving skill is one of the 21st century competencies (Finegold & Notabartolo, 2010) and is regarded as a key component for workplace success in an economy that demands flexibility and innovation (Findeli, 2001).

Expect these generic literacies for being competent workforce, there are five main design expertise including creativity, technology integration, user perspective, social and cultural awareness, and commercial awareness.

Creativity is defined as exceptional human capacity to produce original thought and creation (Ryhammar & Brolin, 1999). Parkhurst (1999) believed fostering creativity in education can help dealing with ambiguous problems and facing an uncertain future. Burnard (2006) emphasized the crucial role of creativity in the economy to cope with increased competition. Demirkan and Hasirci (2009) thought creativity is a natural component of design process, while Demirkan and Afacan (2012) found there is high correlation between design process and creativity.

Technology integration in educational situations is defined as the ability to effectively use technology to accomplish required learning tasks (Davies, 2011). Being competent in integrating technology means being able to explore, visualize and create innovative concepts using technology, as well as analyzing the technical feasibility of complex designs in which technology is integrated (Hummels et al., 2011). The fourth industrial revolution develops smart manufacturing and leads the world to an intelligent era (Collina et al., 2017). The technologies of intelligent era involve cloud computing, big data, AR, VR and IOT etc. The growth of technologies spawn opportunities for exploration and development of innovative products, that requires designers have skills and knowledge about intelligent technology integration (Budd & Wang, 2017).

User-centered design is a classical and widespread design principle initiated by Donald Norman in the 1980s (Abras, Maloney-Krichmar, & Preece, 2004; Pea, 1987). It is later evolving to user experience design, service design and participatory design etc. (E. B. Sanders, 2002). The emerging design movement center around users' needs and require a different approach in that designers can capture users' deeper needs. Thus, gaining **user perspective** is crucial at each stage of design process (Shah & Robinson, 2007). This skill involves empathy and a commitment to socially and ethically responsible design outcomes for producers, users and stakeholders (HKPU, 2020). E. B. Sanders (2002) identified that the roles of designer and design researcher are becoming mutually interdependent. Designers should observe the firsthand user experiences.

Social and cultural awareness refers to the improvement of cultural awareness and the introspection of social situation, that are essential to design students' future growing in cross-cultural environment and international research and practice (Butt, Ratnayake, & Budge, 2016). It includes envisioning concepts in society, place designs in a broader perspective, and evaluate the impact of products or services on society (Hummels et al., 2011). Since the marketplace is no longer local or national but now global, social, and cultural awareness can benefit designer development and promote the rise of multicultural products.

Integrating **commercial awareness** in concept ideation and considering the stakeholders in the initial design process are effective solutions for design problems with many stakeholders (Dam & Siang, 2018). Developing commercial awareness requires students to understand business models and review how best to build a financially sustainable research and practice (HKPU, 2020). In this category, networking skill is important meta skill to support gaining commercial awareness, that refers to the practical ability to identify and source relevant material suppliers and the ability to contact industry professionals (Goldsmiths, 2020). Bonollo and Lewis (1996) emphasized that making recommendations for clients are widely accepted as industrial design expertise. Hummels et al. (2011) suggested designing new products for global market of a dynamic international industrial context requires commercial awareness.

The result of this study also shows that broader boundaries of industrial design provide various career opportunities for students. It has been observed that design graduates can find jobs in various sectors in industry, government, non-governmental organizations (NGO), cultural organizations, health, banking etc. It is also quite common for design graduates to be entrepreneurs and to introduce their own products or innovative business models into the market (Nae, 2017; Tatlisu & Kaya, 2017). The Industrial Designers Society of America (IDSA) member directory listed over 80 specialty employment areas including business development, industrial products, consumer products, design explorations, design strategy, scientific products etc. Industrial design graduates will participate as an informed citizen of future society with general knowledge in the sciences, humanities, social sciences (Bullock, 2020).

5.6.2 Multidisciplinary Design-learning Process

This study has identified several featured examples in design education which include partnerships with the arts, health, education, technology, business, and social sciences. **Multidisciplinary** learning helps design students to bring different perspectives together and bridge the world of new technology, societal trend, and user needs. The top design institutes are extending their industrial design programs, by promoting multidisciplinary design-learning processes, and by offering hybrid degrees. They are also providing opportunities for new disciplines to emerge, based on the re-structuring of traditional disciplinary boundaries (Teixeira, 2010). Stappers et al. (2020) pointed out that new disciplinary knowledge was brought in design education, that is kind of broadening rather than replacing.

5.6.3 Cross-cultural Design-learning Process

The term **cross-cultural** is used to describe the process of designing for other cultures (McMullen, 2016). With the trend of globalization and fierce competition in the global product market, connections between culture and design have become increasingly close (Shin et al., 2011). Applying culture as design elements in product design enhances products' core value, that makes them be culturally innovative products (Chai et al., 2015; R. T. Lin, 2007; Shin et al., 2011). The study has identified two ways to help students gain multicultural experience. One is through organizing global education programs, such as the Master of European Design program, while the other is to take advantage of the ethnic diversity of metropolis and recruit students from different cultural backgrounds. This finding coincides with the research result proposed by

Deardorff (2011) that service learning, education abroad and “internationalization at home” (Nilsson, 2003) are three main mechanisms for creating cross-cultural design setting.

5.6.4 Various Stakeholders

Chen has completed research into learning resources, the results of which show that students depend primarily on people (W. Chen, 2015). This study has identified the various stakeholders in design education, including educators, peers, users, and clients with different backgrounds. Designers recognize the richness of experience comes from communications between stakeholders, whether they are experts, end-users, or social collaborators (Hill, 1998). Gardien, Djajadiningrat, Hummels, and Brombacher (2014) emphasized the involvement of stakeholders in design education helps designers to consider a broader technological and social context in the design process.

Goffin and Koners (2011) point out that the tacit knowledge, described as “know-how” or work-related practical knowledge, can be acquired by shared experience of **educators**. Meanwhile, the input from visiting lecturers and guest speakers will enable students to gain an understanding of relevant contemporary practice, research, and commercial contexts.

Another literature shows that **peers** play an important role in design education (S. Chiu, 2010). When students work collaboratively in a team, they learn from evaluating their partners’ contributions (Hausmann, Chi, & Roy, 2004) and sharing information with each other (Coorey, 2016). The problems faced by designers are becoming more complex and harder to solve, which require design students with diverse knowledge and multidisciplinary backgrounds to group together (Stedman & Adams Pope, 2019). On the other side, peers may cause competition. S. H. Chiu (2010) suggested peers that study in other departments or universities can provide more objective suggestions and support.

With the shift from designing products to designing services, designers tend to focuse on **users**’ purposes and experiences (E. B. N. Sanders & Stappers, 2008). Design education field also saw a shift from “designing with users” notion to “designing for users” (E. B. Sanders, 2002). Gultekin, Bekker, Lu, Brombacher, and Eggen (2016) identified the focus of design research methods has been shifted from understanding users to inviting users as experts of their own experience to participate the design process. The involvement of users is crucial at each stage of design-learning process to maximize their contributions to design outcomes. For the products that have specific target customers, it is necessary to integrate customer feedbacks in the early design stages. The examples of feedbacks can be product functionality, design quality, user experience and ergonomics etc. As a result, designers have been moving increasingly closer to the future users of what they design. Participatory design or co-design are emerging approaches in design field for solving complex problems that are hard to empathize users.

O'Connor (2000) stated designer-client collaborations help designers deeply understand clients' contexts, needs and problems, and generate better ideas and design solutions to satisfy clients' real needs. Involving **clients** as joint problem solvers and co-creating value are regarded as more open approach to innovation (Gardien et al., 2014; Gultekin et al., 2016). Yu and Sangiorgi (2018) agreed that a close designer-client relationship can empower designers to expand the initial scope of design project and achieve radical design-driven innovations.

5.6.5 Multidisciplinary Methods

In design education, close collaborations with other disciplines expand both the design topics and the relevant teaching strategies and learning methods. Curry (2014) thought it very important for educators to identify the correct design methodologies for students in the appropriate contexts. Gultekin et al. (2016) suggested that different stages of design process require different design methods. This study has not attempted to clarify the specific methods needed for future design education, while it identified a general trend whereby the traditional methods of drawing and sketching, forming, and molding are being supplemented and replaced by programming, electronics, and other multidisciplinary methods.

5.6.6 Intelligent Tools

From the analysis of top design institutes, it is found that intelligent tools, such as digital fabrication tools, mixed reality tools and AI tools, can support students to keep abreast of the rapidly-changing technology.

Digital fabrication tools: Di Marco (2019) identified two important industrial technologies in design education: digital design tools (e.g. CAD software) and fabrication tools (e.g. 3D printing, CNC milling and lathing, and laser cutting). The former one is already part of design process. However, these cutting-edge fabrication technologies are normally under-used because of lack of specific skills. D. Y. Kim (2019) identified two categories of digital fabrication tools, that are additive manufacturing (such as parametric design software and 3D printers) and subtractive manufacturing process (such as CNC milling). He emphasized that both of them are important for design education. Di Marco (2019) suggested the most efficient approaches towards digital fabrication technologies in design education is based on coding.

Interaction prototyping tools: Interaction prototyping tools which is for intelligent product development like Arduino platform, Raspberry Pi, help designers implement paper concept into forms of function realization. The boom in IOT, 5G and AI catalyst the emerging of diverse Interaction prototyping tools. Di Marco (2019) argued that Processing and Arduino is the core of interactive design.

Mixed reality tools: mixed reality refers to a continuum of innovative technologies including virtual reality, augmented reality and augmented virtuality (Milgram & Kishino, 1994). Mixed reality tools help design students comprehend 3D spatial design skills (Wu & Chiang, 2013) and enhance multidisciplinary collaborative learning (De Freitas & Neumann, 2009). They are powerful tools for co-design as well. Design students can test future products with end users in virtual environment, that are easy to share, modify and represent in different ways (Füller & Matzler, 2007). The tools offer flexibility and limited cost compared to traditional prototyping. Abdelhameed (2013) found that mixed reality technologies in design studios can increase the awareness of the designer and facilitate the immediate evaluation of a particular design instance. Camba, Soler, and Contero (2017) argued that showing virtual product to users help designers to reduce uncertainty, make decisions throughout refinement and planning processes. Mixed reality tools support ubiquitous and situated learning and avoid making real mistakes when students are practicing tasks. Literatures proved that mixed reality visualization can improve learner outcomes for design education (Dalgarno & Lee, 2010). Despite the various benefits of mixed reality technologies to visualize spatial design, Birt and Cowling (2018) pointed out that the field of design education has yet to fully adopt this new method.

AI-tools: traditional view of the designer at the center of the design process is changing, with the rapid growth in Artificial Intelligence and Data-Driven Design tools that develop an autonomy. Altavilla and Blanco (2020) suggested automated AI tools be integrated during the design processes since the complexity of products and systems is increasing. He introduced the concept of 5-level scale of automation in design field and discussed the interaction of designer-AI tools (Altavilla & Blanco, 2020). And on the fifth level, AI design tools can generate and modify the design outcome automatically without designer interaction. Digitalization of industry and Industry 4.0 revolution that bring artificial intelligence and big data into design process offer new opportunities to discuss the design tools (Altavilla & Blanco, 2020).

Arrighi and Mougenot (2016) found intelligent design tools have the potential to enable users and other stakeholders to actively participant in the design process and to directly interact with representations of the future product. Carvalho and Goodyear (2018) identified growing ubiquity of networked devices and digital technologies providing virtually infinite online learning resources. This requires educators to continue updating their techniques courses and laboratory equipment.

5.6.7 Collaborative Environment

With regard to the collaborative learning environment, different forms in the education context were identified, including double-degree programs, exchange programs, in-course internships and international platforms. They are effective teaching strategies, currently used frequently by the leading design institutes. Bullock (2020) argued that a symbiotic relationship between university and industry helps students to take balance of human, technical and manufacturing factors, and develop leadership in collaborative design process. It empowers students to develop responsibility for developing life-long learning skills (Bullock, 2020). Bishop and Mane (2004) found in their analysis that university-business collaboration significantly increase employment and annual earning. University courses with direct links to the society encourage interaction, deeper understanding and "real world" learning (Warburton, 2003). This requires educators work closely with experts in industry.

In conclusion, design education is a complex issue, with many aspects to be considered. This model is a preliminary framework, which should be validated and refined by involving the front-line educators as well as learners in further investigations.

6. QUESTIONNAIRE ON DESIGN EDUCATION

6.1 Chapter Overview

The thesis follows exploratory sequential design of mixed methods, in which qualitative data are collected first typically with a small sample, and then quantitative data from a larger sample are used to generalize the findings. The previous chapter has developed a design education model based on the analysis of Top 50 design institutes.

This chapter involves further investigation of educators in the front-line of design education in China to gain more firsthand information, rather than the general introductions published on official websites. The main objective of the research described in this chapter was to determine the influencing factors of design education in current situation and future vision from the educators' perspectives for the purpose of refining the proposed education model. This includes gaining an understanding of today's design education, then to compare with the future vision. The experimental data obtained for the study consists mainly of responses to survey questionnaires and a related quantitative analysis.

6.2 Design Education in China

Design education is evolving rapidly in China. With the "market economy" emerged in the 1980s, modern industrial design entered the country (S. Z. Wang, 1989). It then develops rapidly. According to the statistics from the Report of China's Industrial Design Industry Development, in 2020 the total design schools reach 1980, which means there are about 550000 design graduates every year. According to WIPO (2020), China accounted for 52.3% of industrial designs in applications filed worldwide in 2019, representing 711617 designs. It is far exceeding the following countries. These data show that China industrial design education is a good example for further investigation in terms of total population and developing speed.

6.3 Questionnaire Design

The target population of questionnaire was design educators. A three-part questionnaire was designed to collect the data about (1) participants' personal background information, (2) current situation of design education and (3) participants' vision on future design education, as shown in Appendix 6A. The questionnaire contained a structured list questions about the elements of proposed education model including education aims, design processes, stakeholders, design tools and collaborative programs. The participants were also given the opportunity to provide open-ended answers if they wished. 5-point Likert Scale ranging from 1 (not important at all) to 5 (very important) was used to measure the importance of elements of design education. The questionnaire was conducted online, using a professional survey platform https://www.wjx.cn/. The time available to answer the questionnaire was approximately 10 minutes.

6.4 Data Collection Process

The questionnaire was sent to 415 design educators from 63 universities in China. These universities were chosen based on the rankings of top design institutes of China by Airuishen Alumni Network (CUAA, 2020) which is a professional website for university rankings in China. The questionnaire was sent to mailboxes of design teachers and deans, which was obtained from the university’s official website. This study was conducted during the period September 18th to October 5th, 2020. Finally, the research yielded a response rate of 30.4% to the questionnaires. In total, there are 126 effective samples collected from 21 provinces in China, as shown in Appendix 6B.

6.5 Overview of the Samples

The demographic profiles of samples are shown in the Table 6.1 below. 74.6% of samples are design teachers and 25.4% are Directors of design department or Deans of design schools. The average working years is 13.5 years (SD=7.8). They comprised a sufficiently wide-ranging sample of experienced design educators.

Table 6.1 Demographic Profiles of Questionnaire

	Position		**Gender**		
	Teacher	Director or Dean	Male	Female	Secrecy
Number	94	32	76	47	3
Percentage	74.6%	25.4%	60.3%	37.3%	2.4%

	Age Range									
	≤20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	≥60
Number	0	0	6	26	43	26	9	10	4	2
Percentage	0	0	4.8%	20.6%	34.1%	20.6%	7.1%	7.9%	3.2%	1.6%

Working Years	
Average Value (Year)	Standard Deviation
13.5	7.8

Among the 126 samples, 73 participants (58%) reflect that industrial design was mainly subordinate to the school of design, while for the remaining 53 participants, who are from 31 school of art (24%), 14 school of mechanical engineering (11%), 5 school of computer science (4%), 1 school of animation (1%), 1 school of media (1%) and 1 school of architecture (1%).

6.6 Data Analysis Process

The answers of questionnaire were calculated by statistics software SPSS. In order to provide design educators with suggestions about the improvement of design education, paired T-test is used to compare the current situation and future vision of design education. Paired T-test is a type of hypothesis testing that is used when two sets of dependent data are being observed (Wilkerson, 2008). Q9-13 are paired with Q14-16, 19 and 20, asking participants' opinions regarding education aims, design processes, stakeholders, design tools and collaborative programs both now and future. An exploratory factor analysis was used to identify the important elements of design education and later a structural equation model of design education was built to present the research result. The structural equation model implies a structure between the theoretical constructs, which are represented by the latent factors (Hox & Bechger, 1998).

Before processing the data, a value of 0 was assigned to "no participation" or "unused" data for those not currently involved. The reliability of this questionnaire was tested by Cronbach's alpha. Reliability refers to the reliability, stability and consistency of the results measured by the scale (Eisinga, Te Grotenhuis, & Pelzer, 2013). Nunnally (1994) stated that if the constructs are generally above or close to 0.7, then it can be confirmed that the item measurements of the constructs are reliable. The Cronbach's Alpha for the whole 0.838, items ranged from 0.831 to 0.842, indicating satisfactory internal consistency.

6.7 Findings

6.7.1 Multidimensional Education Aims

Previous study identifies a list generic literacies and design expertise as multidimensional education aims including 8 elements, that are communication skills, teamwork and leadership, problem-solving skills, creativity, social and cultural awareness, user perspective, technology integration and commercial awareness. As shown in Figure 6.1, the ranking of education aims both in today's design education and in future are almost the same. The most important skills are creativity and problem-solving skill. They are followed by technology integration skill, with a significantly increased importance (t=-2.741, p=0.007). Social and cultural awareness (t=-3.494, p=0.001) and teamwork and leadership (t=-2.249, p=0.026) both have increased significantly, though their importance (4.43) is lower than the average (4.56) in the current situation. Commercial awareness is the least important skill, and it has increased significantly (t=-3.704, p=0.000) in the future vision. Regardless of the differences among these 8 education aims, they are all important design skills, with a lowest score 4.17 and a highest score 4.87 (4 means important and 5 means very important in this 5-point Likert scale).

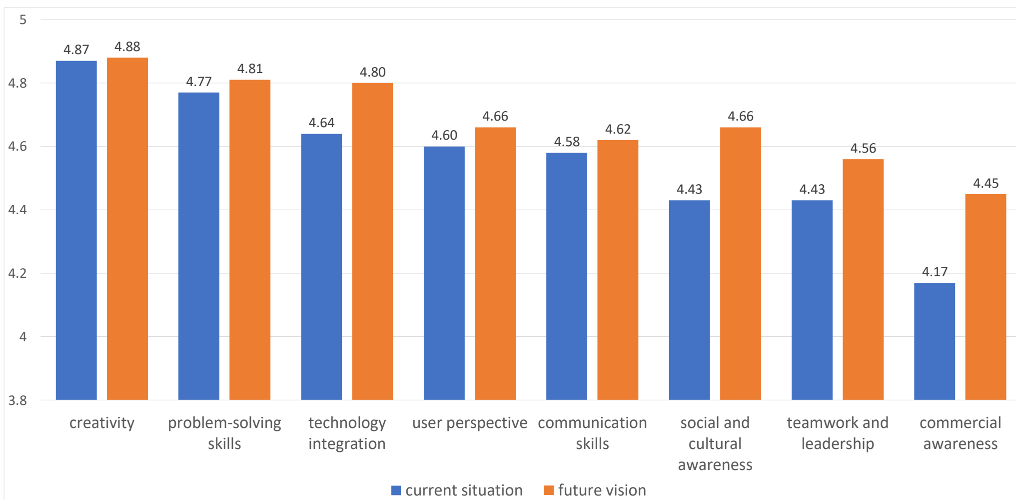


Figure 6.1 Average Scores of Education Aims in Current Situation and Future Vision

Regarding the career options after graduation, product designer is the most popular career option, though it decreases from 84.92% to 76.19% in future vision. With the shifting emphasis of industrial design on digital products, interaction designer is regarded the most popular career option in the future with a penetration rate of 84.13%. Figure 6.2 presents the career options of design graduates in current situation and future vision. The result of paired T test shows that four career options increase significantly in future vision: product manager (t=-4.413, p=0.000), artist (t=-3.348, p=0.000), engineer (t=-3.775, p=0.002) and social activist (t=-5.024, p=0.000). Participants also proposed other career choices in various fields, such as makeup artist, civil servants, design educators, artificial intelligence trainer, project management, technological innovator, system designer, new type designer, experience designer, and any currently unknown career options.

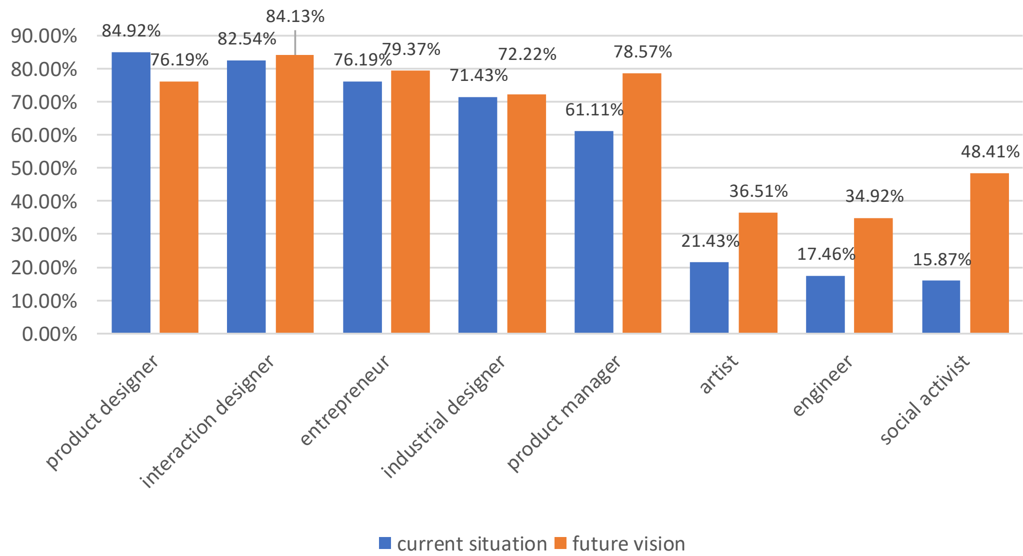


Figure 6.2 Career Options of Design Graduates in Current Situation and Future Vision

6.7.2 Design-learning Process

Participants were asked questions about their experience of educating students with multidisciplinary and cross-cultural design process. 96.88% of high-level design educators have guided students with multidisciplinary projects, while 85.11% of design teachers have similar teaching experience. 71.88% of high-level design educators and 68.09% of normal design educators have educated students with cross-cultural design process. When asked about the importance of design process for design education in future vision, participants give high scores for multidisciplinary design (4.76, SD=0.54) and cross-cultural design (4.54, SD=0.65).

6.7.3 Various Stakeholders

Figure 6.3 presents the average scores of stakeholder category. Peer is the most important stakeholder both now (4.76, SD=0.56) and in the future vision (4.57, SD=0.61). Educator is the second important stakeholder (4.75, SD=0.59), while it is much less important in the future vision (4.41, SD=0.65). Both user (3.84, SD=1.41) and client (3.71, SD=1.44) are not important stakeholders currently with low average scores. It is worth noting that 7.9% participants responded that user is not involved in current design education programs and 7.9% participants responded that client is not involved as well. We conducted paired T test and find the importance of educator (t=4.620, p=0.000) and peer (t=3.211, p=0.002) has declined significantly from now to future vision, while the importance of user (t=-4.638, p=0.000) and client (t=-3.748, p=0.000) has increased significantly.

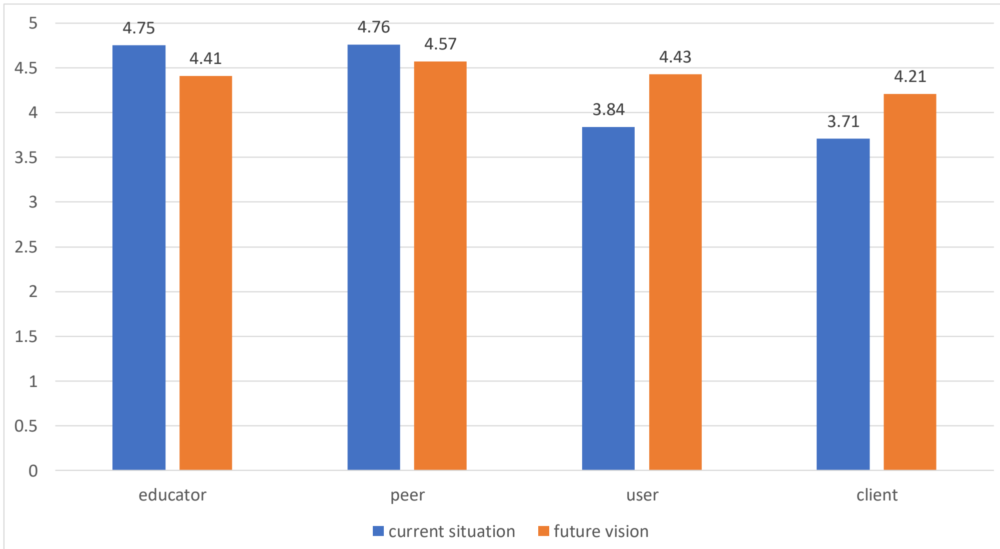


Figure 6.3 Average Scores of Stakeholders in Current Situation and Future Vision

6.7.4 Design Tools

Figure 6.4 presents the average scores of design tools. In today's design education modeling tools are the most important design tools, while the paired T test result shows a significant reduction in future vision (t=5.916, p=0.000). It is worth noting that some participants have not used the remaining intelligent design tools for teaching. For example, digital fabrication tools have 4.76% unused rate, interaction prototyping tools have 7.94% unused rate and mixed reality tools have unused rate of 10.32%. AI tools have the highest unused rate of 17.46%. However, AI tools are regarded as the most important design tools in the future. Paired T test reveals a significant increase in interaction prototyping (t=-3.715, p=0.000), mixed reality tools (t=-6.347, p=0.000) and artificial intelligence tools (p=-8.796, p=0.000) from now to future vision.

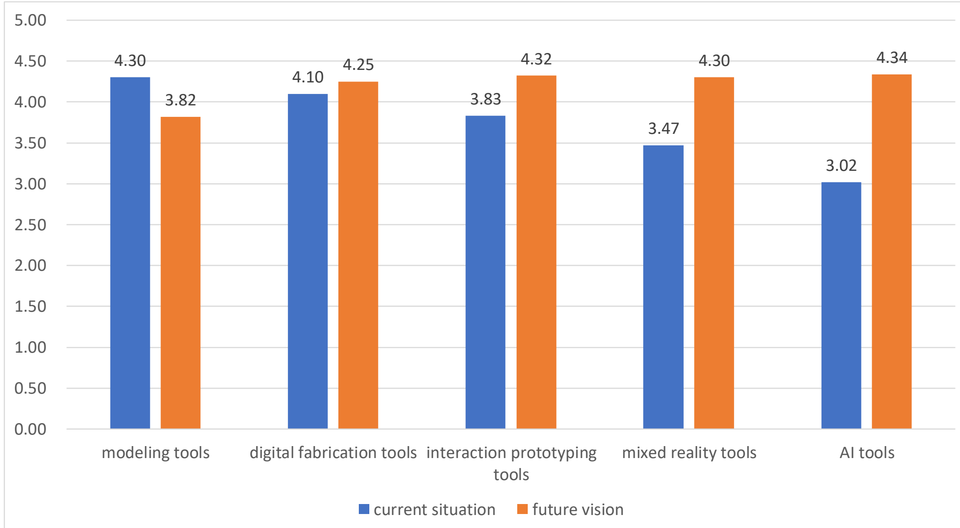


Figure 6.4 Average Scores of Design Tools in Current Situation and Future Vision

6.7.5 Collaborative Programs

Figure 6.5 shows the penetration rates of collaborative programs. In-course internship is the most important collaborative program both in today's design education and in future vision. Fewer than half participants have teaching experiences on double-degree programs (37%) and activities organized by international platforms (22%). Participants respond that their universities offer other collaborative programs to promote design education such as international workshops, university-enterprise cooperation, lectures by famous overseas teachers, scientific research projects and minor courses etc. Paired T test shows there is a significant increase in importance in double-degree program (t=-2.249, p=0.026) and International Design Association project (t=-8.400, p=0.000) from now to future.

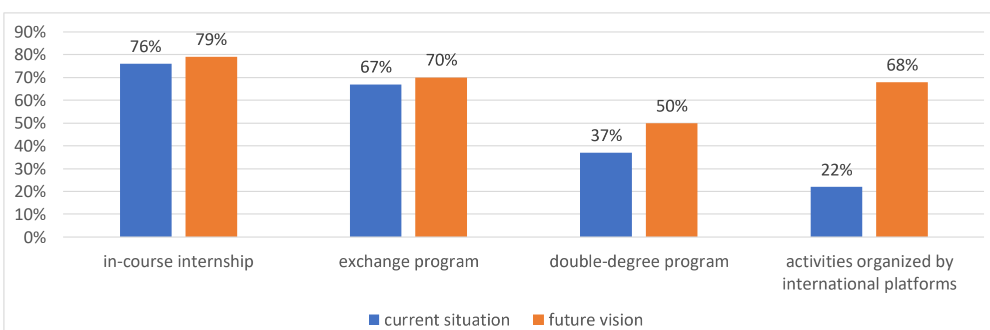


Figure 6.5 Penetration Rates of Collaborative Programs in Current Situation and Future Vision

6.7.6 Exploratory Factor Analysis

Last chapter constructs a theoretical model includes a long list of various education aims and learning resources. In order to determine the important influencing factors of future design education, exploratory factor analysis is conducted based on participants' responses to questions about future vision of design education. Before factor analysis, KMO and Bartlett tests were performed on the data. The KMO is 0.779, greater than 0.6, which meets the prerequisite requirements of factor analysis, meaning that the data can be used for factor analysis research. And the data were tested by Bartlett's test (p<0.01), indicating that the research data were suitable for factor analysis. In order to determine the factors of design education, maximum likelihood factor analysis was conducted. Following Igbaria, Iivari, and Maragahh (1995), an eigenvalue of 1.0 and a factor loading of 0.5 were used as the cut-off points. Through factor analysis, a total of 6 factors were extracted. Since their eigenvalues are greater than 1 and their associated factor loadings are larger than 0.50, they are confirmed to be distinct from each other. The variance interpretation rates of these 6 factors after rotation were 20.553%, 13.447%, 8.857%, 8.803%, 7.551% and 7.503% respectively, and the cumulative variance interpretation rate after rotation was 66.714%, as shown in Table 6.2.

Table 6.2 Factor Analysis

Factor	Number of items	Factor loadings	Eigenvalue	Variance interpretation rates (%)	cumulative variance interpretation rate (%)
1	8	0.552-0.776	6.302	20.553	20.553
2	4	0.673-0.828	2.530	13.447	34.000
3	2	0.742-0.826	1.404	8.857	42.857
4	2	0.578-0.836	1.374	8.803	51.660
5	3	0.423-0.737	1.236	7.551	59.211
6	2	0.612-0.816	1.164	7.503	66.714

In this study, the maximum likelihood extraction method was used (x^2=1133.899, df=210, p<0.001). An orthogonal factor rotation was performed using the Varimax with Kaiser Normalization. The table 6.4 below shows the information extraction of the factor for the research item and the corresponding relationship between the factor and the research item. Following Tabachnick, Fidell, and Ullman (2007), the item's pure measure of the factor increases wither greater loading. It can be seen from table 6.3 that the corresponding common degree value of all the research items is higher than 0.5, indicating a strong correlation between the research item and the factor, and the factor can effectively extract the information.

Table 6.3 Rotated Factor Matrix

	factor loadings						
	Factor 1 multidimensional education aims	Factor 2 intelligent tools	Factor 3 external stakeholders	Factor 4 design process	Factor 5 collaborative environment	Factor 6 internal stakeholders	common factor
Exchange program	0.134	-0.055	-0.086	0.214	**0.729**	0.128	0.622
Double-degree program	0.357	-0.283	-0.168	-0.347	**0.423**	0.039	0.537
Activities organized by international platforms	0.000	0.040	0.182	0.012	**0.737**	-0.061	0.582
Digital fabrication toos	0.101	**0.723**	-0.047	-0.128	-0.182	0.189	0.621
Interaction prototyping tools	0.057	**0.828**	-0.051	0.103	-0.003	0.194	0.740
Mixed reality tools	0.040	**0.808**	0.297	0.051	0.003	-0.071	0.749
AI tools	0.179	**0.673**	0.293	0.237	0.166	-0.095	0.664
Educators	0.112	0.016	0.203	0.024	-0.044	**0.816**	0.722
Peers	0.183	0.368	0.231	0.248	0.155	**0.612**	0.683
Users	0.231	0.217	**0.742**	0.027	0.058	0.233	0.710
Clients	0.250	0.090	**0.826**	0.070	0.039	0.133	0.777
Multidisciplinary design process	0.393	0.069	-0.164	**0.578**	0.100	0.321	0.633
Cross-cultural design process	0.185	0.068	0.100	**0.836**	0.121	0.060	0.765
Creativity	**0.734**	0.155	-0.051	-0.122	0.173	0.236	0.665
Technology integration	**0.644**	0.332	-0.115	0.025	0.158	0.384	0.711
User perspective	**0.711**	0.232	0.215	0.020	0.115	-0.039	0.621
Social and cultural awareness	**0.552**	0.162	0.186	0.443	0.324	-0.099	0.677
Commercial awareness	**0.625**	-0.035	0.255	0.372	-0.144	-0.063	0.620
Communication skills	**0.684**	0.031	0.193	0.254	0.126	0.076	0.592
Problem-solving skills	**0.776**	-0.066	0.141	0.073	0.020	0.144	0.653
Teamwork and leadership	**0.741**	0.049	0.168	0.276	-0.074	0.049	0.664

It is found that the primary factor, which was responsible of 20.533% of the total variance, is composed 8 items that are associated with multidimensional education aims (creativity, technology integration, user perspective, social and cultural awareness, commercial awareness, communication skills, problem-solving skills, teamwork, and leadership). The second factor, which was responsible of 13.447% of total variance, has 4 items that are associated with Intelligent tools (digital fabrication, interaction prototyping tools, mixed reality tools and AI tools). The third factor has 2 items that are external stakeholders (users and clients), which was responsible of 8.857% of total variance. The fourth factor consists of 2 items about design process corresponds to the multidisciplinary and cross-cultural dimension, which was responsible of 8.803% of total variance. The fifth factor consists of 3 items (exchange program, double-degree program and activities organized by international platforms) corresponds to the collaborative environment, which was responsible of 7.551% of total variance. The sixth factor has 2 items that are associated with internal stakeholders (educators and peers), which was responsible of 7.503% of total variance.

6.7.7 Confirmatory Factor Analysis

According to the method of confirming discriminant validity (Hair, Black, Babin, Anderson, & Tatham, 1998), the square root of the average variance extracted (AVE) for each construct should be larger than the correlations of the inter-constructs in the measurement model. The results are shown in table 6.4 that the discriminant validity of each construct is clearly supported.

Table 6.4 Correlation and Squared Root of the AVE

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Factor 1	0.695					
Factor 2	0.283	0.706				
Factor 3	0.443	0.335	0.786			
Factor 4	0.5	0.214	0.236	0.717		
Factor 5	0.263	-0.085	0.065	0.167	0.523	
Factor 6	0.385	0.341	0.393	0.306	0.082	0.712

The six-factor model was further tested for stability with the maximum likelihood confirmatory factor analysis. The model proved acceptable based on the following statistical tests including root mean square error of approximation (RMSEA) = 0.088, standardized root mean square residual (SRMR) = 0.085, root mean residual (RMR)=0.031, comparative fit index (CFI) = 0.826, incremental fit index (IFI) = 0.831. Therefore, since RMSEA and SRMR are less than 0.10, RMR is less than 0.05, and IFI and CFI are above 0.80, it can be concluded that there is model fit.

Nachtigall, Kroehne, Funke, and Steyer (2003) stated that for a model to provide an ideal fit, the p value associated with the model fit x^2 test should exceed 0.05 and being closer to 1.00 is better. Since p <0.001 in this model, it can be assumed that there is no ideal fit for this study. But Saris, Satorra, and Sörbom (1987) found that the x^2 statistic is acceptable only for the large samples. Joy (1998) suggested five subjects per item. In this study, the developed instrument has 21 items, 105 samples are the minimum amount recommended for the application of the statistical techniques. The sample size of this study is 126, that is adequate for applying the statistical techniques.

6.7.8 Structural Equation Model of Future Design Education

The covariance based structural equation model (SEM) is adopted to explain the relations between the education aims, intelligent tools, various stakeholders (internal stakeholders and external stakeholders), collaborative environment, and design process. SEM has the strength to examine and estimate causal relationships even among latent variables that cannot be measured directly. Table 6.5 presents the results of SEM, showing the regression coefficient among different factors. The 21 items (observed variables) are related to 5 latent factors. The stakeholders have a high regression coefficient (0.480) of the multidimensional education aims. The design process has relatively lower regression coefficient (0.418) of the multidimensional education aims. The intelligent tools (0.221) and collaborative environment (0.363) both have positive regression coefficient of the design process.

Table 6.5 Regression Coefficient of the Model

X	→	Y	SE	*z*	*p*	regression coefficient
Various stakeholders	→	Education aims	0.152	3.055	0.002	0.480
Collaborative environments	→	Design-learning process	0.476	2.440	0.015	0.363
Intelligent tools	→	Design-learning process	0.126	2.194	0.028	0.221
Design-learning process	→	Education aims	0.053	3.496	0.000	0.418

As shown in Figure 6.6, the loadings of the stakeholders range from 0.367 to 0.797 with the lowest being educators and the highest being users. The loadings of collaborative environments range from 0.306 to 0.807 with the lowest being double-degree programs and the highest being exchange programs. The loadings of intelligent tools range from 0.544 to 0.850 with the lowest being digital fabrication tools and the highest being mixed reality tools. The loadings of design process range from 0.568 to 0.961 with the lowest being cross-cultural design process and the highest being multidisciplinary design process. The loadings of multidimensional education aim range from 0.616 to 0.748 with the lowest being commercial awareness and the highest being teamwork and leadership.

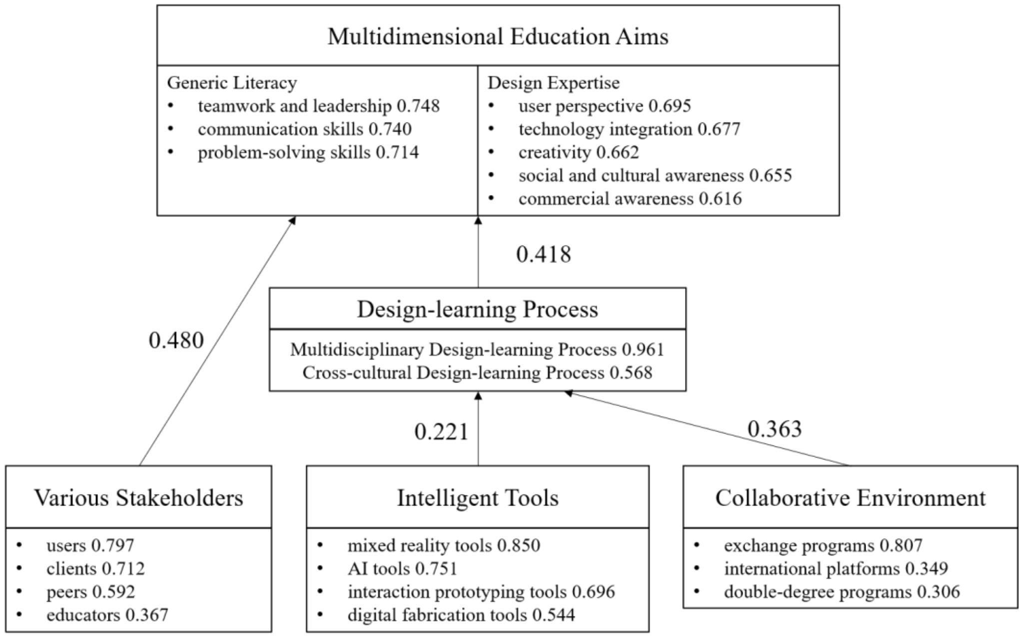


Figure 6.6 Structural Equation Model of Future Design Education

6.8 Discussion and Conclusion

6.8.1 Multidimensional Education Aims

The exploratory factor analysis identifies 8 items in the factor of education aims, which is consistent with the result from Top 50 design institute. In total, there are 8 important skills, with each of which has subskills. For example, problem-solving skills includes critical mindsets, analytical skills, adaptability, and flexibility, etc. The result of the study gives weight and ranking to the education aims, which is helpful for educators to organize the teaching activities effectively and efficiently. It is interesting to find from the data that the ranking of education aims in today's design education is almost the same with the one in future vision. Among them, creativity is the most important design skill. The paired T test result presents that the importance of 4 skills will increase significantly in future, which are technology integration skills, social and cultural awareness, teamwork and leadership, and commercial awareness.

Regarding the career options, product designer is the most popular job for design graduates while interaction designer is regarded as the most popular career option in ten years. It indicates that the emphasis of industrial design is shifting from traditional manufacturing industry to digital economy.

6.8.2 Design-learning Process

The data of questionnaire shows that multidisciplinary design process and cross-cultural design process are very important in the future vision from design educators' perspectives. However, there are a number of educators have never guided students with multidisciplinary projects (11.90%) and cross-cultural design projects (30.95%). In order to implement cross-cultural design, design institutes need to provide global education programs or recruit students from different cultural backgrounds to help students gain multicultural experience, which is not easy for many institutes.

6.8.3 Various Stakeholders

According to the data of the questionnaire, users and clients seem less important in current situation, while in the long run they will be critical stakeholders of design education. This requires the design institutes to work closely with industry. The roles of traditional stakeholders of design education (educators and peers) are regarded to decrease slightly. However, peers are always the most important facilitators for design students.

6.8.4 Design Tools

It is interesting to find that the ranking of important design tools in current situation is exactly the opposite of the one in future vision. Modeling tools are the most prevalent tools today, while they may become the least important design tools in the future. Traditional techniques of modeling lay a professional foundation for industrial design students. However, students cannot fulfill design demands in intelligence era only by grasping the traditional tools. Thus, the participants give low expectation in the future. On the contrary, design educators and students should focus on practicing with intelligent tools, such as interaction prototyping tools, mixed reality tools and especially AI tools. This result is consistent with the results of expert interviews and Top 50 design institutes. AI tools are regarded as the most important design tools in the future, while they have the highest unused rate of 17.46% currently. Harvard Business Review stated that companies that do not use AI tools will soon be obsolesce (Davenport, Brynjolfsson, McAfee, & Wilson, 2019). In design education, there has always been a struggle on how to best integrate technology, while maintaining focus on design (Coorey, 2016). with an aim of preparing students for the future, educators are challenged to utilize appropriate intelligent tools during design-learning process.

6.8.5 Collaborative Environment

From the data of questionnaire, there are only few design educators have teaching experiences on double-degree programs (37%) and activities organized by international platform (22%). Though the result of paired T test shows that both of the collaborative education programs will increase significantly in the future. Deardorff (2011) stated there is a great need for programs to bring domestic and international students together in meaningful interactions. He suggested such programs would have specific intercultural learning goals for all participants and encourage meaningful domestic-international interactions through relationship-building opportunities (Deardorff, 2011). Hennessy and Murphy (1999) argued that students learn how to negotiate meaning, how to deal with different opinions and how to coordinate schedules with team members in collaborative learning environment. However, Bullock (2020) argued that collaboration is challenging because it takes more time than teaching alone. Inexperienced students may get lost in teams without detailed and frequent guidance (Bullock, 2020).

6.8.6 Implications on Design Education

In summary, this chapter investigates the front-line design educators in China to determine the influencing factors for future design education. Through regression analysis, a structural equation model is constructed to show the relationship between the factors. Intelligent tools and collaborative environments will lead to multidisciplinary and cross-cultural design-learning process. And with various stakeholders, design students can achieve multidimensional education aims. The result coincides with the proposed theoretical model to a large extent. The study also identifies a huge gap between current situation and future vision in terms of learning resources. It highlights the directions of improvement for design institutes and design educators. As shown in Figure 6.7, the items with stars are the most important factors in a category which should be paid more attention to, and the items with up arrows need the design educators to make more efforts to improve. How to bridge the gap to face the future challenges is a question for design educators, that demands them to rethink about the design of learning activities and learning strategies for design students.

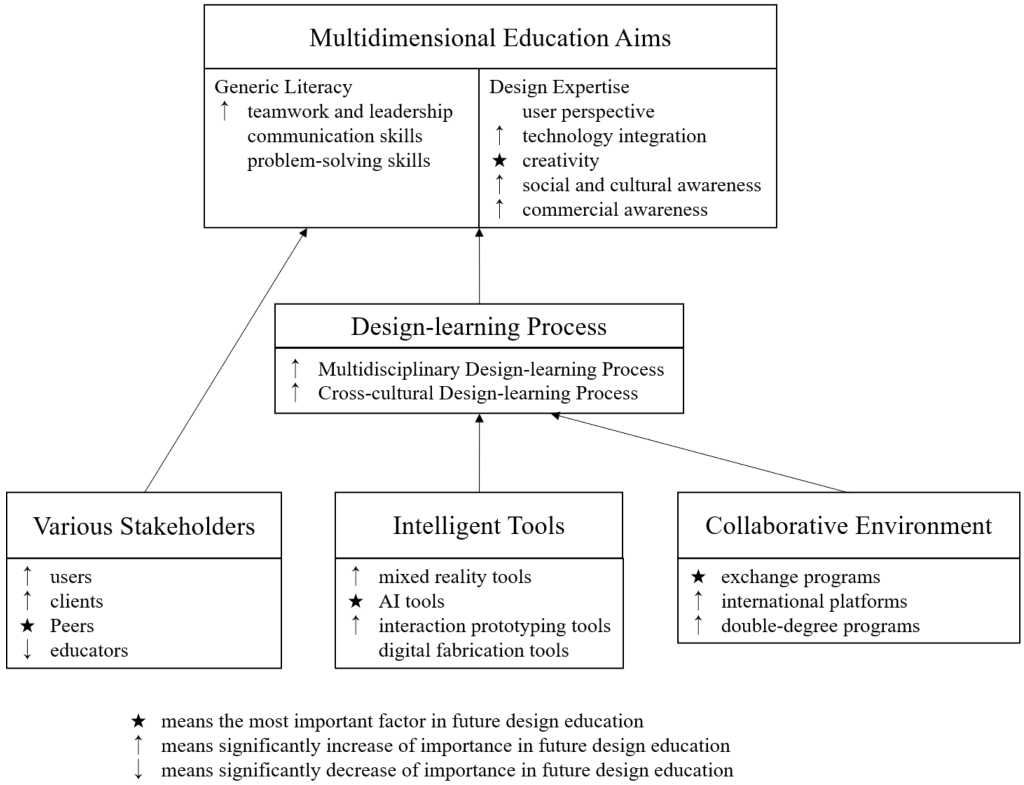


Figure 6.7 Design Education Model with Highlighted Importance

7. AI-SUPPORTED COLLABORATIVE LEARNING STRATEGY

7.1 Chapter Overview

Last chapter has determined the influencing factors of design education in current situation and future vision from design educators' perspectives. The result of quantitative data analysis demonstrates the specific aspects of design education with significant increasing importance for future, where the design educators should make more efforts to explore and improve. The proposed theoretical model is holistic and comprehensive. In order to better guide design educators, the focus of research should transform from theory to practice, and the scope of research should narrow down to the specific education activities. Eisner (1997) said that the development of educational curriculum is a process of transforming the vision for education into a process. In addition to the theoretical contribution, this chapter ticks the boxes of some of these important aspects to apply the relevant learning strategies in educational practice. To facilitate the proposed theoretical model, an AI-supported learning strategy is developed. This chapter describes the components of proposed learning strategy and the technical details of an intelligent tool to facilitate the learning strategy.

7.2 Components of Learning Strategy

Now it is very clear that, multidisciplinary and cross-cultural design-learning process, various stakeholders, intelligent tools and collaborative environment are important factors for future design education. In order to achieve the ideal education aims, it is necessary to systematically adjust various relevant factors in the teaching process and improve the setting of learning resources (Su & Zhang, 2021). Among these influencing factors, some aspects need to be explored and improved greatly according to the data of questionnaire.

(1) The data of questionnaire demonstrates that peers are the most important stakeholders both now (4.76, SD=0.56) and in the future vision (4.57, SD=0.61). Thus, the learning strategy should include **peers** as important components.

(2) The data of questionnaire demonstrates that AI tools are the most important design tools in the future (4.34, SD=0.73). Harvard Business Review emphasized that companies that do not use AI tools will soon be obsolesce (Davenport et al., 2019).

However, there are 17.46% educators have never used the tools, which shows a big gap between now and future for applying AI tools in design education practice. As a result, **AI tool** is important component of the proposed learning strategy. This study aims to explore how AI technology can be integrated in design process and how it can influence design students' learning efficiencies and effects.

(3) The data of questionnaire demonstrates that collaborative environments are important factors for future design education including exchange programs, international platforms and double-degree programs. Paired T test shows there is a significant increase in importance in double-degree program ($t=-2.249$, $p=0.026$) and International Design Association project ($t=-8.400$, $p=0.000$) from now to future. Due to the limitations of time and the feasibility of empirical study, this study emphasizes the **collaboration** between peers instead of implementing a complete education program.

(4) The data of questionnaire demonstrates that cross-cultural design process is important in the future vision from design educators' perspectives. However, there are a number of educators have never guided students with cross-cultural topics (30.95%). Thus, **cross-cultural design** is a component of the proposed learning strategy, this study specifically explores how AI tools can facilitate cross-cultural design process.

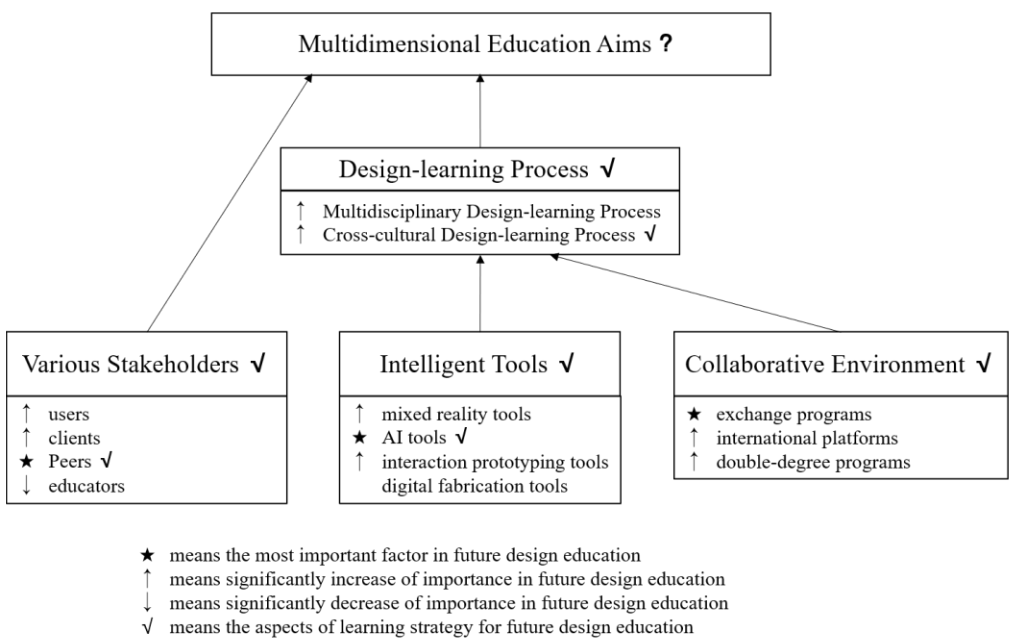


Figure 7.1 Components of Learning Strategy for Future Design Education

In summary, Figure 7.1 presents the rationale of developing the learning strategy. The boxes of important factors are ticked, and the proposed learning strategy follows these principles:

(1) The learning strategy should facilitate **cross-cultural design**.

(2) The learning strategy should facilitate the **collaborative learning** between **peers**.

(3) The learning strategy should apply **AI tool** as solution.

The following sections will explain these three main aspects respectively and finally present the new AI-supported design tool.

7.3 Cross-cultural Design

The connections between culture and design have become increasingly close (Shin et al., 2011). Cross-cultural design means designing products or systems with characteristics that are accepted across diverse cultures, which is the result from globalization (Stefanou, 2014). While the market tends toward "globalization", design heads toward "localization". So the designers have to think globally for the market, while act locally for design (Rungtai Lin, Sun, et al., 2007). Different cultures have a rich and various resources that provide designers with unlimited inspirations for new ideas (Ren, 2013). Designer can benefit from understanding cultural values in order to translate them into powerful visual designs. By doing so, a sense of respect for culture could be achieved as well (Moalosi, Popovic, & Hickling Hudson, 2010). Cultural product has its aesthetics and market value, and conveys the cultural connotation and symbols (Hsiao, Lee, Hsueh, & Tseng, 2018). Kyriakoullis and Zaphiris (2016) stated that considering cultural aspects in product design is fundamental to its success and acceptance. For example, A. Smith, Dunckley, French, Minocha, and Chang (2004) combined design theories with culture models to develop usable cross-cultural websites. Cyr and Trevor‐Smith (2004) emphasized that culturally sensitive websites allow users have increased access to content and enhanced user experience. H. Wu et al. (2020) conducted a study about users' gesture preferences and found that some gesture choices are strongly influenced by the cultural background of users. They proposed design guidelines for gesture-based interface design (H. Wu et al., 2020). Zangerle, Pichl, and Schedl (2020) integrated the culture-related socio-economic features into a culture-aware recommender system to improve the music recommendation quality. Luo and Dong (2017) conducted an exploratory experiment about cultural product design and found that design students create more creative outcomes with cultural-textual inspiration. The result of their research proves that cultural features generation affect the originality of design outcomes (Luo & Dong, 2017). Applying culture as design elements enhances products' core value and identity, and it also makes them to fulfill consumers' experiences (Chai et al., 2015; R. T. Lin, 2007; Shin et al., 2011). Tolba (2003) emphasized the need for understanding the role of culture in shaping the human-computer interaction (HCI) field, where users from different cultures may tend to process the systems differently. Alsswey, Al-Samarraie, El-Qirem, Alzahrani, and Alfarraj (2020) argued that integrating certain cultural values of specific groups of users into the design of UI would increase their acceptance of the technology. Thus, introducing cross-cultural elements into the design process can have positive impacts on the design results.

7.3.1 Cultural Elements

This section discusses the specific forms of cultural elements which can be applied as design elements. Barber and Badre (1998) found that there are some design elements that are culturally specific, and these specific elements are relevant to native users' performance and preferences. The notion of culture is multidimensional. Tylor (1871) presented that culture is "a complex whole which includes knowledge, belief, art, morals, law, custom and any other capabilities and habits acquired by man as a member of society". This classical definition shows that the scope of culture is broad and cultural elements are various. There are models of culture developed from the perspectives of psychology (Edmundson, 2007; Triandis & Gelfand, 1998), anthropology (S. Hall, 1996), intercultural communication (Hofstede, Hofstede, & Minkov, 2005) and business (P. B. Smith, Dugan, & Trompenaars, 1996). They have traditionally explained humanity and provided frameworks for cross-cultural analysis and research. For example, S. Hall (1996) described culture as an unseen but powerful force that holds everyone captive. Hofstede et al. (2005) explained culture as the software of the mind, which is all patterns of thinking, feeling, and acting. This theory stressed that culture should be distinguished between individual culture and societal culture. It can be concluded that culture isn't something homogeneous, which is changing through time. Nardon and Steers (2006) compared these most popular models of culture and proposed the "big five" cultural dimensions, as shown in Figure 7.2. It is a widespread agreement among existing models about five dimensions: relationship with the environment, social organization, power distribution, rule orientation and time orientation (Nardon & Steers, 2006).

Cultural Dimensions	Focus of Dimensions	Scale Anchors
Relationship with the Environment	*Relationship with the natural and social environment:* Extent to which people seek to change and control or live in harmony with their natural and social surroundings.	Mastery vs. Harmony
Social Organization	*Role of individuals and groups:* Extent to which social relationships emphasize individual rights and responsibilities or group goals and collective action.	Individualism vs. Collectivism
Power Distribution	*Power distribution in society:* Extent to which power in a society is distributed hierarchically or in a more egalitarian or participative fashion.	Hierarchical vs. Egalitarian
Rule Orientation	*Relative importance of rules:* Extent to which behavior is regulated by rules, laws, and formal procedures or by other factors such as unique circumstances and relationships.	Rule-based vs. Relationship-based
Time Orientation	*Time perception and tasks:* Extent to which people organize their time based on sequential attention to single tasks or simultaneous attention to multiple tasks.	Monochronic vs. Polychronic

Figure 7.2 "Big Five" Cultural Dimensions (Nardon & Steers, 2006)

E. T. Hall (1989) proposed an "iceberg model" of culture demonstrating that the visible aspects of culture only represent the tip of the iceberg while the invisible aspect of culture forms the foundation. As shown in Figure 7.3, the outermost material layer includes tangible aspects of cultural differences, such as material objects, products, services and processes. Behavioral level includes practices, rituals and interactions with individuals. The inner intangible level includes beliefs, attitudes and ideology. The core value level refers to the system of values that represent a cultural group.

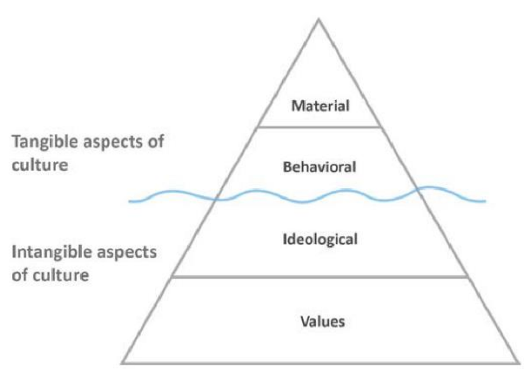


Figure 7.3 Iceberg Model of Culture (E T Hall, 1989)

Most literatures and models are hard to apply to product design process (Hsu, Lin, & Lin, 2011). Young (2008) defined the nature of culture in design is creative since culture is created and recreated by man's production. A prevalent culture-based model in design research divided cultural elements into three levels: (1) the outer level (objects with visible forms); (2) the middle level of human behaviors, rites and regulations in the form of words and language (systems of communication and interaction); and (3) the inner level of the manifestation of human ideologies (thinking activities) (Leong & Clark, 2003). This cultural element model describing cultural elements is proved useful in design field and further developed by researchers (Chai et al., 2015; Hsu et al., 2011; R. T. Lin, 2007; Trompenaars & Hampden Turner, 2011). Figure 7.4 shows how the three-level culture model is integrated with design features (Rungtai Lin, Sun, et al., 2007).

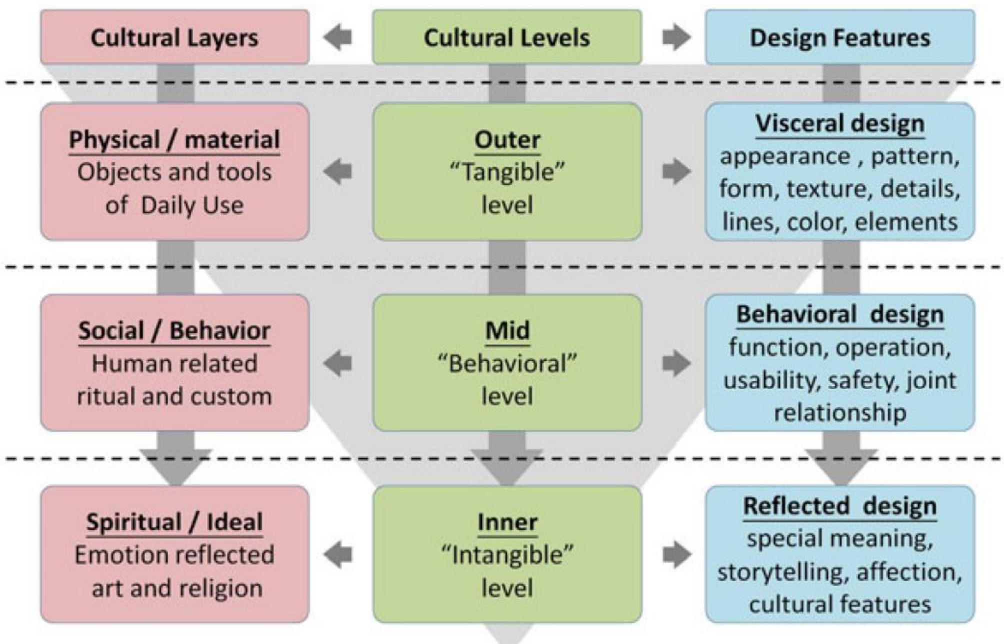


Figure 7.4 Three Levels of Culture and Design Features (Rungtai Lin, Sun, et al., 2007)

Among these three levels, the outer level of culture involves the objects with visible forms that are most relevant to cultural product design (Lee, 2004). This level deals with cultural elements such as color, material, pattern and form (Hsiao et al., 2018; Leong & Clark, 2003). They are cultural elements as well as visual design elements (Ren, 2013). Visual languages can convey ideas, beliefs, values, meanings and understanding about culture (Karayev et al., 2013). They provide a synthetic idea or a metaphor of complex ideas (Botturi, 2006). Well-designed visual forms enable people to share information beyond language barriers (Kamihira, Aoki, & Nakano, 2011). Thus, all these visual cultural elements represent cultural values, which have been integrated into cultural objects and provide the designers with cultural identity.

Color: Color relates to culture closely. Color has many expressive qualities, which is regarded as the most powerful design element related to human's emotional response and cultural background (Ware, 2010). Some responses are universal, while most of them are culturally biased. Cyr and Trevor-Smith (2004) demonstrated that color has various psychological and social associations in different cultures. Various cultural traditions endow different colors with meanings (Evans & Thomas, 2012). For example, white is the color of bride's dress in western countries while the color of funeral in Asian countries. Simon (2000) found that Asians prefer less bright colors, while Europeans and North American prefer brighter colors to make the product more modern. When designers consider a color, it almost always refers to different properties such as hue, saturation, value, primary color, secondary color, warm, and cool (Karayev et al., 2014).

Material: Different cultural backgrounds lead to differences in attributing particular meanings to materials (Siu, 2001). Karana and Hekkert (2010) considered material as a design element that relates to a cultural experience. In other words, certain materials combined with artifacts can bring out the expression of human's cultural values. For example, some cultures do not regard plastics as kitchenware, because they may fear that a plastic cooking pot might melt when heated (Margolin & Dormer, 1992). The same material may represent various meanings under different cultural conditions (Ren, 2013). For example, wood is a common material in Scandinavia, while is perceived as a luxurious and valuable material in Mediterranean countries.

Pattern: Sun (2016) proposed pattern is the best visual element to embody cultural connotation. Similarly, Z. Yang, Bao, and Shen (2020) found that the most influential cultural element is a dermatoglyphic pattern through a study with design students. It means that pattern is an important design element in the cultural product design. Barber and Badre (1998) argued that patterns are "metaphors" denoting actions of users. Gong (2008) believed pattern has profoundly symbolic implication that people built up common visual symbols in their daily lives. It is the representation of lifestyles of a certain culture. The material also contributes to the pattern. For example, a lotus and carp represent “successive years of surplus” in Chinese culture. At times, the material is the texture or pattern of an artifact (Ren, 2013).

Form: Form is defined as “the shape or the structure of an object” in webster’s dictionary. The form of an object is an important aspect of the overall design (Karana & Hekkert, 2010). Forms can provide countless possibilities. Designers need to understand the visual metaphors and symbolisms of form from user perspective with a certain cultural background (Ren, 2013).

7.3.2 Cross-cultural Design Process

Cross-cultural design process refers to the process of designing for other cultures (Guirdham, 1999), that focuses on rethinking and reviewing the cultural elements and then integrating them in a new product to satisfy target users (Hsu et al., 2011; Taylor, 2012). To implement cultural product design successfully, Taylor (2012) suggested the design process should be viewed from the perspective of culture. McMullen (2016) suggested designers understand the images and ideas of different cultures, and then merge these with their own design skills to create an entirely new work. Haas and Steiner (1995) explained that successful cross-cultural design is about transformation rather than quotation or mimicry. As shown in Figure 7.5, R. T. Lin (2007) proposed a cross-cultural design process model that consists of three main steps: (1) identification involves extracting cultural elements from an original cultural objects; (2) translation involves transforming the cultural elements into design information and design elements; (3) implementation involves designing the cultural product.

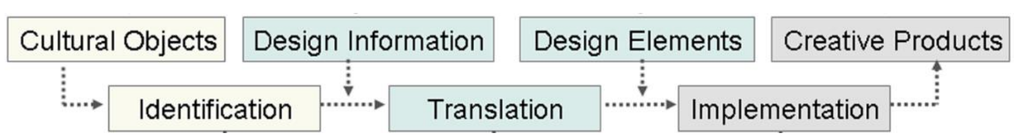


Figure 7.5 Cross-cultural Design Process (R T Lin, 2007)

Hsiao et al. (2018) also summarized three main steps of cultural creative thinking including (1) analyze the meaning of cultural elements; (2) redesign the cultural elements through contrast, hierarchy, extension, intensify and transformation; (3) generate new ideas and creations. Dhadphale, Yilmaz, and Paepcke Hjeltness (2017) suggested that the design students need to take balance between adapting to a specific culture and bringing new perspectives. Thus, what and how cultural elements can be identified and transformed during design process are critical issues (Kotro & Pantzar, 2002; RT Lin, 2005).

7.4 Collaborative Learning

It is of ongoing importance that the design education should utilize a collaborative approach where design students work within teams of various backgrounds (Cho & Cho, 2014; D. Jonassen, Strobel, & Lee, 2006). In design education, the studio setting is the main pedagogical framework for teaching (Oxman, 2004). In a studio, students work together as a team to learn how to design by engagement with a collaborative design process and a suite of possible design methodologies and tools.

A prevalent definition of collaboration is "working together to create value while sharing virtual or physical space" (Rosen, 2007). McMahon and Bhamra (2016) identified two key features toward the collaborative process, that are synergy and communication. Synergy means that the collaborative process goes beyond the basic sharing of resources and the outcome of group work is of greater significance than the sum of its parts. It reveals that collaborative team can create something "novel and valuable" by working towards a common and agreed goal. Communication in design collaboration means the processes of consultation, negotiation, evaluation and confirmation (Chiu, 2002). Collaboration essentially entails interaction (Strijbos et al., 2004). Gokhale (1995) claimed that active exchange of ideas within collaborative teams not only increase interest among the students but also promotes critical thinking. Some researchers found that shared work through collaboration leads to efficiency and effectiveness more than individual work (Arias, Eden, Fischer, Gorman, & Scharff, 2000). Murphy and Hennessy (2001) stated that collaborative learning provides students with rich learning experiences, such as constructing knowledge with others, sharing resources, and receiving feedbacks. Achten (2002) regarded collaborative learning best suits the needs of tacit knowledge transfer. In collaborative learning, each student of the team is given the position of "expert of their experience" and plays an important role in knowledge development, idea generation and concept development (E. B. N. Sanders & Stappers, 2008). The advantage of collaborative learning is mutual learning and peer learning, where designers learn from their teammates of other disciplines and backgrounds. Cho and Cho (2014) emphasized that design students generate more creative solutions through sharing the workload, brainstorming and exchanging ideas. In employing collaborative learning and peer learning, students take responsibility for their educational experience, rather than being dependent on their educators (Arrighi & Mougenot, 2016). Compared to non-collaborative learning activities, collaborative learning promotes shared understanding, better information retention and deeper processing (Jorczak, 2011).

Collaboration between students with different “cultural background” leads to global solutions (A van Boeijen & Badke Schaub, 2007) and helps producing innovative ideas (Annemiek van Boeijen, Sonneveld, & Hao, 2017). McLeod, Lobel, and Cox Jr (1996) concluded that ethnically diverse groups generate ideas of higher quality than those of homogeneous groups. Cultural diversity among peer students is acknowledged as enriching and inspiring (Jonsen, Maznevski, & Schneider, 2011). Research shows diversity supports creativity (Friis, 2015). When students design across cultures, they can draw on different kinds of cultural knowledge and perspectives (Paletz, Sumer, & Miron-Spektor, 2018). Deardorff (2011) proposed that collaboration in cross-cultural teams entails intercultural competence, which is based on development of relevant attitudes, knowledge, and skills.

Though the benefits are obvious, it is challenging to implement collaborative learning in the context of cross-cultural design process. Many students tend to resist collaboration due to the difficulty in communication and disproportionate participation (Webb & Miller, 2006). The different cultural backgrounds of team members may add complication to the communication and lead to misunderstanding and confusion. Cho and Cho (2014) emphasized that effective collaboration require team members to improve communication skills, and balance individual strengths and weakness. Deutsch (2014) pointed out that designers may hesitate to collaborate because they fear the loss of individual identity and mediocre outcome. One student may lead and dominate the discussion, while the rest students depend on him (Webb & Miller, 2006). Friis (2015) stated that design teams with diverse backgrounds are more likely to produce different perspectives, running the risk of disagreement and conflict, which makes most team members uncomfortable. What is more, the collaboration often fails to realize synergy effects. The ideal collaborative design process will be like Figure 7.6(a). However, Researchers pointed out that collaborators often fall back into their expertise without recognizing the need for a holistic approach (Clark, Perez-Trejo, & Allen, 1995). Kvan (2000) found that in real world designers always compromise and cooperate instead of collaboration, as shown in Figure 7.6(b). In cooperative design, each participant works as an individual expert addressing design issues from their perspectives. They work together for moments and divide up and go their separate ways. The cooperative design process is discrete, individual, parallel, and not intimately linked. Slavin (1980) stated that cooperative design is associated with well-structured problems, while collaborative design deals with ill-structured problems that are common in the design domain. Kvan (2000) concluded that the main difference between collaboration and cooperation is the creative aspect of working together. Therefore, collaborative design-learning process requires a higher sense of working together to achieve a more creative result than cooperative design.

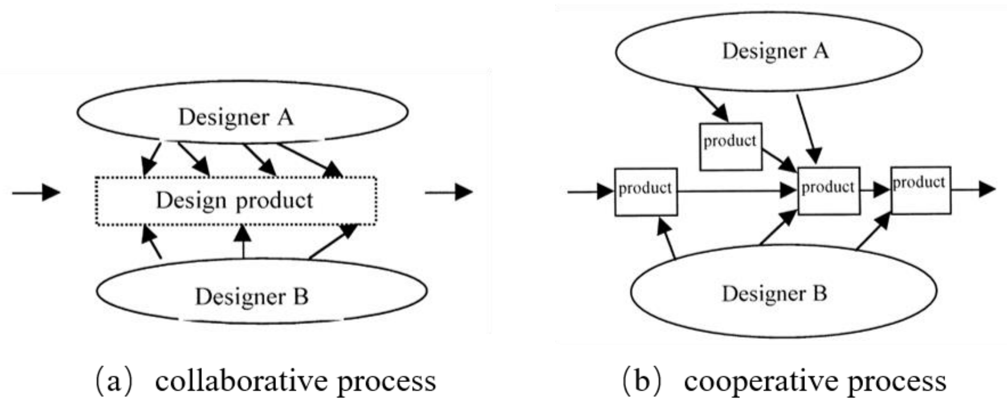


Figure 7.6 Collaborative Process and Cooperative Process (Kvan, 2000)

7.5 Cross-cultural Collaborative Design-learning Process

To summarize the information of the last two sections, the current cross-cultural collaborative design-learning process is illustrated, as shown in Figure 7.6. Firstly, design students are working together as a team to have a collaborative learning environment. Secondly, according to the current design-learning processes reviewed in Section 2.5.2 (e.g. d.school's five-stage design process (Rauth et al., 2010), Technology University of Eindhoven's flexible transformative design process (Hummels & Frens, 2008) and Kolb et al. (1999)' experiential learning process), designers need to go through the relevant design and learning activities including researching, analyzing, abstracting, transforming, ideating, integrating and prototyping. Thirdly, adapt to R. T. Lin (2007)'s model, the cross-cultural design process consists of three main steps, namely (1) identifying cultural elements, (2) transforming cultural elements into design elements (color, material, form and pattern) and (3) implementing creative designs. Figure 7.7 shows the current situation of cross-cultural collaborative design-learning process without any design tools' support. The next section reviews the design tools that facilitate cross-cultural design process and collaborative learning process.

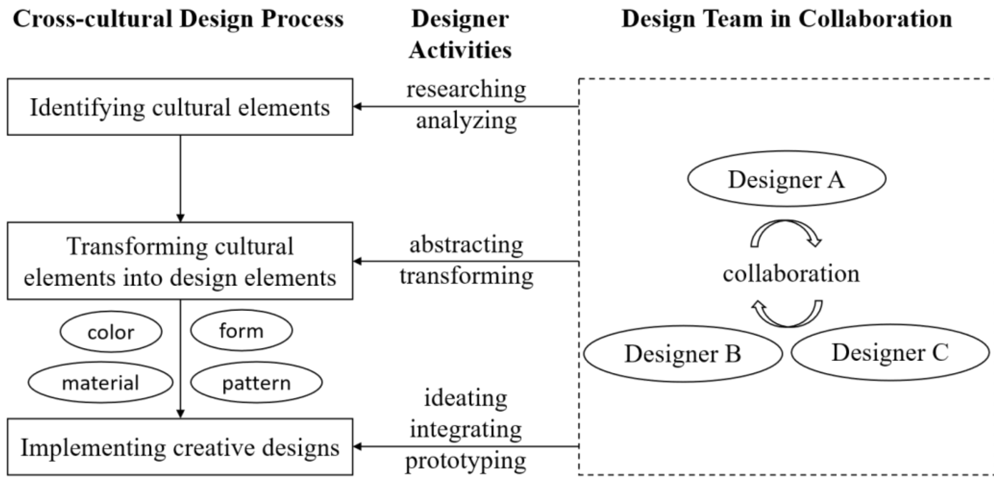


Figure 7.7 Cross-cultural Collaborative Design-Learning Process

7.6 Design Tools

7.6.1 Tools to Facilitate Cross-cultural Design Process

Embracing cultural elements in the context of design practice has a long history and there are a number of classic methods for conducting in-depth cultural inquires like surveys, interviews and passive observations that focus on what people say, think and do (E. B. Sanders, 2002). However, these traditional methods are time-consuming and cost-expensive, that require designers to collect and analyze enough data to produce an unbiased result. In order to accommodate cultural differences, it is necessary to integrate more sophisticated culture analysis tools into the design process in further research. Researchers proposed various tools to facilitate different phases of cross-cultural design process. For example, Vanka and Klein (1995) proposed ColorTool to assist designers in making informed cross-cultural color choices. Cultura (A van Boeijen & Badke Schaub, 2007) and the Crossing Cultural Chasm card set (AGC Van Boeijen, 2015) are tools that provide designers with a lens to examine cultures of intended users. Figure 7.8 is an example of Crossing Cultural Chasm card set.

Figure 7.8 A Card from Crossing Cultural Chasm Card Set (AGC Van Boeijen, 2015)

Rungtai Lin, Sun, et al. (2007) presented a cultural product design model that uses scenarios and story boards to identify and translate cultural features from cultural objects. Rungtai Lin, Cheng, and Sun (2007) established a digital archive database as a reference for designers to learn Taiwan local cultural features during the product design phase. As shown in Figure 7.9, the digital archive database provides information about a cultural object in the aspects of physical, material, customs, ceremonies, and spirituality among the object (Rungtai Lin, Cheng, et al., 2007). Overall, these methods and tools help designers to understand the cultural element (Rungtai Lin, Cheng, et al., 2007), examine cultures of target users (AGC Van Boeijen, 2015; A van Boeijen & Badke Schaub, 2007), translate cultural elements (Rungtai Lin, Sun, et al., 2007) and make informed cross-cultural design decisions (Vanka & Klein, 1995). However, these tools still rely heavily on designer's design skills and require time and effort (Lee, 2004).

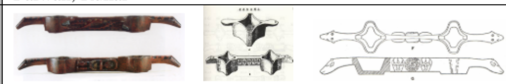
Object	Linnak or twin cup
Type	Drinking container
Tribe	Paiwan, Rukai
Picture	
Material	Wood
Color	Natural wood color or painting with colors
Pattern	Figure, human-head, long-hooded pit viper pattern, Deer pattern
Principle of formation	1. Embossment on handles with a variety of patterns. 2. Total length from 43cm to 91cm, pitch from 29cm to 42cm, and cup capacity from 300c.c. to 600c.c. 3. Single cup with a rectangular column shape and handle on both sides. 4.The Linnak contains two rectangular column cups, a beam bridge in between and a handle on both sides.
Classification	Twin-cup, Single-cup and Tri-cup.
Operation	Two drinkers are required to hold the handles with left and right hand on each when drinking alcohol.
Using Scenario	1. Single cup is created only for the chief to drink liquid in the Paiwan tribe. Sometimes it was used to contain rice alcohol and to reward a hunting hero for demonstrating valor. 2. The twin -cup was created for use in wedding ceremonies where the bride and groom were required to drink alcohol together. 3. The Tri-cup was created for the groom and bride and chief (a witness), who stands between groom and bride to drink alcohol together which represents the greatest honor and wish for the couple.
Cultural content	1. The long- hooded pit viper or ancient figure pattern on the cup enhances the value of cup. 2. The twin-cup was mostly used in ritual or festival ceremonies to demonstrate a warm and harmonious spirit. 3. To drink with the twin cup represented the commitment in love between a male and female in tradition culture. 4. Drinking together represents eternal friendship.

Figure 7.9 An Example of Digital Archive Database

7.6.2 Tools to Facilitate Collaborative Learning Process

A variety of technologies are used to support collaborative learning. Resta and Laferriere (2007) identified current practices including network-enhanced learning environment, blended learning environment, and virtual learning environment. Regarding the design tools to facilitate collaborative learning process, researchers argued that visual media such as sketches and concept diagrams enables multiple forms of discussion and evaluation of the design ideas (Adams, Daly, Mann, & Dall'Alba, 2011; Dorta, Kinayoglu, & Boudhraa, 2016; Goldschmidt, 1994). Stempfle and Badke-Schaub (2002) and Cho and Cho (2014) suggested that collaboration in a design team is based on visualization, which are effective means of communication and creating (Chiu, 2002; Hong, Yu, & Chen, 2011). Basadur (2004) proposed the idea of “shared process language” and suggested a shared and visualized design process. Karakaya and Şenyapılı (2008) proved that the visualization capabilities of collaboration tools help designers engage more deeply in the design process. Visualization can also enhance idea generation and creativity (Atilola, Tomko, & Linsey, 2016; Dorst & Cross, 2001).

A term computer-supported collaborative learning was used to describe a dynamic, interdisciplinary, and international field of research focused on how technology can facilitate the sharing and creation of knowledge and expertise through peer interaction and group learning process (Lipponen, Hakkarainen, & Paavola, 2004). Resta and Laferriere (2007) identified a trend that individuals who are distributed in place and time will work in a virtual workspace. There are various computer-supported tools developed to support collaborative learning process. For example, Park (2011) proposed a learning management system (e.g. blackboard) for design education where the actions and decisions can be reviewed and evaluated. Vosinakis and Koutsabasis (2013) designed a virtual world for idea sharing during learning process as shown in Figure 7.10.

Figure 7.10 Virtual Group Workplace (Vosinakis & Koutsabasis, 2013)

Asojo (2007) uses videoconferencing technology to support cross-cultural collaboration. Camba et al. (2017) applied immersive visualization technologies to facilitate collaborative design education. Strijbos et al. (2004) stated that collaborative technology are dedicated tools designed to provide specific support such as dialogue structuring, diagrammatic representations, and discussion prompts. In summary, applications like these examples provide technical functions for draft approval, brainstorming and commenting via communication and prototype manipulation tools.

Researchers has identified a number of benefits of the tools to facilitate collaborative learning process. Resta and Laferriere (2007) reviewed the research on the application of technology in support of collaborative learning in education. They argued that computer-supported collaborative learning can increase student satisfaction with learning experience and improved productivity, and using technology in support of collaborative learning can add flexibility of time and space for learning process (Resta & Laferriere, 2007).

Though tools to support collaboration are proved be useful, the dedicated tools and techniques that facilitate cultural diversity in the collaborative design-learning process is limited and less attention is paid to the designers' own cultural background and how this relates to the context they are designing for (Annemiek van Boeijen et al., 2017).

7.6.3 AI Tools

Machine learning and deep learning is gradually used in the computer-aided design process, offering new possibilities for designers. For example, Bell and Bala (2015) proposed an approach for learning the visual similarities between design elements in product design process. Z. Hu et al. (2017) presented a visual classification method for furniture design styles with deep learning approach, which is proved to have a higher accuracy of the traditional approach. Kwong, Jiang, and Luo (2016) proposed an AI-based methodology which integrates affective design, engineering and marketing for defining design specifications of new products. J. Kim, Song, and Lee (2019) also proposed an approach to figuring out design elements and recognizing the design features of them using region-based CNN, as shown in Figure 7.11.

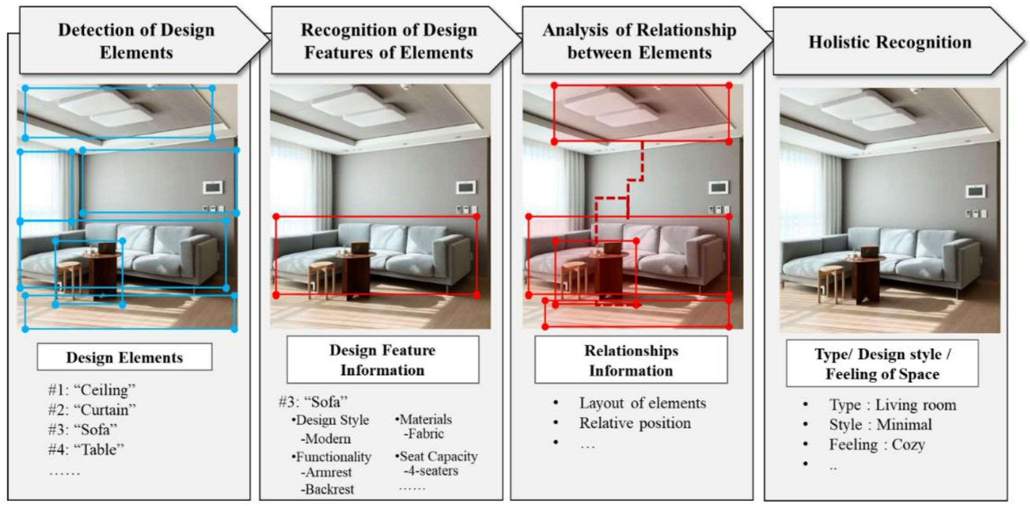


Figure 7.11 Steps of Design Features Recognition (J. Kim et al., 2019)

J. Kim and Lee (2020) further described an approach for identifying interior design style information with reference images and a deep-learning model which can automatically recognizes the design styles of given interior images. Similarly, H. H. Wang and Chen (2020) used deep learning to recognize the design feature of car styling. Yonekura and Hattori (2019) proposed a framework for design optimization using deep reinforcement learning. Akay and Kim (2020) used natural language processing powered by neural networks to enhance early-stage design by abstracting key functional requirements. Liu, Li, Xiong, and Cavallucci (2020) proposed a function-based patent knowledge retrieval tool for conceptual design of innovative by using a semi-supervised learning algorithm. The result of their experiment demonstrated that the tool can assist designers to generate more ideas and the novelty of ideas is higher (Liu et al., 2020). J. Wu et al. (2020) used deep convolutional neural networks to analyze image features, which can help to evaluate the aesthetic level and reveal the whole quality of the design proposal.

Among these deep learning approaches, style transfer is a research direction with increasing attentions. Style transfer is creating a synthetic image based on a content image and a style image through CNN (L. A. Gatys, A. S. Ecker, & M. Bethge, 2015; Jing et al., 2019). L. Gatys, A. S. Ecker, and M. Bethge (2015) introduced a model for producing high quality natural textures based on feature spaces of CNN. A study firstly implemented style transfer for art (L. A. Gatys et al., 2015), showing how different styles of famous art works can be used to create artistic images, as shown in Figure 7.12.

Figure 7.12 Content of a Photograph (A) with Three Styles of Well-known Artworks (B, C, D) (L A Gatys et al., 2015)

Researchers have used style transfer for a variety of purposes in the field of visual design. For example, Shih, Paris, Barnes, Freeman, and Durand (2014) presented an approach to style transfer portrait pictures with the aim to lighten the work for photographers. The algorithm studies the facial features (eye, skin, mouth, hair etc.) of an example photo made by photographer, and transfers the visual style onto another headshot (Shih et al., 2014), as shown in Figure 7.13. From these studies, it can be concluded that the core advantage of style transfer is combining an arbitrary picture with a preferred visual style efficiently.

Figure 7.13 Headshot Portrait Style Transfer (Shih et al., 2014)

These works demonstrate that deep learning can transform abstract design information into structured data, which can be turned into usable design tools through neural networks. However, little work has been done for cross-cultural design process.

To summarize this section, Table 7.1 presents the functions, examples and problems of current methods and tools. The traditional methods of increasing cultural awareness are time-consuming and cost-expensive. Through there are many tools to facilitate cross-cultural design process, they stills rely on designer's design skills and require time and effort, which is not intelligent enough. Intelligent tools such as deep-learning-based design tools have been applied in various conditions of design process, such as visual search, visual classification, recognizing design features etc. However, little work has done for cross-cultural design process. Even in the field of tools to facilitate collaborative learning, there is no dedicated tool to facilitate cultural diversity of the design team.

Table 7.1 Review of Current Methods and Tools

Methods and tools	**Functions and examples**	**Problems**
traditional methods	increase cultural awareness (surveys, interviews, and passive observations)	time-consuming, cost-expensive
tools to facilitate cross-cultural design process	understand cultural element (Rungtai Lin, Cheng, et al., 2007) examine cultures of target users (AGC Van Boeijen, 2015; A van Boeijen & Badke Schaub, 2007) translate cultural elements (Rungtai Lin, Sun, et al., 2007) make informed cross-cultural design decisions (Vanka & Klein, 1995)	rely on designer's design skills and require time and effort
tools to facilitate collaborative learning process	learning management system (Park, 2011) virtual world for idea sharing (Vosinakis & Koutsabasis, 2013) videoconferencing (Asojo, 2007)	no dedicated tool to facilitate cultural diversity
deep-learning-based design tools	visual search (Bell & Bala, 2015) visual classification (Z. Hu et al., 2017) defining design specifications (Kwong et al., 2016) recognizing design features (J. Kim et al., 2019; H. H. Wang & Chen, 2020) design optimization (Yonekura & Hattori, 2019) abstracting functional requirements (Akay & Kim, 2020) patent knowledge retrieval (Liu et al., 2020) evaluate design quality (J. Wu et al., 2020)	little work has done for cross-cultural design process

	style transfer (L. A. Gatys et al., 2015; Shih et al., 2014)

As a result, the short review of design tools demonstrates that there are research gaps and opportunities of design tools to facilitate cross-cultural design process. The implications on developing a new design tool are summarized:

(1) The tool should facilitate some phases of **cross-cultural design process** (identification, transformation, and implementation).

(2) The tool should make use of students' own cultural background so as to facilitate **cultural diversity** in the collaborative design-learning process.

(3) The tool should facilitate a higher sense of **working together** between students.

(4) The tool should utilize **shared visual language** for collaboration.

(5) The tool should apply latest **AI technology** such as deep learning to assist designers to implement cross-cultural design more **efficiently** and **intelligently**.

7.7 A New AI-supported Design Tool

Based on the literature review of relevant fields, a design tool by emerging AI technology for design education is developed. It applies Convolutional Neural Network (CNN) (Krizhevsky, Sutskever, & Hinton, 2012) in the field of the state-of-the-art deep learning techniques because of its powerful function in visual perception and image processing. This AI-supported tool aims to facilitate designers to select and transform cultural elements during cross-cultural design process. The tool has three main functions: (1) identifying cultural elements of image candidates based on cultural dataset; (2) selecting the most suitable image with cultural elements from all image candidates according to designers' cultural style expectations and their own preferences; and (3) transferring cultural styles to designers' work.

To realize these functions, a cultural image dataset was collected to provide the cultural information for the later trained machine learning models. Before using the tool, the designer is required to upload a set of cultural style image candidates and design content image. A cultural image selection module is proposed to replace the human designer to automatically select the most suitable culture image from the candidates. In particular, a culture style classification CNN is trained to generate the culture style distribution of each culture image. Then, images are ranked based on the similarities between their culture styles and the expectation as well as the user's own preference. After selecting the top-ranked culture image, the style transfer module will automatically generate the culture-specific design images.

To realize these functions, the tool consists of three main components, as shown in Figure 7.14: (1) a cultural image dataset to provide the images with cultural information for the later trained deep learning models; (2) a cultural image selection module to automatically select the most suitable culture image from all uploaded cultural image candidates, by using a CNN model that is trained based on the cultural image dataset; and (3) a cultural style transfer module to automatically generate a culture-specific image that not only has the same content as the uploaded design sketch but also has the cultural style of the selected culture image, by utilizing style transfer technique (L. Gatys et al., 2015) without any human effort.

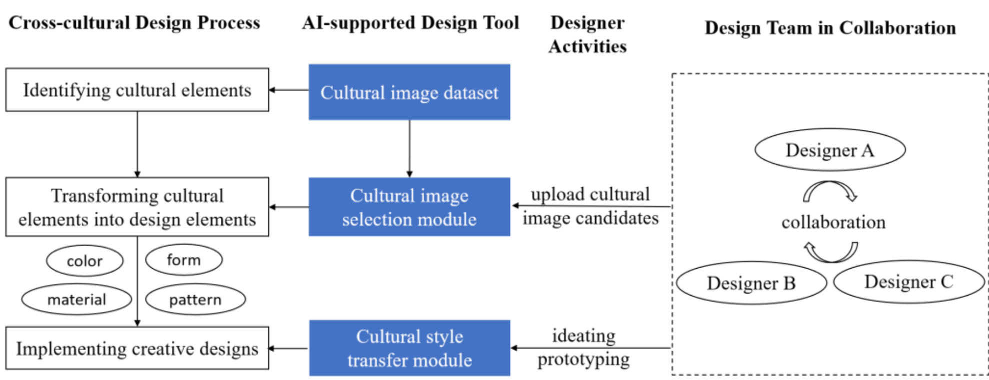


Figure 7.14 AI-supported Cross-cultural Collaborative Design-Learning Process

In particular, the proposed tool takes a content image such as design sketch that contains the designed product appearance, and a cultural style image that contains the cultural elements. The goal is to generate an image not only keep the content of original designed sketch but also has the cultural style of the required cultural style.

Regarding the collaborative design-learning process, Figure 7.15 shows how the tool supports designers to work together in a high sense. For example, designer A with specific cultural background is responsible for selecting cultural image candidates. The cultural image selection module supported by the cultural image dataset will transform the cultural elements into design elements such as color, form, material, and pattern. Designer B and designer C are responsible for ideating and prototyping respectively. The design works produced by designer A, B and C will be combined through cultural style transfer module to generate creative designs. Thus, the AI tool facilitates a high sense of working together and creates a shared visual language for collaboration. The details of three main components of this AI tool are further explained.

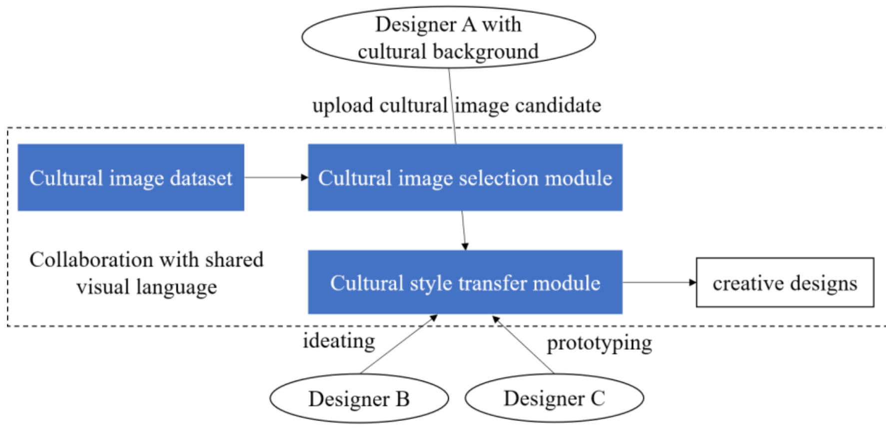


Figure 7.15 AI-supported Collaborative Design-Learning Process

7.7.1 Cultural Image Dataset

The aforementioned CNN models are normally trained by a prepared image dataset. Prevalent datasets for images classification can be divided into two main categories, that are datasets for object classification and datasets for visual style classification. Object-based datasets can be served as training and evaluation benchmarks for algorithms in computer vision research (Krizhevsky et al., 2012). Object-based datasets have three kind of annotation dimensions, including object classification, object detection and semantic scene labeling (T. Y. Lin et al., 2014). Typical object classification database include Caltech-256 (Griffin, Holub, & Perona, 2007), ImageNet (Deng et al., 2009) and Pascal visual object classes (Everingham, Van Gool, Williams, Winn, & Zisserman, 2010). Microsoft COCO dataset (Caesar, Uijlings, & Ferrari, 2018) is typical dataset for object detection, while Sun dataset (Xiao, Hays, Ehinger, Oliva, & Torralba, 2010) is representative database for semantic scene labeling.

There are also several image datasets mainly focus on visual style classification. For example, Murray, Marchesotti, and Perronnin (2012) proposed a large-scale database for aesthetic visual analysis. Karayev et al. (2013) presented a large-scale dataset of photographs annotated with style labels, that embodies several different aspects of visual style of photographs including photographic techniques, composition styles, atmosphere, moods, genres and colors based on the images uploaded on Flickr groups. Wikipaintings is a dataset of high-art images labeled with artist, style, genre, date and free-form tag information (Karayev et al., 2013). Some image datasets focus on texture recognition (Cimpoi, Maji, & Vedaldi, 2015) and emotion recognition (You, Luo, Jin, & Yang, 2016).

Since visual languages convey meanings and understanding about culture (Karayev et al., 2013), cultural datasets belong to datasets for visual style classification. Researchers regard databases are the most suitable applications for culture subject-specific information collection (Tsirliganis et al., 2002). A cultural dataset is a database that can provide with information related to cultural objects, monuments, museums, heirlooms etc. There are already a few cultural image datasets. For example, Cultural and Educational Technology Institute in Greece (Tsirliganis et al., 2002) has provided cultural dataset on pottery and heirlooms. Mensink and Van Gemert (2014) built a museum-centric dataset with artworks from the Rijksmuseum. They annotated the images based on four elements including artist, type, material, and creation year. However, none of these cultural datasets are prepared for product design. This study proposes a cultural image dataset, that contains images with various cultural labels of four dimensions, which are color, material, pattern, and form. For conducting a pilot study, a small-scale cultural image dataset was built that contains images with typical Dutch styles. Through consulting Dutch cultural experts and reading relevant literatures, four typical Dutch cultural elements were selected.

Color: Though the colors of Dutch flag are red, white and blue, the national color of the Netherlands is orange (Lakens, 2011). Dutch teams normally wear orange uniforms to indicate their country at international sport events.

Material: Delftware is a kind of blue-and-white ceramics, that is regarded as Dutch national product (Odell, 2018). Since the 17th century, Dutch people painted images of “Dutchness” on the vessels to present Dutch femininity and domesticity (Odell, 2018).

Pattern: De Stijl in Dutch means “The Style”, which was originally a radical and artistic movement of the 1920s (Jaffé, 1956). It can be regarded as Modernism in Dutch. Artists showed their works by trying to create peace and order after the chaos of World War I. The visual compositions of De Stijl are simplified to lines and surfaces, that represent pure abstraction and harmony (Samuel, 2005).

Form: Tulip is the national flower of the Netherlands. In Dutch culture, it also represents the briefness of life (Christenhusz et al., 2013).

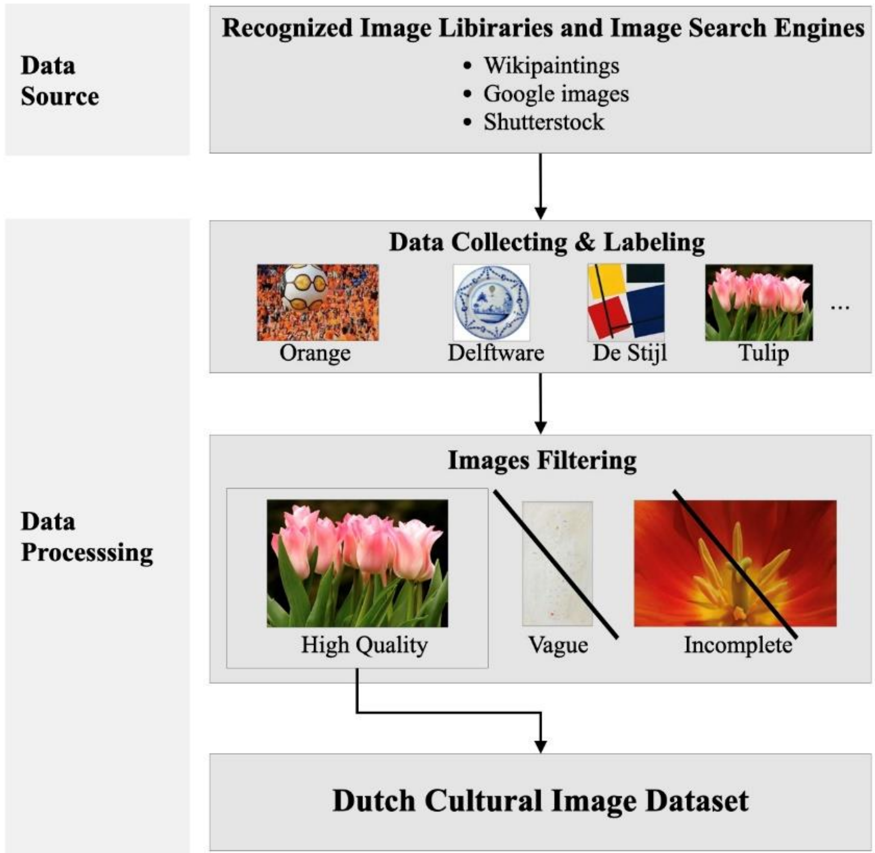


Figure 7.16 Dutch Cultural Image Dataset

Figure 7.16 presents the process of building the Dutch cultural image dataset. Images with these Dutch cultural elements were collected by searching for the relevant keywords (e.g. Dutch & orange, delftware, De Stijl, tulip) from the recognized image libraries such as Wikipaintings (Karayev et al., 2013), Google images (Google, 2020) and Shutterstock (Shutterstock, 2020), that are all large-scale datasets with labeled images. To ensure a good recognition accuracy, some vague pictures and incomplete images were deleted, which are not conducive to style recognition. Then a cultural image dataset with 1200 images about Dutch culture was built, in which each Dutch cultural element has 300 effective images. To support the algorithm training, 300 candidate images unrelated to the four Dutch cultural elements were randomly downloaded from Wikipaintings (Karayev et al., 2013). As shown in Figure 7.17, a small-scale cultural image dataset containing four categories of images with Dutch cultural elements and some other random images.

Figure 7.17 Examples of Cultural Image Dataset

7.7.2 Cultural Image Selection Module

The cultural image selection module aims to replace the human designer in selecting cultural images and identifying cultural elements. The module consists of two main sub-blocks: (1) cultural elements analysis and (2) cultural image ranking, as shown in Figure 7.18. It starts with computing the culture probability distribution of each uploaded cultural image, and then rank cultural images based on the culture similarities with the pre-defined culture style expectation as well as designer's preference. The final top-ranked image is then used as the cultural image to provide cultural style for designing cultural product.

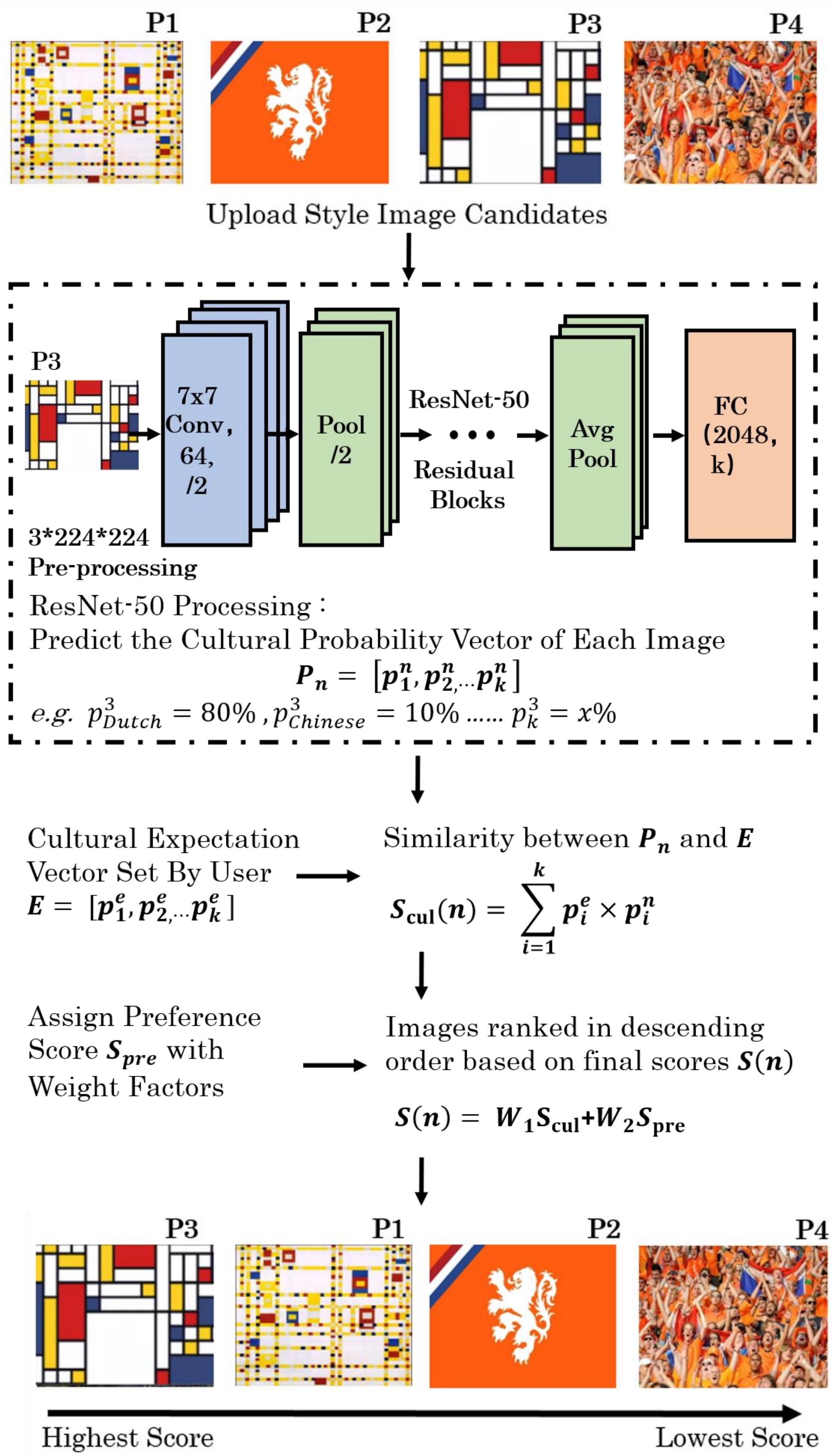


Figure 7.18 Cultural Image Selection Module

Cultural Elements Analysis

The first block of the cultural image selection module is the cultural elements analysis, i.e., identifying the cultural elements of the uploaded culture images. To achieve this, Convolutional Neural Networks (CNNs) technique were applied, which makes breakthroughs across many image-related applications such as information retrieval and classification (Aceto, Ciuonzo, Montieri, & Pescapé, 2019; Babenko, Slesarev, Chigorin, & Lempitsky, 2014; He, Zhang, Ren, & Sun, 2016; Karpathy et al., 2014), security system (Lawrence, Giles, Tsoi, & Back, 1997; J. Yang, Lei, & Li, 2014), medical system (Feichtenhofer, Pinz, & Wildes, 2017; Song, Jaiswal, Shen, & Valstar, 2020), physical layer (O'shea & Hoydis, 2017), as well as style transfer (X. Chen, Xu, Yang, Song, & Tao, 2018; Gatys, Ecker, & Bethge, 2016; J. Johnson, Alahi, & Fei-Fei, 2016), etc. CNNs are most commonly applied in computer vision applications (Y. Taigman, M. Yang, M. A. Ranzato, & L. Wolf, 2014) and are data-driven approaches for the identification of significant patterns of given images (LeCun, Bengio, & Hinton, 2015). A CNN consists of a feature extractor that can calculate the main features of images for classification (J. Kim & Lee, 2020). It provides fast and accurate image attributes with a fully automatic process and thus it is suitable for image selection process.

Networking Setting: In this study, the CNNs are prone to overfitting during training due to the size of the Dutch cultural dataset is small. Conventional CNNs are susceptible to gradient loss and degradation as the degradation as the depth of network structure increases (Bengio, Simard, & Frasconi, 1994; He & Sun, 2015; Srivastava, Greff, & Schmidhuber, 2015). Therefore, the Residual Neural Network (ResNet-50) is employed as the identity mapping operation in the residual block makes the network model can be deepened without degradation and overfitting (He et al., 2016). The basic architecture of ResNet mainly consists of the convolutional layers, the pooling layers and a fully-connected layer with SoftMax function (He et al., 2016). The residual block structure introduced by the ResNet is shown in Figure 7.19, which establishes a shortcut connection with constant mapping relationship.

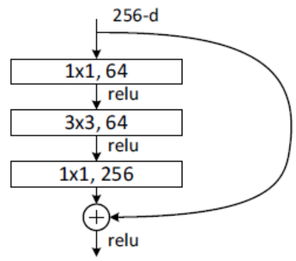


Figure 7.19 “Bottleneck” Residual Block Structure

Generally, the convolutional and pooling layers were used to extracts visual feature data, such as color and texture etc., from the input image, and the visual feature data in form of multi-dimensional vectors representing the image features were fed into the classifier to determine the style of the corresponding image.

To train a CNN model that can predict cultural elements of the input image, each training image is paired with a unique cultural label (e.g., Dutch) based on its color, material, pattern, and form. These labelled images were first input into the ResNet model, and a 7×7 convolutional layer with 64 channels was used to extract the features from the input image and then the average pooling layer was used to reduce the dimensionality of the feature map. Then the results obtained by the pooling layer are fed into 16 “Bottleneck” residual blocks for feature learning, the network is trained with Adam optimizer (Zijun Zhang, 2018). Cross-entropy (Zhilu Zhang & Sabuncu, 2018) is used as the loss function during the network training, which treated the task as a multi-class classification problem.

Finally, the feature maps obtained from the residual blocks are pooled on average, and the pooling results are fed into a fully connected layer to transform them into feature vectors, which are then classified by a SoftMax classification layer to obtain identification results (He et al., 2016). Since the classification task of ResNet framework only need to specify 2 categories of image style, the output result of the fully connected layer is set to be 2. Then the SoftMax function will continue to calculate the results of multiple classifications as probabilities. The Tensorflow (Saha, Khabir, Abir, & Islam, 2019) is used for the implementation of this ResNet model.

Model Training: To train a CNN model that can predict the cultural elements of an input image, each training image is paired with a unique cultural label (e.g., Dutch) based on its color, material, pattern, and form. As the size of the cultural style image dataset is small, direct training of the network model will produce problems such as overfitting or low recognition accuracy. Transfer learning is a way to transfer the model parameters trained in the large dataset ImageNet to the ResNet model to be trained, which can improve the training efficiency of the model and avoid previously stated problems (Oquab, Bottou, Laptev, & Sivic, 2014; Yosinski, Clune, Bengio, & Lipson, 2014). Therefore, the transfer learning method is introduced to use the parameters originally trained in the ImageNet dataset for the problem of cultural style recognition. The original trained model using ImageNet dataset was used to classify 1000 categories of images such as dogs and cats etc., which need to be modified with final fully connected layer output set to 2.

In the process of transfer learning, the images in the cultural style dataset were directly divided into the training set and validation set in the ratio of 8:2 for training and validating. Due to the total number of images in the cultural style dataset, it was necessary to appropriately increase the learning rate to 0.0001, reduce the batch size to 20 and save the network parameters after the transfer was completed (S. L. Smith, Kindermans, Ying, & Le, 2017). After applying such as strategy, the well-trained ResNet network learns cultural style information from the collected cultural image dataset and achieved 98% recognition accuracy on the validation dataset, where the accuracy is denoted as

$$Accuracy = \frac{N_T}{N_T + N_F} = \frac{N_T}{N_{Total}}$$

Here, N_T represents the number of correct predictions and N_F represents the number of incorrect predictions. The sum of $N_{Total} = N_T + N_F$ is the total number of predictions, which equals to the number of cultural images in the validation dataset. The result indicates that the network parameters successfully transferred from the source domain to the target domain, with significant transfer learning effectiveness and no negative transfer (Yosinski et al., 2014). The recognition of cultural elements can be considered a matter of interpretation (J. Kim & Lee, 2020) for designers when design for a foreign culture.

Inference: Once the image selection module has received the uploaded cultural image candidates, they are fed to the ResNet, which has been pre-trained by the cultural image dataset. This block takes the intermediate output from the ResNet, i.e., the vector generated by the final SoftMax layer (soft predictions). Such soft predictions can be represented as the probability vector $[p_1, p_2, \ldots, p_k]$.

of all cultural classes (k classes) of the given image, where p_i is the probability of the input image that belongs to i_{th} cultural class. This can be obtained generated from the softmax activation function of the network's output layer. Here $\sum_{i=1}^{k} p_i = 1$. For example, if k = 4 and four classes are: Dutch, Chinese, British, and others. Then, an input image may be classified as 70% of Dutch, 22% of British, 5% of Chinese and 3% of others. The pseudo of the cultural elements analysis block is shown below.

Input: Style Images I
Output: Style Probability Vector $V = [p_1, p_2 \cdots p_n]$

I_R : Resized style image
I_P : Preprocessed style image with desired image properties
M_{Res} : Conventional ResNet-50 model
M_{Adj} : Adjusted ResNet-50 model with desired number of output
W_{CID} : Weights of the model trained with Culture Image Dataset
M_{Cla} : Modified model that can be used as classification tool

for each user input style images I **do**
    Resize the user inputted image to I_R with length times width equal to 224x224 pixels;
    Preprocess the resized image I_R to I_P with modified RGB channel values;
    Load the ResNet-50 model M_{Res} and adjust it to M_{Adj} which could generate a probability vector that contain desired number of elements;
    Load trained weights W_{CID} into the modified ResNet-50 Model to assemble the classification module M_{Cla};
    Pass the preprocessed image I_P into the classification module M_{Cla} in a single batch;
    Produce the predicted probabilities for different image style in the form of a vector V;
end

In summary, once the cultural image candidates are uploaded to the tool, the cultural elements analysis block will produce a vector containing the cultural elements percentage for each cultural image candidate respectively.

Cultural Image Ranking

After obtaining the cultural classification probability vectors of all uploaded cultural images, a human-computer cooperative ranking scheme is used to select the final used cultural image. Given a designer cultural expectation E ($E = [p_1^e, p_2^e, \ldots p_k^e]$, e.g., 50%

of p_1 , 50% of p_2 , 0% of p_3 , and 0% of p_4) and a set of predictions [P_1, P_2, …, P_N] corresponding to the cultural probability vectors of N uploaded images ($P_n = [p_1^n, p_{2,}^n ... p_k^n]$), which are generated by the well-trained ResNet. Then, each image is assigned a unique score by computing the similarity between the expectation vector and the cultural probability vector of each image, respectively:

$$S_{\text{cul}}(n) = \sum_{i=1}^{k} p_i^e \times p_i^n$$

Besides the cultural similarity, the designer assigns a style preference score $S_{pre}(n)$ to all uploaded cultural images. This aims to add the human sensual preference to the final decision. As a result, both cultural similarity and designer's subjective preference score are taken into consideration to make the final score for each image:

$$S(n) = W_1 S_{\text{cul}} + W_2 S_{pre}$$

where W_1 and W_2 are weights and $n = 1, 2, \cdots, N$. Finally, N images are ranked in descending order based on their corresponding scores and the top 1 image is chosen as the cultural image for the style transfer module. The pseudo of the cultural image ranking block is shown below.

Input: Users' Cultural Expectation E and Image Style Preference P
Output: Recommendation ranking list R

S_{cul} : Calculated general cultural score of an input image
W_P : Weights for balancing user's preference and cultural score
S_{fin} : Final score used for ranking

for each user's input culture image **do**
Combine the user's cultural expectation E with predicted style probability vector of each image V to calculate the unique cultural score S_{cul} of different images;
Apply preference weights W_P to user's preference and cultural score to obtain final ranking score S_{fin};
Sort the final ranking scores S_{fin} form a high to low order;
Form the recommendation list R based on the sorted final ranking scores;
end

7.7.3 Style Transfer Module

The cultural style transfer module aims to automatically generate a culture-specific image that has the same content as the uploaded design sketch and has the cultural style of the selected style image, by utilizing style transfer technique without any human effort. The core of style transfer module is convolutional neural network (CNN). CNN is biologically inspired vision models that has near-human performance (Krizhevsky et al., 2012; Y. Taigman, M. Yang, M. Ranzato, & L. Wolf, 2014). Convolution is a special operation and the core of CNN. CNN consists of convolutional layers of small computational unites that process visual information of images hierarchically in a feed-forward manner (Krizhevsky et al., 2012). Each convolutional layer is regarded as a collection of image filters that extract certain features from the input image (L. A. Gatys et al., 2015). Deconvolution function can visualize what the convolutional layers actually has learned from an image (Zeiler, Taylor, & Fergus, 2011). Take Figure 7.20 as an example, the low-level layers extract more detailed visual information such as color, dots and lines, while the high-level layers extract more abstract visual information and overall arrangement such as the shape of the fish (Siddiqui et al., 2018). As a result, CNN can be used to represent the content and style of images separately.

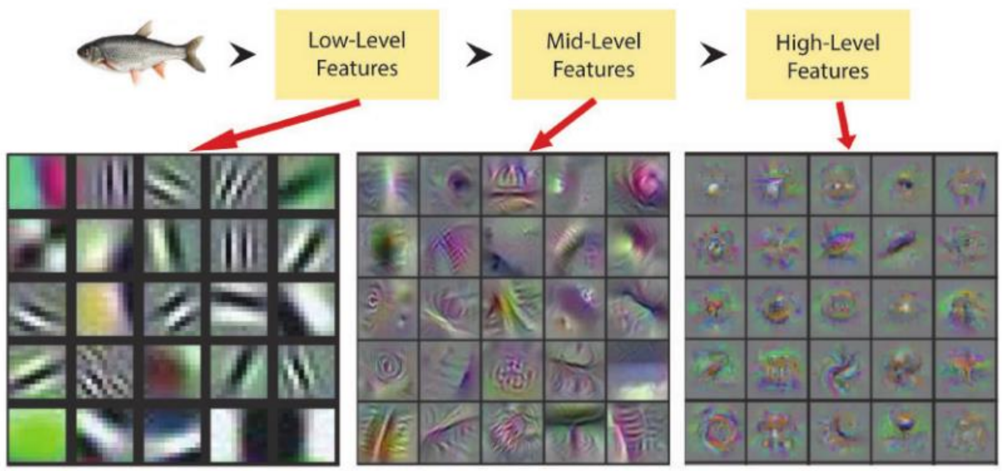


Figure 7.20 Hierarchical Representation Learning by a CNN (Siddiqui et al., 2018)

Content Representation: Since higher-level layers in the CNN capture the high-level content in the form of object and global arrangement of the image, the feature responses in higher layers are used as the content representation.

Style Representation: To represent the style of a cultural image, feature space is used to capture texture information while discarding information of the global arrangement (L. Gatys et al., 2015). Feature space consists of the correlations between the different features extracted from each convolutional layer. It is “a stationary, multi-scale representation of the input image” (L. A. Gatys et al., 2015). A Gram matrix is used for style representation (Russakovsky et al., 2015), whose formula is shown below. $G_{i,j}$ is the inner product between the vectorized feature map i and j. It is used to generate a texture that matches the style of a given image.

$$G_{i,j} = \sum_k F_{ik} F_{jk}$$

Gram matrix focuses on the color and texture information of the image, ignoring the spatial information. An example provided by Gatys et al. (2016) displayed the style extract after the CNN plus the Gram matrix, as shown in Figure 7.21. The style of the input image is constructed from a style representation built on different subsets of CNN layers (a: conv1_1; b: conv1_1 and conv2_1; c: conv1_1, conv2_1 and conv3_1; d: conv1_1, conv2_1, conv3_1 and conv4_1; e: conv1_1, conv2_1, conv3_1, conv4_1 and conv5_1). Style reconstruction creates images that match the style of a given image on an increasing scale while discarding information of the global arrangement of the scene. It is very clear that styles extracted in the low-level convolutional layers are pixel colors, while the styles extracted in the high-level convolutional layers show a clearer details of input image.

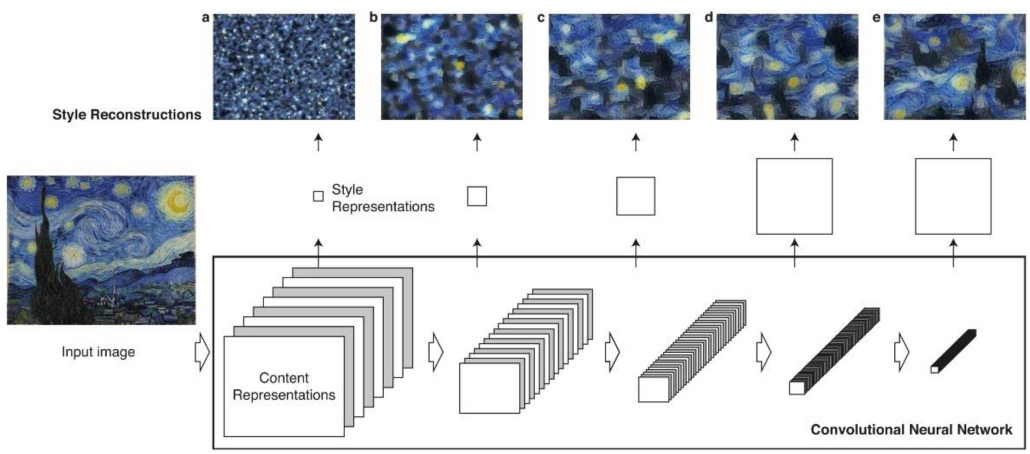


Figure 7.21 Style Reconstructions (Gatys et al., 2016)

Because CNN can differentiate the content and style of an image, a new and culturally meaningful image can be created by mixing the content and style representation from two different source images with visual cultural elements. The details of style transfer module are explained in the following paragraphs.

VGG-Net: The style transfer module is composed of two VGG-Net, which is a type of CNN that executes object recognition. Simonyan and Zisserman (2014) proposed VGG-Net during the ImageNet Large-scale Visual Recognition Challenge that outperformed its competitors by classifying images with better accuracy. Figure 7.22 outlines the configuration of VGG-Net. As shown in the figure, the width of convolutional layers (the number of channels) is rather small, starting from 64 in the first layer and then increasing by a factor of 2 after each max-pooling layer until it reaches 512 (Simonyan & Zisserman, 2014). The depth of the configurations increases from the left (A) to the right (E) as more layers are added. In this study, VGG-16 network is used, since it is aware of the semantic content of images (J. Johnson et al., 2016).

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 7.22 ConvNet Configurations (Simonyan & Zisserman, 2014)

The module is composed of two VGG-Nets that are Image Transform Network and Loss Network (J. Johnson et al., 2016), and supported by COCO dataset (T. Y. Lin et al., 2014).

Image Transform Network: The function of Image Transform Network is transferring the style of an input image x under the premise of style target y_s and content target y_c to an output image $\hat{y}$, as shown in Figure 7.23.

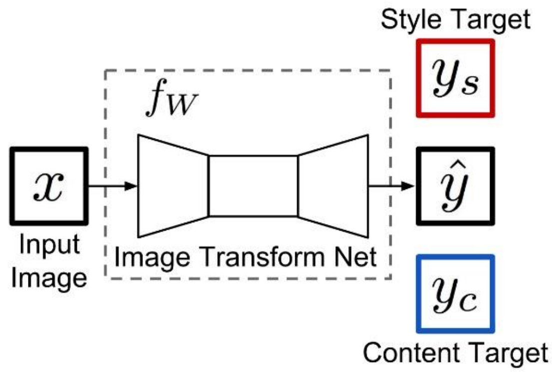


Figure 7.23 Image Transform Net (J Johnson et al., 2016)

Loss Network: Since there is no image perfectly matches both content representation and style representation, the Loss Network is used to minimize the differences between the synthesized image with content image and style image. As shown in Figure 7.24, the Loss Network Ø is used to define a feature reconstruction loss $\ell_{feat}^{\emptyset}$ and a style reconstruction loss $\ell_{style}^{\emptyset}$ that measures differences between content and style images (J. Johnson et al., 2016). As shown in this figure, Loss Network measures the difference between $\hat{y}$ and y_s and the difference between $\hat{y}$ and y_c . Because higher-level convolutional layer is used as the content representation, here this figure uses relu3_3 for representing content. Relu1_2, relu2_2, relu3_3 and relu4_3 for style representation. With Loss Network, the emphasis on either the content or style can be regulated smoothly.

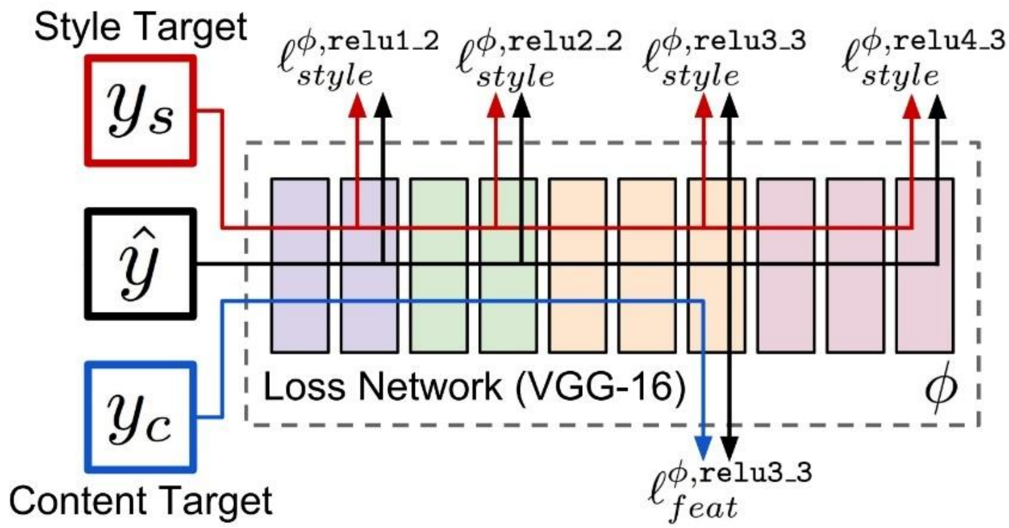


Figure 7.24 Loss Network (J Johnson et al., 2016)

COCO Dataset: For the style transfer several open-source datasets are provided to use. In this research the Microsoft COCO dataset is used. The COCO dataset provides a set of 80 things and 91 stuff classes (Caesar et al., 2018; T. Y. Lin et al., 2014) the dataset comes with the annotation hierarchy labeling see Figure 7.25. This provides an overview of how the dataset link a certain annotation towards another. The COCO dataset is important to classify stuff and things by image captioning. The dataset contains more than 80000 pictures in relation to most of the content in life. Studies done by (Caesar et al., 2018; Cui, Yang, Veit, Huang, & Belongie, 2018; T. Y. Lin et al., 2014) demonstrate both the quality and efficiency of the dataset, making it suitable to for training.

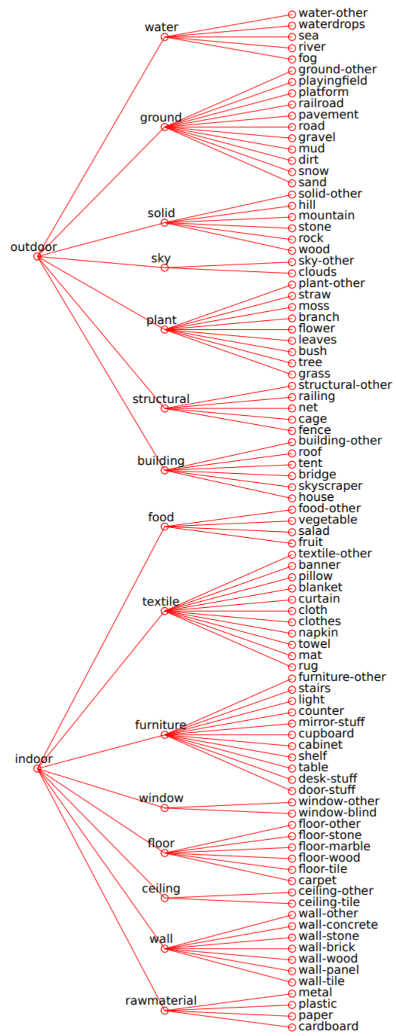


Figure 7.25 COCO Dataset Label Hierarchy (Caesar et al., 2018)

Overall Structure: Figure 7.26 shows the overall structure of how the style transfer functions. It consists of Image Transform Network and Loss Network. Image Transform Network transfers the style of the input image x (given by the COCO dataset) to the output image $\hat{y}$. A pre-trained VGG -16 Loss Network minimize the differences between the synthesized image ŷ with style target y_s and content target image y_c by loss function. The system iteratively modifies the parameters of style representation and content representation based on the difference between y_s and y_c and calculate them by $\hat{y}$. Finally, the system computes a feature space consists of the correlations between the different features extracted from each convolutional layer. It is “a stationary, multi-scale representation of the input image“ (L. A. Gatys et al., 2015).

And the Image Transform Net replace the style of arbitrary image while preserving the content of the image.

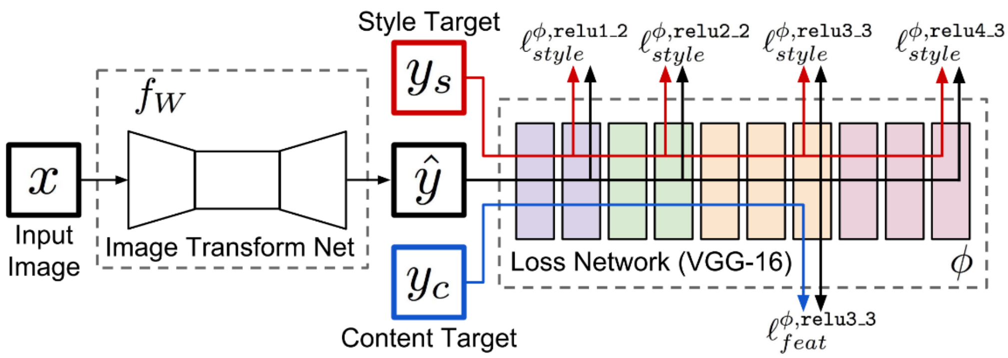


Figure 7.26 Overall Structure of Style Transfer (J Johnson et al., 2016)

Cultural Style Transfer: The cultural style representation focuses on the edge style, colors, etc. Because CNN can differentiate the content and style of an image, a new and culturally meaningful image can be created by mixing the content and style representation from two different source images with visual cultural elements. Both feature representations are feeded in a decoder-style CNN network to produce the final culture-specific design sketch, as shown in Figure 7.27. The study treats the design sketch as the content image and the selected cultural image as the style image in this method.

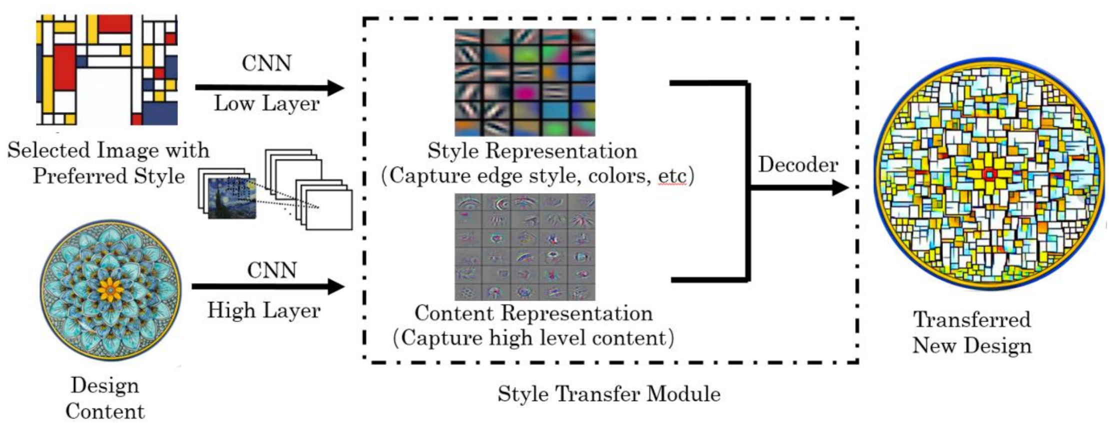


Figure 7.27 Style Transfer Process

The pseudo of the style transfer module is shown below.

Input: Selected Style Image I_{St} and Design Image I_{De} Output: Target New Design Image I_{new} M_{De} , M_{St} : Content feature map and Style feature map

L_{De} , L_{st} : Content loss function and Style loss function
L_{De_up} , L_{St_up}: Updated content loss function and Updated style loss function
L_{total} : Total loss function

for each user selected style image I_{St} and Design Image I_{De} **do**
Pass the selected design image I_{De} to a CNN model to obtain the content feature map M_{De} at a certain layer of the CNN;
Pass the selected style Image I_{St} to a CNN model to obtain the output map at the same layer and process this output map with Gram Matrix to represent the style feature map M_{St};
Set the original target image to be a white noise image I_{Wh} and obtain M_{Wh};
Calculate the content loss function L_{De} and style loss function L_{st} to represent the difference between M_{Wh} , M_{De} and the difference between M_{Wh} , M_{St};
Update the loss functions using Stochastic Gradient Descent Method to achieve minimum differences;
Assemble the updated loss functions L_{De_up}/L_{St_up} with corresponding content weight α and the style weight β to get total loss function $L_{total} = \alpha L_{De\_up} + \beta L_{St\_up}$;
Adjust the weights α and β to set whether the resulting image is more content or style orientated;
Use L_{total} with I_{Wh} to decode the final target new design image I_{new} that merges the I_{St} and I_{De};
end

7.7.4 Interface of the AI-supported Design Tool

To realize the above functions, the user interface of the AI-supported design tool is developed. The interface design follows the principle of simplicity. It has mainly two parts: (1) Style Image Gallery for designers to upload and select appropriate images with cultural elements and (2) Cultural Style Transfer part for designers to generate creative visual designs.

Style Image Gallery: Figure 7.28 illustrates the user interface of style image gallery. Designers can upload several cultural style image candidates to the style image gallery and mark their own preferences on each image candidate with stars. As shown in the figure, there are three ways to rank the style image candidates: (1) AI rating, which is based on the probability of designers' cultural style expectations calculated by AI (in this example, the cultural style expectation is chosen as Dutch culture, the probability is like 95% and 92% respectively), (2) User rating, which is based on designer's preferences (such as five stars and four stars) and (3) Overall rating, which is based on an overall score taking both AI rating of designers' culture style expectations and preferences into consideration (such as 9.7, 9.5 and 7.5). The various choices of rating system help designers to select the most suitable cultural image based on different needs.

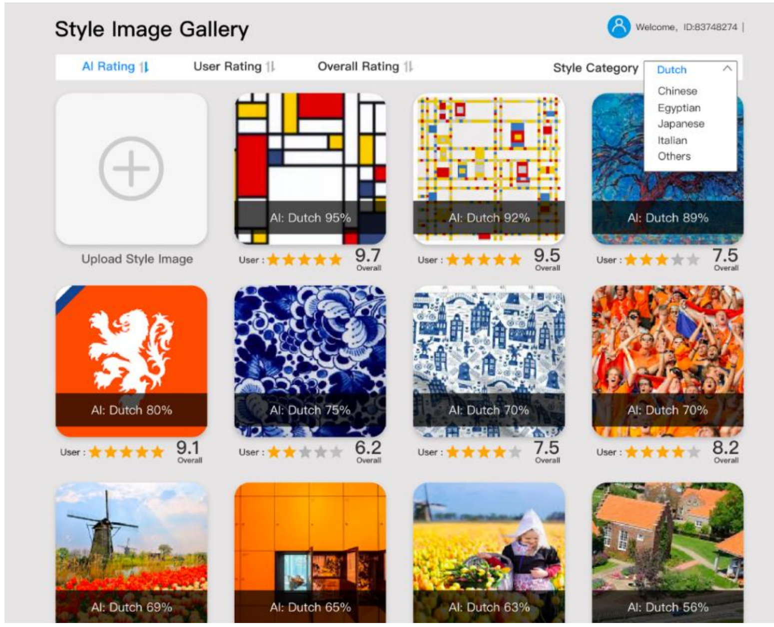


Figure 7.28 Style Image Gallery of the Tool

Cultural Style Transfer: Figure 7.29 shows an example of combining a design work with the style of a typical pattern of Dutch culture (a painting by Mondrian). The designer chose the top 1 image of Style Image Gallery based on the overall ranking, and then upload his own design work. Once he clicked the "transfer" button, the tool will take few seconds to generate an image not only has the same content as the uploaded design work but also has the Dutch style.

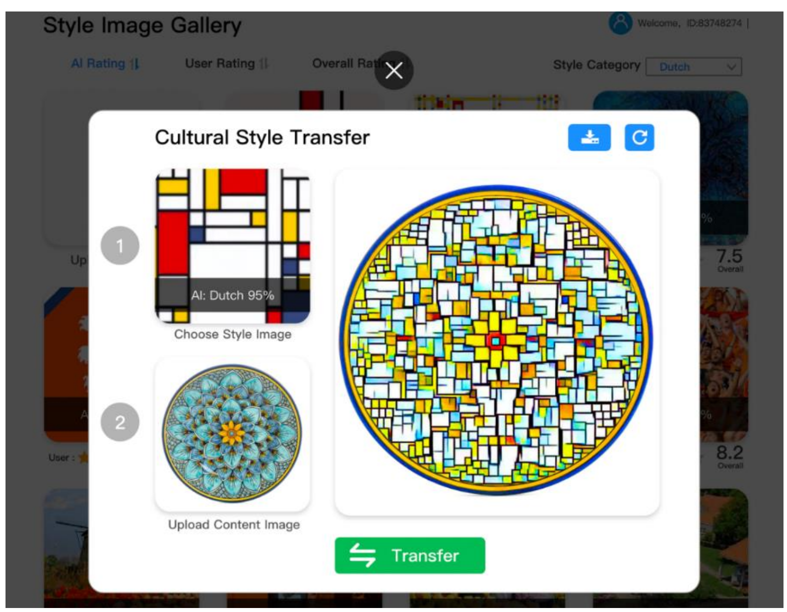


Figure 7.29 Cultural Style Transfer of the Tool

7.8 Discussion and Conclusion

As a design-based research project on design education, this study seeks to contribute to emerging issue on collaborative design-learning process with cultural diversity by developing AI-supported collaborative learning strategy. This study gives a different meaning to AI technology, which is a cultural style transfer tool for cross-cultural design process. Normally cross-cultural design requires designers to understand a foreign culture, identify and select suitable cultural elements, and finally transform them to product design. This process is extremely expensive and time-consuming. And the quality of design outcome relies much on designers' design skills and cultural awareness (Rungtai Lin, Cheng, et al., 2007). The AI-supported collaborative learning strategy saves designers' work on culture research.

The proposed design tool is an innovative and efficient tool to help designers for idea generation and fast prototyping. Before using the AI tool, the designer is required to upload the design content image and a set of cultural image candidates. An image selection module is proposed to replace the human designer by automatically selecting the most suitable style image from the cultural image candidates. In particular, a cultural style classification CNN is trained to generate the cultural style distribution of each style image. Then, style images are ranked based on the similarities between their cultural styles and the cultural style expectation as well as the designers' own preference. The selected top-ranked cultural style image is fed along with the design content image, into our style transfer module to automatically generate a culture-specific design image. This saves designers having to work on cultural research. It is an efficient and innovative approach to integrate cultural elements. To the best knowledge, this is the first work that extends the deep learning techniques to facilitate cross-cultural design.

Strijbos et al. (2004) argued that a tool is technologically possible does not imply that it is educationally desirable. Designers should not think that students use technological support exactly in the way intended. Thus, the learning effectiveness and user experience of the AI-supported collaborative learning strategy in real world need to be further explored.

8. CASE STUDY AND EVALUATION

8.1 Chapter Overview

Last chapter has proposed collaborative learning strategy and developed an AI-supported tool to facilitate cross-cultural design process. In order to evaluate the learning strategy in design education practice, a case study in real world was conducted.

8.2 Setting of Case Study

Pea (2004) emphasized that successful collaboration requires careful design of the learning environment and support by the educator. Strijbos et al. (2004) proposed a process-oriented design methodology for computer-supported collaborative learning (CSCL) settings consists of six steps, including (1) determine the learning objectives, (2) select the task type, (3) determine whether and how much pre-structuring is needed, (4) determine group size and (5) determine how computer support can be applied to support CSCL. Based on these six steps, the setting of case study is designed:

(1) Learning objective: The case study aims to develop students' generic literacy and design expertise such as cultural awareness, creativity, teamwork, communication skills etc.

(2) Task type: Since the aim of this study is to develop design students' generic literacy and design expertise that are open skills, this case study uses ill-structured tasks which have a considerable degree of uncertainty regarding the rules and principles that can be applied and often have no clear-cut solution (D. H. Jonassen, 1997). Chapter 7 has introduced a small-scale Dutch cultural dataset, so this case study focusses on the topic of designing a product with Dutch cultural elements. The design task is designing masks for Dutch users. It is proved that wearing mask can produce reductions in infection rates of covid-19 (Greenhalgh, Schmid, Czypionka, Bassler, & Gruer, 2020). The Netherlands has been one of the countries worst affected Europe's second wave of Covid-19 (BBC, 2020). From the 1st December 2020, it has been announced that masks will be a demand in the Netherlands. However, due to cultural cognition, people from many countries thought only sick patients have to wear masks and refused to wear masks. And covering faces may lose people's identity since they cannot show their facial expressions (Judkis, 2020). Wearing a face mask has changed the way people perceive on another and has made it hard for people to read faces. There is a desire to show personal preferences, needs and functionalities through the face masks. Thus, the challenge of designing face masks requires designers to understand and apply cultural elements in design practice. The design task is generating creative ideas of face masks for cross-cultural (in this case study Dutch) consumers. The design students are free to use any methods and techniques for brainstorming and the study does not constrain the number and direction of generated ideas.

(3) Level of pre-structuring: In order to achieve the expected interaction, what kind of pre-structuring should be considered carefully. Too much structure may result in forced artificial interaction, while no structure may result in fragmented interaction (Strijbos et al., 2004). In this case study, the "Jigsaw" structure (Aronson & Thibodeau, 1992) is used that the design students are asked to contribute their work and the group aims for convergence. This structure ensures task division and interaction while still leaves freedom for creativity. The proposed AI tool helps participants separate the design tasks, and there is non-teacher involvement during the interaction process. The students will be graded based on their group performance, that requires participants work collaboratively.

(4) Group size: Gros (2001) pointed out that group size must be considered with respect to expected interaction and collaborative learning process. Veerman, Andriessen, and Kanselaar (2001) observed a more intensive discussion flow in three-member groups compared to dyads in higher education setting. Schellens and Valcke (2006) stated that learning group needs to be small enough to enable students to participate fully and to build group cohesion. Resta and Laferriere (2007) stated that heterogeneous groups in terms of participants' gender and culture are more productive for collaborative learning. In this case study, three design students are working together, and their works are combined into an integrate outcome with the proposed AI-supported design tool. Two designers have Chinese cultural background, while the other design has Dutch cultural background. They take their own responsibilities while the group work is built on all students' contributions. With this setting, the group interaction takes balance of "positive interdependence" and "individual accountability".

(5) Computer support: In this case study, the AI-supported tool described in Chapter 7 is applied to facilitate cross-cultural design process. The expected interaction of this case study focuses on the exchanging and creating design works. According to Strijbos et al. (2004), designing group interaction needs to consider two important principles, that are positive interdependence (D. W. Johnson, 1981) and individual accountability (Slavin, 1980). It means that the performance of a single participant is dependent on the performance of all others, while each participant is held individually accountable for tasks. In order to develop the aforementioned open skills, the students need to reciprocally build on each other's contributions (Strijbos et al., 2004). As shown in Figure 8.1, in this AI-supported cross-cultural collaborative design-learning process, designer A with Dutch cultural background is responsible for selecting cultural image candidates. Design B and C can also mark their preferences on image candidates. Then the cultural image selection module will rank all the style image candidates based on the probability of designers' cultural style expectations and subjective preferences. The tool provides three ways of ranking for design team to choose the most appropriate cultural image according to different conditions. Designer B and designer C are responsible for ideating and prototyping. The design works produced by designer B and designer C will be combined with cultural elements through cultural style transfer module to generate creative designs. The AI tool facilitates a high sense of working together and creates a shared visual language for collaboration.

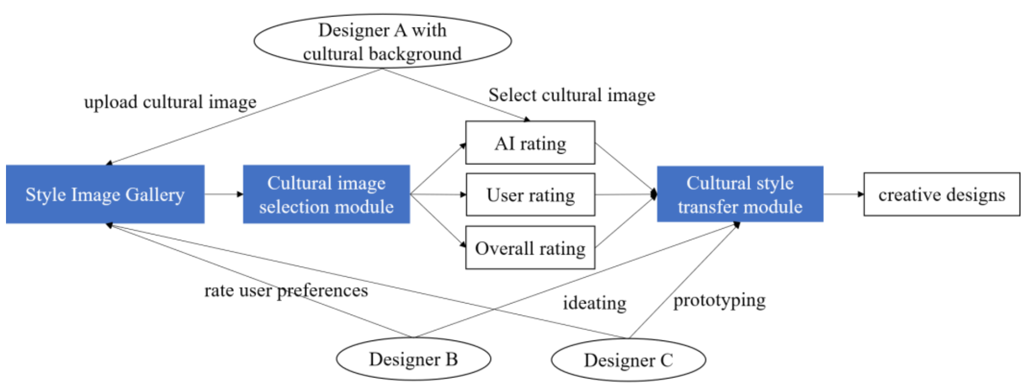


Figure 8.1 AI-supported Cross-cultural Collaborative Design-Learning Process

Based on these general settings of case study, a design workshop was organized as an experiment to evaluate the proposed learning strategy. The details of the workshop are explained below.

8.3 Overview of the Samples

The tool employs the local artistic style of the Netherlands as a research source to implement sample testing. To make up cross-cultural design teams, the design workshop invited Dutch design students and Chinese design students as team members.

Participants were recruited online among Industrial Design students from Zhejiang University, China and Technology University of Eindhoven, Netherlands. The participant information collection forms (Appendix 8A) were used to collect information about participants' gender, age, English skills and Dutch cultural awareness. Through screening, 11 Dutch design students (M=22.91, SD=2.71; 3 male and 8 female) and 22 Chinese designers (M=24.82, SD=1.75; 11 male and 11 female) with adequate English communication ability and design skills were recruited. Almost all participants (97.0%) had not used any AI-supported design tool before. Only one participant responded that he had used PS Priart, which is an AI-supported plug-in.

8.4 Experiment Design

Biggs (1989) proposed 3P model for assessing the added value of technology support for collaborative learning, which includes (1) presage variables that provide the context in which a learning experience is conducted; (2) process variables that include the interactions of educational experiences; and (3) product variables that include the quality of learning outcomes. This model emphasized student participation and quality of learning outcomes. Dreamson (2017) argued that quality of collaborative design needs to be measured with building of socio-cultural skills and values among team members. Deardorff (2011) suggested some evidences that can be collected to assess students' cross-cultural competence, including learning process, self-reflection and learning performances. In this study, a within-subject design was used. The independent variable was the design tool used with two conditions. The dependent variables included (1) number of ideas generated within 30 minutes, (2) quality of the design outcome, (3) participants' subjective rating on cultural awareness, (4) participants' subjective rating on design collaboration, and (5) participants' user experience in varying design conditions. counterbalancing was performed by placing participants in groups and presenting conditions to each group in a different order. For example, Group 1 was given the condition A with traditional design tools followed by the condition B with the proposed tool. While Group 2 was given condition B followed by condition A.

8.4.1 Questionnaire and Interview

To evaluate the effectiveness of the tool and participants' user experiences, a quantitative questionnaire and a qualitative interview were designed based on the discussions about the cross-cultural collaborative design process and learning experiences in the literature.

The questionnaire had 7 questions in total and consisted of four sections: (1) the participants' Dutch cultural awareness; (2) the specific phase of design process that was supported by the AI tool; (3) the collaboration during the design process; and (4) the usability of the tool. Specifically, Q1-Q4 asked Chinese participants' Dutch cultural awareness of four cultural element dimensions (color, material, pattern, and form). Q5 asked the participants about the specific phase of design process when they used the proposed tool. The options for Q5 reference the literatures in Section 2.5.2, which include design research (W. Chen, 2015), idea generation (Bonollo & Lewis, 1996; Hummels & Frens, 2008; Rauth et al., 2010), prototyping (Rauth et al., 2010), evaluation (Bonollo & Lewis, 1996) (Rauth et al., 2010), and design communication (W. Chen, 2015; Lewis & Bonollo, 2002). Q6-Q7 referenced Dreamson (2017)' questionnaire about design collaboration, and asked participants about the communication quality and team relationship during the collaborative design process. These questions used 5-point Likert scales, where 1 denoted "very bad" and 5 denoted "very good". The interviews aim to collect the participants' quantitative feedback for better performance of the AI tool, and the questions were: (1) advantages and disadvantages of the tool; and (2) improvements or suggestions for the tool.

8.4.2 Procedure of the Experiment

The experiment was conducted in the form of design workshop, with the challenge of designing a face mask for Dutch users. Participants were randomly divided into 11 groups, with one Dutch design student and two Chinese design students working together in each group. There is a moderator allocated in each design group to guide the participants to follow the procedure of experiment. All the participants and the moderator of a design group were connected via Skype.

Prior to the experiment, the participants were getting familiar with each other, and at the same time the moderator was checking the sounds and screen sharing work well for each participant. Once making sure the internet connection is ok, the participants were briefed about the purpose of the experiment and the design challenge: designing face masks for Dutch users.

Considering the limited availability of the participants, the design task was intended to be accomplished within 30 minutes. The workshop has two 30-minute sessions, which are conducted with and without the AI tool. Five design groups started with the session with the tool and then the session without the tool. The remaining six design groups had the opposite order. For the session with the tool, the participants began with watching a video showing the usage of the tool. They could also ask questions to the moderator in case they didn't understand how to use the tool. There are 5 minutes between the two sessions for the participants to take a rest. During each session, participants were free to use any familiar design software (such as Photoshop, Illustrator etc.) to finish the design task. The participants were required to share the screen to let the everybody in the design group watch the design process and offer suggestions. Participants were encouraged to think aloud through the design process. The moderator kept silence during the whole design process except there were any technique problems. At the end of each 30-minute session, the participants were asked to submit a final design outcome and complete a questionnaire about their awareness of four Dutch cultural elements. For the session with the tool, the participants were asked an extra question about the specific phases of design process when they used the tool. The complete questionnaire is shown in Appendix 8B. At the end of the design workshop, all the participants had an interview together talking about their experience and performance in the design task. With the consent of the participants, the whole process of the experiment was screen recorded and audio recorded. Table 8.1 presents the detailed descriptions of two collaboration projects.

Table 8.1 Description of Two Collaboration Sessions

	Session with the AI tool	**Session with normal tools**
Collaboration period	30 minutes	30 minutes
Collaboration task	Design a mask that can be used in leisure and entertainment scenarios for Dutch users	Design a mask that can be used in working scenarios for Dutch users.
Collaboration requirement	Designers are required to use the proposed AI tool	Designers can freely use familiar design tools
Final outcome	A presentation with design brief and description of inspiration sources	A presentation with design brief and description of inspiration sources
Deliverable template		

8.5 Data Analysis Process

In analyzing the data, both qualitative and quantitative approach was used to find insights for usability and user experience of the AI tool. The quantitative data of questionnaires was analyzed in SPSS. To assess whether the questions formed a reliability scale, Cronbach's alpha was computed. The alpha for all questions was 0.915, indicating the data has reasonable internal consistency reliability. Descriptive statistics and non-parametric two samples test of Wilcoxon test was used to analyze quantitative data (number of ideas generated within 30 minutes and user's subjective rating on cultural awareness and design collaboration). The qualitative data were analyzed based on grounded theory (Strauss & Corbin, 1994), using an affinity diagram technique (Widjaja, Yoshii, Haga, & Takahashi, 2013). The data were divided into three stages: creating notes, clustering notes and documentation. First, notes were created, using handwritten sticky notes, for data regarding the cross-cultural design process evoked during the study. Then the notes were clustered, merged and arranged by the researcher when posting them on the wall. Finally, in documentation, relevant user quotes were picked to communicate the main findings. The participants were coded in the name of their group number. For example, the two Chinese designers and Dutch designer in group 5 were coded as P5A, P5B and P5 respectively. The findings covered the opinions of each participant while still referring to the original sources, making the structuring process more transparent and closer to the original sources. This process was conducted by two researchers in parallel to avoid personal bias. Besides the data analysis on questionnaire and interview. The design outcomes were evaluated by three design experts respectively and the average scores of the design outcome were used for comparison.

8.6 Findings

8.6.1 Cultural Awareness

The data about Dutch cultural awareness of designers before and after the session with the AI tool were collected and compared. As shown in Figure 8.2, the average scores of Dutch cultural awareness increased for all cultural elements.

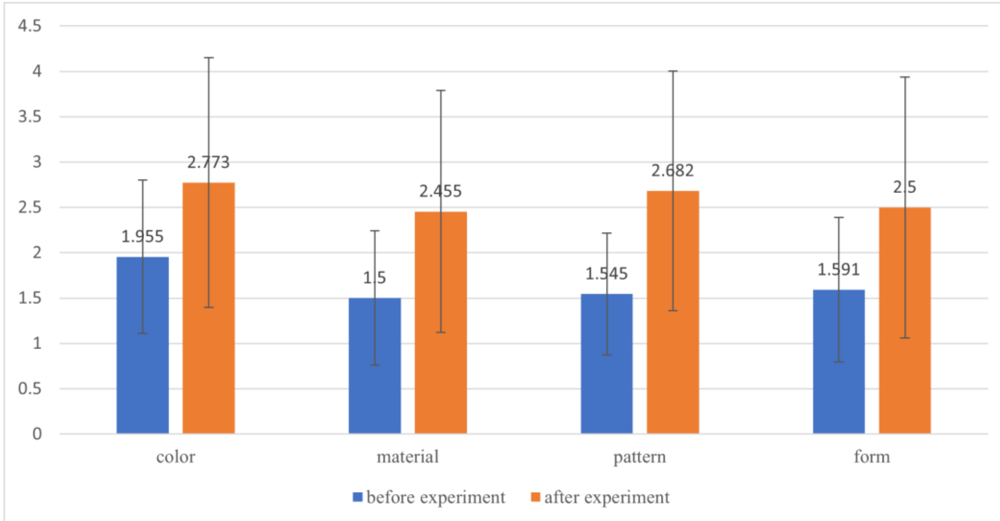


Figure 8.2 Average Scores of Dutch Cultural Awareness

Through Wilcoxon test, statistical differences ($p < 0.05$) of cultural awareness were found after participants using the AI tool, especially for three cultural elements (material, pattern and form) with *p* value less than 0.01 (see Table 8.1).

Table 8.2 Wilcoxon Test Result for Dutch Cultural Awareness (with AI Tool)

Cultural Design Elements	***z***	***p***
Color	2.496	0.013*
Material	3.13	0.002**
Pattern	3.482	0.000**
Form	3.133	0.002**
* p<0.05 ** p<0.01		

The cultural awareness before and after the session with the traditional design tools were analyzed as well. As shown in Table 8.2, statistical differences (p<0.05) for Dutch color awareness were found after participants had implemented the design task. It means that the design collaboration with Dutch users help Chinese designers understand Dutch color. From the comparison, it can be concluded that the proposed tool help designers to increase cultural awareness especially for cultural element dimensions of material, pattern and form.

Table 8.3 Wilcoxon Test Result for Dutch Cultural Awareness (with Traditional Tool)

Cultural Design Elements	***z***	***p***
Color	1.996	0.049*
Material	1.648	0.099
Pattern	1.743	0.081
Form	0.364	0.716
* p<0.05		

During the interviews, some participants further emphasized how the tool helped them to understand and utilize cultural elements. For example, P4B said "*The most significant thing is that, as a designer without cross-cultural design experience, this tool is a good channel for me to understand foreign culture. The ranking based on the probability of Culture inspires me to search for more cultural images and explore.*" Similarly, P5 stated "*I think it's a great way to combine culture and my design*", while P9A argued that the tool showed promising results for capturing the state-of-art of culture more clearly and accurately. In his words "*It is obviously helpful for culture studies. The most important thing is that it helps us to modernize and transform cultural elements.*"

8.6.2 Facilitating the Design Process

During the experiment, participants were free to use the tool to solve the design task. Then they were asked to choose the phase of the design process in which they used the tool. The majority (72.7%) used the tool for idea generation, while 36.4% of all participants used the tool for prototyping. A few participants (18.2%) used the tool for user research, evaluation and testing, and design communication. This means that the tool can mainly facilitate the idea generation phase and has the potential to support prototyping and other phases of the design process.

Table 8.4 Percentage of Participants Used the Tool During the Specific Phase of Design Process

Design Process	**Percentage**
User Research	18.2%
Idea Generation	72.7%
Prototyping	36.4%
Evaluation and Testing	18.2%
Design Communication	18.2%

Nelson, Yen, Wilson, and Rosen (2009) emphasized that the number of different concepts generated by designers is an important metrics for evaluating idea generation. The log data indicated that participants had made more design attempts and generated more designs during the session with the proposed tool (12.36, SD=2.307) than the session with traditional design tools (2.91, SD=0.668).

Take one group as example, they decided to use De Stijl as the cultural element for designing the masks. During the session with traditional design tools, they spent the most time discussing the visual language of De Stijl with the Dutch participant when selecting the cultural images, and they produced only two concepts in total. During the session with the proposed tool, this group had created 14 concepts. Figure 8.3 shows some images generated by the group. Since generating an image cost few seconds, the design group had more images to reference from.

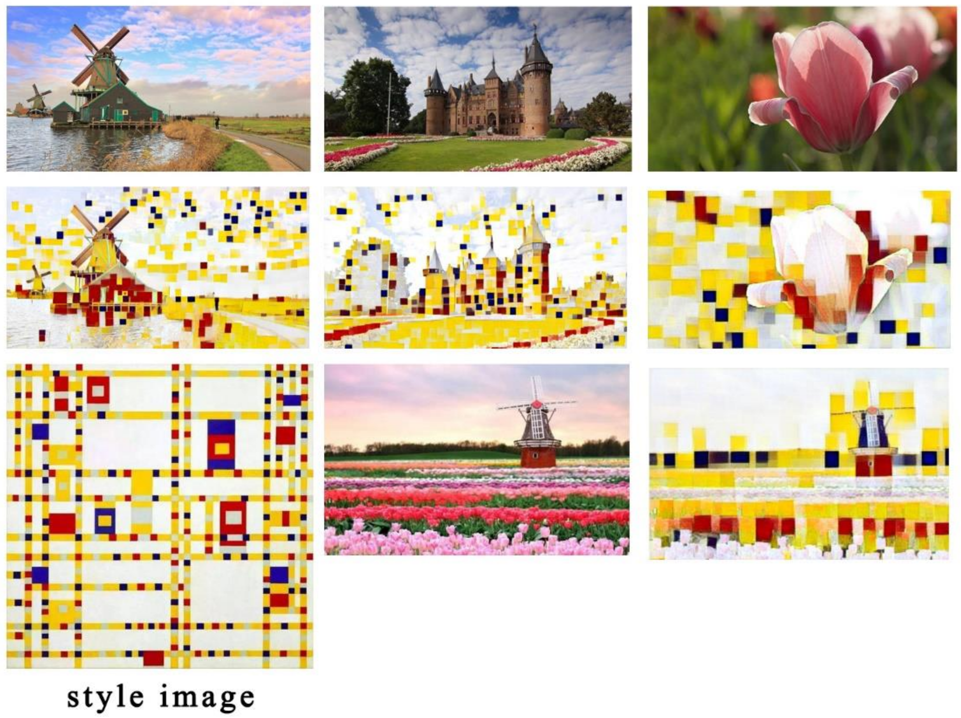


Figure 8.3 Images Generated by the Tool

During the interviews, the participants explained how the tool could facilitate the design process. For example, P4A used the tool to mix different visual styles. P1A mentioned how the style image gallery had inspired him to upload more style images and to make additional design attempts. Both P7 and P1B agreed that the tool is useful for brainstorming, while P7B emphasized how the AI ratings had helped him to make decisions about choosing appropriate images for the design challenge. Some participants also found more specific scenarios for the tool. For example, P11A and P3B thought the tool could unify the visual styles of different design elements, which could be very useful when undertaking a series of visual designs.

8.6.3 Design Collaboration

The data about design collaboration of participants during the session with and without the AI tool were collected and compared. As shown in Table 8.4, the average scores of communication quality and team relationship during the session with the AI tool were higher than that of the session with traditional design tools. Through Wilcoxon test, statistical differences ($p< 0.05$) of communication quality were found of two sessions, with p value less than 0.05. The observations of the collaborative design process show that participants tend to communicate by images instead of other channels (i.e., verbal and text communication) because visual form is dominantly in the design process. It enables more efficient cross-cultural collaboration which leverages the misunderstanding and confusion due to language barrier.

Table 8.5 Questionnaire Data of Design Collaboration

Characteristics of design collaboration	**AVG (AI)**	**SD (AI)**	**AVG**	**SD**
Communication quality	3.909	0.868	3.318	1.171
Team relationship	4.364	0.727	4.091	1.065
Wilcoxon test	***z***	***p***		
Communication quality	2.109	0.035*		
Team relationship	1.732	0.083		
* *p*<0.05				

8.6.4 Design Outcome

Three design experts evaluated the quality of design outcomes with 5-point Likert scales. To assess the design outcome fairly and transparently, benchmarks were provided to the design experts based on current literature as reference points to aid in their grading. The benchmarks include culture integration (Kotro & Pantzar, 2002), culture transformation (Haas & Steiner, 1995) and general design quality of the outcome, as shown in Table 8.6.

Table 8.6 Benchmarks for Assessing the Design Outcomes

	Culture integration	Culture transformation	Design quality
1	Barely any evidence of cultural elements	Strong evidence of directly quotation of cultural elements	Low design quality or no finished work
2	Few evidence of cultural elements integrated	Adequate evidence of quotation of cultural elements	Rather low design quality
3	Some evidence of cultural elements integrated	Some evidence of quotation of cultural elements	Acceptable design quality
4	Adequate evidence of cultural elements integrated	Almost redesign of cultural elements	Adequate evidence of work with creativity and elaboration
5	Strong evidence of cultural elements integrated	Successful cultural transformation	Strong evidence of work with creativity and elaboration

The Chi-square analysis proved that the order of the sessions had no influence on the design outcomes. The data demonstrates that the session with the proposed tool (4.18 SD=0.664) has better scores than the session with traditional design tools (3.32, SD=0.894), meaning the tool could help designers generate better design outcomes. Meanwhile, some interesting findings were observed about the design outcomes.

During the session with traditional design tools, the quality of design outcomes mainly depends on designers' skills. For example, a design group with low creativity simply copied the work of Mondrian, as shown in Figure 8.4.

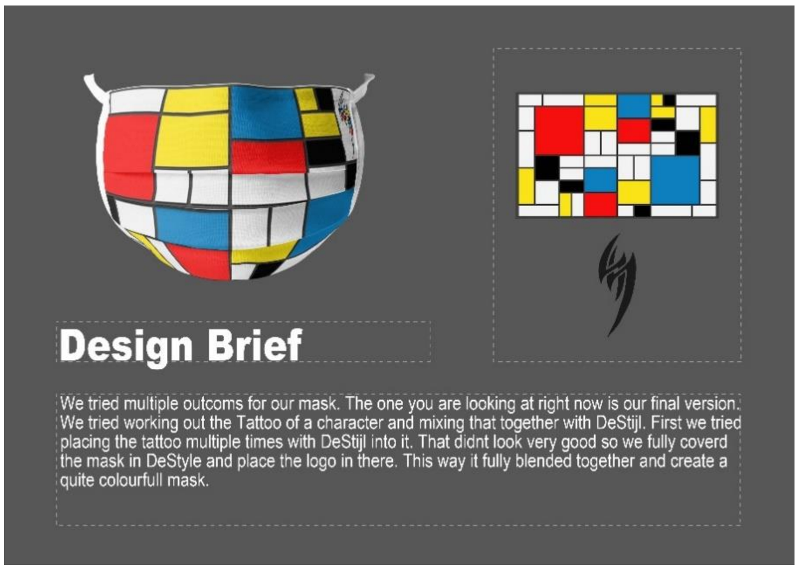


Figure 8.4 Design Outcome by Traditional Design Tools 1

Some groups spent the most of time communicating and discussing about the functions of masks and did not manage to create an elaborated design outcome, as shown in Figure 8.5.

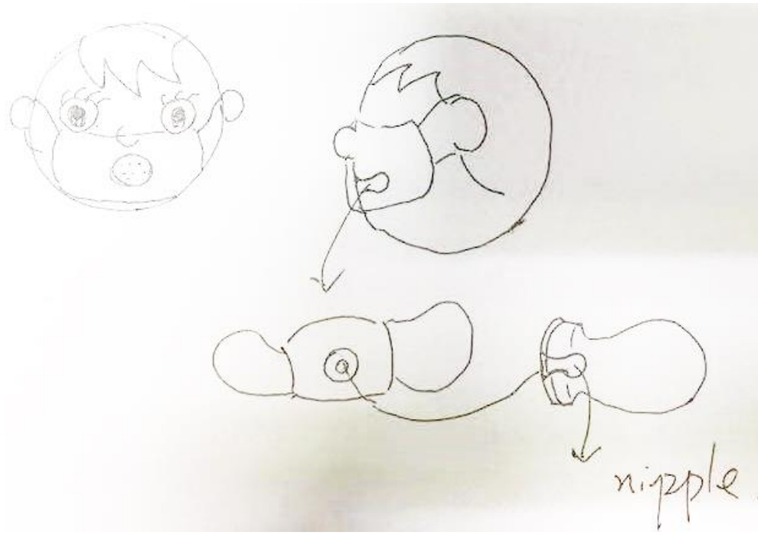


Figure 8.5 Design Outcome by Traditional Design Tools 2

Some participants with good design skills produced the concepts with the symbolic meanings of cultural elements though they directly referenced some existing cultural elements, as shown in Figure 8.6.

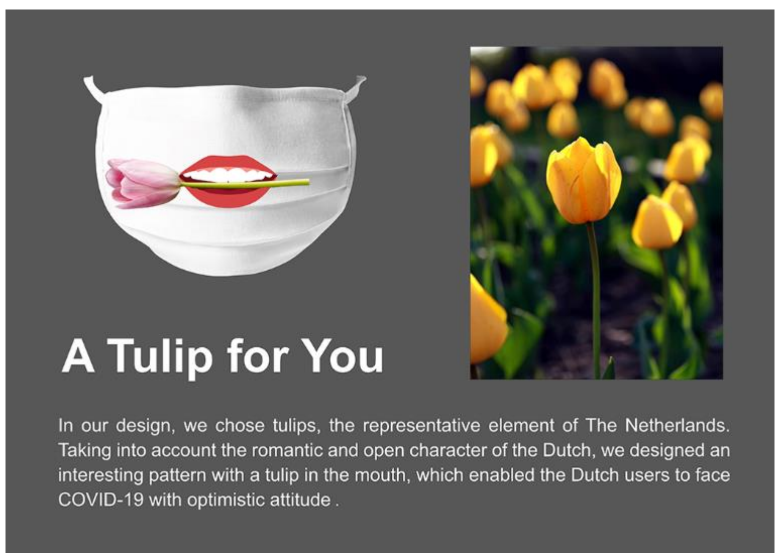


Figure 8.6 Design Outcome by Traditional Design Tools 3

During the session with the proposed tool, the participants were provided with cultural relevant suggestions and inspirations for idea generation. In addition, they had sufficient time to explore more concepts, so the design outcomes were considered better than that of using the traditional design tools. The designers without sophisticated design skills could also quickly generate some new concepts with the cultural elements, as shown in Figure 8.7. With the same cultural element, Figure 8.7 was regarded better by the experts than Figure 8.4, since Haas and Steiner (1995) has emphasized that successful cross-cultural design is about transformation rather than quotation or mimicry.

Figure 8.7 Design Outcome by the AI Tool 1

For the participants with better design skills, the images generated by the proposed tool could be intermediate reference of the final design concepts. Figure 8.8 shows an example, in which the designers applied the AI-generated image as a source of the final design.

Figure 8.8 Design Outcome by the AI Tool 2

From the observations of design processes and design outcomes, it can be found that Chinese participants spent a considerable amount of time thinking and communicating with the Dutch participant about the symbolic meanings of cultural elements when they did not have the AI tool to help with their designs. Because of limited time available, they simply copied and pasted existing cultural elements. While with the proposed tool, participants had sufficient time to explore and various concepts to reference from. In summary, the proposed was considered promising to help designers to improve both quality as well as quantity of the design outcomes regardless of the design skills of a designer. The tool strongly supports designers to transform the cultural elements instead of mimicry.

8.6.5 User Experience

The participants were asked to talk about their experiences of using the AI tool. They shared a variety of opinions. 25 participants (75.8%) expressed positive attitudes using terms such as "cool", "fun", "surprising" and "interesting" to describe their feelings after experiencing the tool. For example, P6 said "*It was rather fun! I am satisfied with both the tool and the design outcome.*" P7 stated that "*it was pretty interesting to interact with the AI tool. Maybe in the future I see myself using stuff like that.*" According to their responses, three main benefits of the AI tool were summarized: (1) **inspiring creativity**: the tool can generate different concepts and variations of combinations for designers. For example, P2A said "*sometimes our imagination is limited, so the tool helps us to expand our design.*" (2) **time efficiency**: the tool can help designers to explore and express ideas efficiently. For example, P9 said "*normally you have to put in a week's worth of designing, but now you can do it in 30 minutes. And then it really finished with really cool results.*" (3) **ease of use**: people with little design skills could use the tool. For example, P5 said "*I really like the tool because I can easily combine two images.*" P3B acknowledged that the tool simplified the design process.

Nevertheless, some participants also pointed out some weaknesses of the tool: (1) **not sufficiently intelligent**: six participants thought the cultural style transfer module could not generate images in line with their expectations. For example, P10A argued that the tool did not translate the cultural style very well, and he suggested having additional options to modify the final results. P7B believed that a human artist would do better, so he emphasized his analysis that the tool could assist rather than replace designers. (2)

poor quality of design: three participants thought the generated images were too rough, with a low level of design quality. For example, P7 said "*The image quality is not good enough. I would mostly use this for brainstorming, and I wouldn't use it for finalizing products.*" (3) **restricting freedom of design**: two participants expressed their concerns about using the tool during the design process. P3A said "*It makes images directly. It restricts my freedom*", while P5B pointed out "*this tool only works on visual design; it cannot be used to design the functions of products.*"

8.7 Discussion and Conclusion

Cross-cultural design involves understanding cultural information, transferring cultural elements, and implementing product design. It is a complex design process that requires designers' creativity, cultural awareness, research skills and design skills. AI is proved to exceed human performance in many areas, such as recognition, calculation, automation, and translating, among others (Grace, Salvatier, Dafoe, Zhang, & Evans, 2018). This study explored how AI will perform when it is applied in a situation that requires human creativity and extensive cultural understanding. The results of the experiment are surprising:

Cultural awareness: Firstly, there is a significant increase in participants' cultural awareness after they used the tool, especially for the cultural element dimensions of material, pattern and form. Rimmershaw (1999) has stated that computer-supported collaborative learning can enhance cognitive performance or foster deep understanding of knowledge.

Facilitating design process: Secondly, the tool is regarded to be useful for the cross-cultural design process, especially for idea generation and prototyping. The tool strongly supports designers to transform the cultural elements instead of mimicry. Dylla (1991) argued there is a correlation between the amount of design space considered during idea generation and the quality of the final design outcome. Idea generation is a key step in the design process, and had a significant impact on the quality of the final creative solution (W. Zhang, Zhang, & Song, 2015). On the other side, W. Chen (2015) found concept generation was the most difficult design task, with the majority of students experiencing problems. Nelson et al. (2009) emphasized that the number of different concepts generated by designers is an important metrics for evaluating idea generation. The log data indicated that participants had made more design attempts and generated more designs during the session with the AI tool than the session with traditional design tools. Kornish and Ulrich (2014) emphasized the value in the accurate selection of ideas during the design process. Van den Ende, Frederiksen, and Prencipe (2015) agreed that ideas should be appropriately selected and managed during the fuzzy front end of the design process. Some participants responded that the tool helped them to make decisions about choosing appropriate images for the design challenge.

Design collaboration: Resta and Laferriere (2007) argued that online social interaction is considered a source of cognitive advancement and play an important role in academic achievement. Cho and Cho (2014) stated that collaboration provides opportunities for students to enhance their interpersonal and communication skills. Webb and Miller (2006) argued that students tend to resist collaboration because of difficulty in communication and disproportionate participation. The tool is proved to support design collaboration especially at the aspect of communication quality. The tool support participants to communicate via sending appropriate images and visualizing the design outcomes immediately. It enables more efficient cross-cultural collaboration which leverages the misunderstanding and confusion due to language barrier. It also strengthens the collaboration among design students, since it allows designers in a team to participate in collaboration equally and contribute to the final design outcome respectively. As shown in Figure 8.1, designer A with Dutch cultural background is responsible for selecting cultural image candidates. Designer B and designer C are responsible for ideating and prototyping. The design works produced by designer B and designer C will be combined with cultural elements through cultural style transfer module to generate creative designs. The tool facilitates a high sense of working together and creates a shared visual language for collaboration. As a result, the tool helps to develop students' communication skills, and facilitates a high sense of design collaboration.

User experience: Cho, Cho, and Kozinets (2015) had compared student experience in both face-to-face collaboration and visually supported collaboration technology, and found that students demonstrated significantly higher achievement and confidence in completing design tasks with visually supported collaboration technology. This study generates similar results that the tool provides an efficient and simplified means of inspiring designers to generate a wider variety of ideas within a limited time period.

Design outcome: Lastly, the tool can help designers to improve the quality of their design outcomes regardless of their design skills. However, some participants thought that the tool could not generate satisfactory result compared to what as human artist could provide. They argued that the tool only works for visual design, rather than for functional design. Hristov (2016) emphasized that aspects of emotion, intuition and imagination, which characterize art are often deemed to be lacking in AI-generated art. This study shows that AI will not totally change the role of designers, but it can be a very useful tool for designers seeking to maximize their creativity and increase their working efficiency.

Dee (2018) argued that the advancements by generative AI systems in the field of art has disrupted the way in which art is created, thus raising questions about its creation, ownership and protection. Currently the copyright system constricts AI-generated art, which means that the term "author" pertains only to a human author. AI systems have led to a blurring of the distinction between art created by humans and art created by machines. Dee (2018) stated that AI-generated art may be divided into two distinct categories: creation by human guidance, and autonomous creation. In the former situation, the ownership is attributed to the human author who directed the inputs, while in the latter situation, the AI system does not have a legal personality, so it is not an inventor or creator. Thus, works created by an AI system is not copyrightable, which inhibits an author from creating and disseminating their works. This study is more in line with the former situation, where the user of the tool uploads a content image and a style image, and uses the tool to fuse them intentionally. So, the human user of the tool owns the copyright of the end product. This leads to another issue: whether an AI system that trains itself by reduplicating and modifying copyrighted works infringes the copyright of input data? The responsibility may lie with the human author. The tool is essentially a computer-aided design tool, similar to Photoshop or Illustrator, the function of which is to fuse two images. Thus, the doctrine of fair use protects the use input images in the tool. The users should be reminded of this important issue.

In conclusion, the tool contributes to cultural studies, product design, and HCI, by using a design tool for designers that works within a cross-cultural setting. The research opens the field for more exploration into finding correlations between AI and design tools.

9. DISCUSSION

9.1 Chapter Overview

The thesis has introduced three studies including expert interview, Top 50 design institute analysis and a survey on design education. Through these studies, two main contributions were made: (1) propose a theoretical education model for future design education, and (2) propose AI-supported collaborative learning strategy to enhance design education based on the proposed model. This chapter discusses the key findings from the research, with reference to the previous literatures. The original contributions to the knowledge area are presented.

9.2 Trends in Design Education

The thesis contributes to an increased understanding of the state of the art of industrial design education. Design education was created at the Bauhaus in 1919, when it was anchored in the fine arts tradition. Findeli (2001) defined design as a process or a way of knowing based on processing an intervention, which differentiates design from fine art, science, and professional disciplines. He also appealed to "lay down new foundations for design education" (Findeli, 2001). The experts identified that the boundaries of industrial design are blurred and emphasized the importance of design in multidisciplinary teams during the interview studies. The results of top 50 design institutes illustrate that the majority (70%) of leading design institutes now have independent design schools. Industrial design education is no longer part of art education or engineering education, which have their own education missions and teaching styles.

Whether design education should be generalist-oriented or specialist-oriented has been debated for several years (M. Y. Yang, You, & Chen, 2005). The data from our study shows that, among the 259 samples, fewer than one quarter of the programs were general industrial design programs, while the remaining 197 programs (76.1%) have 149 different program titles contributing a wide range of specialized design programs. This data may provide a good response to the ongoing debate. The variety of design programs illustrate the long-tail strategy (Brynjolfsson, Hu, & Smith, 2006) through which the leading design institutes are trying to cultivate innovative problem solvers for different contexts, and to ensure they can differentiate themselves from their competitors. The shift in design education has moved from design as a science to design as a mindset (Brenner, Uebernickel, & Abrell, 2016), and it is evident that promoting "design thinking" (Johansson Sköldberg et al., 2013; K, 2011) is more beneficial than promoting "design" itself according to the changing circumstances of industry (Wormald & Rodber, 2008). Su and Zhang (2021) pointed out that design is changing from improving the human-centered interaction to a core strategy of creative innovation.

9.3 The Theoretical Model for Future Design Education

Demand for new models of design education has never been greater, and it is evident that methods and strategies of teaching must be rethought and redesigned. A review of the literature has made it clear that there are many theories and programs to promote design education, however, they have not reflected the impact on design education of social change and technology development. This research has proposed a new education model that fits the opportunities and challenges of future design education. It has three main components, namely: multidimensional education aims, multidisciplinary and cross-cultural design-learning processes and learning resources.

9.3.1 Multidimensional Education Aims

The aims of design education have a broad scope and multiple dimensions, including a list of generic literacy and design expertise, as shown in Table 9.1. The result of the study gives weight and ranking to the education aims, which is helpful for educators to organize the teaching activities effectively and efficiently.

Table 9.1 Education Aims of Future Design Education

	Education aims	**Definition**
	User perspective	empathy and a commitment to socially and ethically responsible design outcomes for producers, users and stakeholders (HKPU, 2020).
↑	Technology integration	the ability to effectively use technology to accomplish required learning tasks (Davies, 2011).
★	Creativity	exceptional human capacity to produce original thought and creation (Ryhammar & Brolin, 1999).
↑	Social and cultural awareness	the improvement of cultural awareness and the introspection of social situation, that are essential to design students' future growing in cross-cultural

		environment and international research and practice (Butt et al., 2016).
↑	Commercial awareness	considering the stakeholders in the initial design process for design problems with many stakeholders (Dam & Siang, 2018).
↑	Teamwork and leadership	the skills of devising, planning, and organizing practice-based learning activities and design outcomes (RCA, 2020).
	Communication skills	the effective use of spoken and written language skills (OECD, 2005).
	Problem-solving skills	goal-directed thinking and action in situations for which no routine solution procedure is available (Goldsmiths, 2020).
(★)	means the most important factor in future design education	
(↑)	means significantly increase of importance in future design education	

Finegold and Notabartolo (2010) had identified 15 competencies for the work force of the 21st century including creativity, critical thinking, information literacy, problem solving, decision making, flexibility and adaptability, research and inquiry, communication, self-direction, productivity, leadership and responsibility, collaboration, ICT operations, digital citizenship and media literacy. It is interesting to find that nine of these important competencies in the future coincide with the design skills in the proposed model. In total, there are 8 important skills, with each of which has subskills. For example, problem-solving skills includes critical mindsets, analytical skills, adaptability, and flexibility, etc. Ideally students should be equipped with every competency mentioned above. However, such competencies are extensive and numerous. Buchanan (2001) commented that it is difficult for design education to "form a designer who has adequate special knowledge but also possesses the wide perspective that is needed in the complex environment that we are likely to face in the future". Leblanc and Gagnon (2016) pointed out that the quality of design education would be damaged by adding more content to education programs without increasing their duration. Huselid, Beatty, and Becker (2009) suggested designers differentiate the value of skills depending on the situational context. Meyer and Norman (2020) recommended that design institutes cover a set of core principles, but offer unique advanced courses that might lead to specialties within design. As for students, they have no need to develop all skills, since large and complex design projects in the future will always be undertaken by teams.

The result of this study also shows that broader boundaries of industrial design provide various career opportunities for students. It has been observed that design graduates can find jobs in various sectors in industry, government, non-governmental organizations (NGO), cultural organizations, health, banking etc. M. Y. Yang et al. (2005) compares the competencies and qualifications for different industrial design jobs. They proposed that industrial design students should choose and specialize their career pursuit in one area such as interface design or design management instead of gaining all the skills. Dall'Alba (2009) was the first educator to suggest that students should establish a sense of who they are becoming as a professional, and to imagine who they might be. Many universities and scholars have proposed that students should develop their personal identities in design education (Aalto, 2020; Dall'Alba, 2009; Hummels et al., 2011; Sydney, 2020; Monica W. Tracey & Hutchinson, 2016; M. W. Tracey & Hutchinson, 2018; UAL, 2020). Personal identity requires students to take responsibility for their own education aims and career development, which stimulates active learning (Coorey, 2016). When students take an active role in the learning process, the learning is optimized (Smart & Csapo, 2007). Some universities give students more freedom to organize their learning activities, for example, California College of the Arts even offers an Individualized Program that provides students with the opportunity to access resources within and across faculties.

9.3.2 Design-learning Process

According to the expert interview, the process of industrial design and the learning process of design education coincide in that they both emphasize their multidisciplinary and cross-cultural aspects. The Top 50 design institute analysis has identified several featured examples in design education which include partnerships with the arts, health, education, technology, business, and social sciences. Multidisciplinary learning helps design students to bring different perspectives together and bridge the world of new technology, societal trend, and user needs. The top design institutes are extending their industrial design programs, by promoting multidisciplinary design-learning processes, and by offering hybrid degrees. They are also providing opportunities for new disciplines to emerge, based on the re-structuring of traditional disciplinary boundaries

(Teixeira, 2010). Some researchers believe that the support of academic institutions is a key factor for the successful implementation of multidisciplinary learning (Camba et al., 2017). Stappers et al. (2020) pointed out that new disciplinary knowledge was brought in design education, that is kind of broadening rather than replacing.
With the trend of globalization and fierce competition in the global product market, connections between culture and design have become increasingly close (Shin et al., 2011). Applying culture as design elements in product design enhances products' core value, that makes them be culturally innovative products (Chai et al., 2015; R. T. Lin, 2007; Shin et al., 2011). The study has identified two ways to help students gain multicultural experience. One is through organizing global education programs, such as the Master of European Design program, while the other is to take advantage of the ethnic diversity of metropolis and recruit students from different cultural backgrounds. This finding coincides with the research result proposed by Deardorff (2011) that service learning, education abroad and "internationalization at home" (Nilsson, 2003) are three main mechanisms for creating cross-cultural design setting.

The data of expert interview and questionnaire show that multidisciplinary design process and cross-cultural design process are very important in the future vision from design educators' perspectives. However, there are a number of educators have never guided students with multidisciplinary projects (11.90%) and cross-cultural design projects (30.95%). In order to implement cross-cultural design, design institutes need to provide global education programs or recruit students from different cultural backgrounds to help students gain multicultural experience, which is not easy for many institutes.

9.3.3 Learning Resources

In the learning resources category, students are supported by various stakeholders, intelligent tools, and collaborative learning environments.

Various stakeholders: The study of Top 50 design institute analysis has identified the various stakeholders in design education, including educators, peers, users, and clients with different backgrounds. Designers recognize the richness of experience comes from communications between stakeholders, whether they are experts, end-users, or social collaborators (Hill, 1998). Gardien et al. (2014) emphasized the involvement of stakeholders in design education helps designers to consider a broader technological and social context in the design process. According to the data of the questionnaire, users and clients seem less important in current situation, while in the long run they will be critical stakeholders of design education. This requires the design institutes to work closely with industry. The roles of traditional stakeholders of design education (educators and peers) are regarded to decrease slightly. However, peers are always the most important facilitators for design students. When students work collaboratively in a team, they learn from evaluating their partners' contributions (Hausmann et al., 2004) and sharing information with each other (Coorey, 2016).

Intelligent tools: The relationship of design and technology is one in constant flux. In the case of the tools required to support the design-learning process, technology has influenced what we design and how we design (Carulli, Bordegoni, & Cugini, 2013), such that every new technology transforms the nature of design. Educators and students must adapt the evolvement of technology. Coorey (2016) argued that technology should be taught as a tool, like sketching or user studies. Designer's toolbox evolves in response to the industrial revolution. Budd and Wang (2017) identified three significant evolutionary stages of design tools in the past 20 years. Before 2000, the primary set of design tools include sketching, model making, ergonomics, materials and manufacturing, drafting, graphic design and understanding of marketing (Budd, 2011). With the widespread access of internet in 2000s, industrial designer's toolbox include additional design tools for computer illustration, 3D modeling, rapid prototyping and programming for the internet (Woodham, 2003). W. Chen (2015) identified a trend towards using the internet and information technology for both learning and teaching. Budd and Wang (2017) commented that the emerging demands for industrial designers are to understand diverse user needs and requirements and frame them with agile prototyping. This change leads to new set of design tools from user experiences to interactive technologies (Budd & Wang, 2017). The digital industry and Industry 4.0 revolution offers new opportunities of design supported tools. From the analysis of top design institutes, it is found that intelligent tools, such as digital fabrication tools, mixed reality tools, interaction prototyping tools and AI tools, can support students to keep abreast of the rapidly-changing technology. According to the data of questionnaire, AI tools are regarded as the most important design tools in the future, while they have the highest unused rate of 17.46% currently. In design education, there has always been a struggle on how to best integrate technology, while maintaining focus on design (Coorey, 2016). with an aim of preparing students for the future, educators are challenged to utilize appropriate intelligent tools during design-learning process.

Collaborative Environment: Collaborative programs connecting with industry and other universities will be helpful learning environments in the form of double-degree programs, exchange programs, and international platforms. Bullock (2020) argued that a symbiotic relationship between university and industry helps students to take balance of human, technical and manufacturing factors, and develop leadership in collaborative design process. It empowers students to develop responsibility for developing life-long learning skills (Bullock, 2020). Bishop and Mane (2004) found in their analysis that university-business collaboration significantly increase employment and annual earning. University courses with direct links to the society encourage interaction, deeper understanding and "real world" learning (Warburton, 2003). However, from the data of questionnaire, only few design educators have teaching experiences on double-degree programs (37%) and activities organized by international platform (22%). Though the result of paired T test shows that both of the collaborative education programs will increase significantly in the future. Deardorff (2011) stated there is a great need for programs to bring domestic and international students together in meaningful interactions. He suggested such programs would have specific intercultural learning goals for all participants and encourage meaningful domestic-international interactions through relationship-building opportunities (Deardorff, 2011).

In summary, the thesis proposes a theoretical and holistic model describing the influencing factors of future design education. With operable strategies, this model provides educators with clear directions for the future of design education requirements in an authentic context.

9.4 The AI-supported Collaborative Learning Strategy

As a design-based research project on design education, this study seeks to contribute to emerging issue on collaborative design-learning process with cultural diversity by developing AI-supported collaborative learning strategy. The proposed AI-supported collaborative learning strategy saves designers' work on culture research. The main contributions of this study can be summarized as follows: (1) a deep-learning-based style transfer technique was extended to the cross-cultural design field, which can automatically generate a culture-specific design image from an original design content image and a set of cultural style images; (2) a deep-learning-based novel image selection module was developed, which takes both designers' cultural style expectations and their own preferences into consideration during the cultural image selection process; (3) a small-scale cultural image dataset was built to support the tool, containing four cultural element dimensions (color, material, pattern, and form); (4) empirical study indicated that applying deep learning in cultural studies can increase designers' cultural awareness and working efficiency. For facilitating design process, this tool can be used to inspire creativity and make prototypes. It is an innovative and efficient tool to help designers for idea generation and fast prototyping. To the best knowledge, this is the first work that extends the deep learning techniques to facilitate cross-cultural design.

This new approach for conveying deep learning for the purpose of cross-cultural design has contributes to cultural studies, collaborative learning and AI-supported strategy. It opens the field for more exploration into finding correlations between AI and design tools.

9.4.1 Contribution to Cultural Studies

Normally cross-cultural design requires designers to understand a foreign culture, identify and select suitable cultural elements, and finally transform them to product design. This process is extremely labor-intensive and time-consuming. And the quality of design outcome relies much on designers' design skills and cultural awareness (Rungtai Lin, Cheng, et al., 2007).

This study proposes an efficient and innovative approach to integrate cultural elements. Before using the AI tool, the designer is required to upload the design content image and a set of cultural image candidates. An image selection module is proposed to replace the human designer by automatically selecting the most suitable style image from the cultural image candidates. Then, style images are ranked based on the similarities between their cultural styles and the cultural style expectation as well as the designers' own preference. The selected top-ranked cultural style image is fed along with the design content image, into our style transfer module to automatically generate a culture-specific design image. The proposed approach can significantly accelerate the design process, i.e., the approach can generate a novel culture-specific design in a second with almost zero cost. This saves designers having to work on cultural research. The results of the experiment show that there is a significant increase in participants' cultural awareness after they used the tool, especially for the cultural element dimensions of material, pattern and form.

9.4.2 Contribution to AI-supported Strategy

There have been too much attention paid to the application of latest technology. Early in 1986, Mitter (1986) has raised the question “should artificial intelligence take culture into consideration?”. He realized that there is great diversity across cultures and culture must be considered for transferring knowledge within or across human groups. Heaton and Trappl (2004) agrees that culture is important in the design of technologies. Harvard Business Review stated that companies that do not use AI tools will soon be obsolesce (Davenport et al., 2019). And it also argued that companies want to adapt AI within their business should explore the opportunity where they can embed the technology directly into their business instead of focusing on creating a better algorithm.

AI has most of the time an empirical and engineering orientation (Umbrello & De Bellis, 2018). The ethical implications and social impacts of AI technology are topics of compelling interest to industry and researchers in academia. However, current research discussing AI is limited especially outside the USA and western Europe (Hagerty & Rubinov, 2019).

This study empowers new meanings to a kind of AI technology style transfer, helping design students relate their design works to the cultural background of users. It explores how emerging technology and culture can influence design process in terms of quality of learning in China. Form the result, it can be concluded that AI will not totally change the role of designers, but it can be a very useful tool for designers seeking to maximize their creativity and increase their working efficiency.

9.4.3 Contribution to Collaborative Learning

It is of ongoing importance that the design education should utilize a collaborative approach where design students work within teams of various backgrounds (Cho & Cho, 2014; D. Jonassen et al., 2006). Collaboration between students with different “cultural background” leads to global solutions (A van Boeijen & Badke Schaub, 2007) and helps producing innovative ideas (Annemiek van Boeijen et al., 2017). Cultural diversity among peer students is acknowledged as enriching and inspiring (Jonsen et al., 2011). Research shows diversity supports creativity (Friis, 2015). When students design across cultures, they can draw on different kinds of cultural knowledge and perspectives (Paletz et al., 2018). Dhadphale et al. (2017) argued that co-creation is valuable for studying the tacit and latent aspect of culture.

Though the benefits are obvious, it is challenging to implement collaborative learning in the context of cross-cultural design process. Many students tend to resist collaboration due to the difficulty in communication and disproportionate participation (Webb & Miller, 2006). The different cultural backgrounds of team members may add complication to the communication and lead to misunderstanding and confusion.

This study proposes a design tool that facilitates designers with a high sense of working together, utilizing shared visual language for collaboration. Resta and Laferriere (2007) argued that there is a substantial body of knowledge on collaborative learning in face-to-face settings, while less is known about computer-supported collaborative learning. Through empirical study, the proposed tool is proved to support design collaboration especially at the aspect of communication quality. The tool support participants to communicate via sending appropriate images and visualizing the design outcomes immediately. Participants tend to communicate by images instead of other channels (i.e., verbal and text communication) because visual form is dominantly in the design process. It enables more efficient cross-cultural collaboration which leverages the misunderstanding and confusion due to language barrier. Kalay (2006) stated that the impact of intelligent tools on design learning and practice is changing from "command and control" to "coordination and communication". Technology has transformed the world into a network-based society that builds further on digital designs (Çakmakçıoğlu, 2017; Koc, 2006), and enables design students to interact and collaborate without or less time and location constraints in design education (Dreamson, 2017).

9.5 Conclusion

This chapter discusses the main contributions of the research. Theoretically, this research proposed a model indicating the influencing factors for future design education, with suggestions about learning strategies. In educational practice, the research focuses some most important aspects of design education for improvement and develop an AI-supported learning strategy. A case study was conducted for evaluation and proved that the proposed design tool has made contributes to cultural studies, collaborative learning and AI-supported strategy.

10. CONCLUSION

10.1 Chapter Overview

This research was initiated to address the research questions proposed in Chapter 1, which are some issues concerned by design educators for cultivating future designers. It a mixed method research that employed both qualitative and quantitative data. This chapter draws together answers to the research questions tackled in this thesis, identifying limitations and further research issues.

10.2 Answers for Research Questions

10.2.1 Current Theoretical Models of Design Education

Research Question 1: What are the current theoretical models of design education?

To answer this question, Section 2.5 reviewed current theories and frameworks about design education and identified three main components of design education, which are education aims, design-learning process and learning resources. Education aims refer to the design expertise or competency that students need to acquire to face the challenges in the rapidly-changing world. Design-learning process (Dominici, 2017; D. Smith et al., 2009) that refers to the iterative cycles of learning construction (P. A. Cooper, 1993; Dorst & Dijkhuis, 1995) and reflection (Schwartz & Schon, 1987). Literature review identified that design process and learning process are intertwined, both of which emphasize students' activities like researching, ideating, prototyping and reflecting. Learning resources refer to the stakeholders in education programs (W. Chen, 2015), design methods (Rauth et al., 2010), design tools (W. Chen, 2015; Dominici, 2017; Rauth et al., 2010) and the learning environment (W. Chen, 2015) to support the design-learning process.

The current models lay a good theoretical foundation of design education. However, they still suffer some flaws for cultivating design students to prepare for the demands of future designers. The majority of current models focus on only one aspect of design education, which lack a whole picture of the research domain, such as Curry (2014)'s "seven levels of design expertise" model to facilitate designers' development from a novice to expert, Hummels and Frens (2008)'s reflective transformative design process model and Wright and Davis (2014)'s learning environment model. There are several integrated models that describe design education in a holistic way. However, they may work within the scope of a design course rather than a whole education program (D. Smith et al., 2009), oversimplify the design-learning process (Van Merriënboer & Kirschner, 2001) and teaching methods (T. Zhang et al., 2017), or lack operational teaching strategies (Wright & Wrigley, 2019). Last but not least, most models have not reflected the impact on design education of social change and technology development. Previous research has revealed that there is currently no satisfactory and comprehensive model for future design education.

10.2.2 Influencing Factors of Design Education

Research Question 2: What are the influencing factors in shaping a theoretical model for future design education?

To address this research question, the thesis follows the exploratory design and multi-phase design of mixed methods research (Cohen et al., 2002) by conducting three mini studies. The process of exploring the influencing factors and developing the theoretical model is summarized in Figure 10.1.

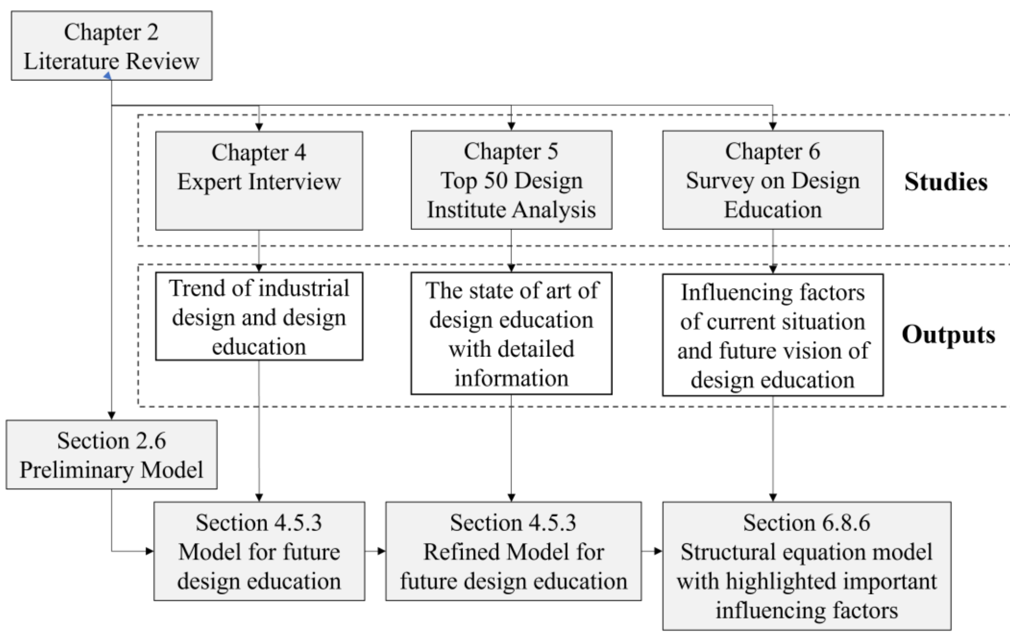


Figure 10.1 Process of Developing the Theoretical Model for Future Design Education

Firstly, through the expert interview, the study identified the trend of industrial design and design education: (1) the aims of design education will have a broader scope and additional dimensions; (2) the process of industrial design and the learning process of design education coincide such that they both emphasize the relevant multidisciplinary and cross-cultural aspects; (3) intelligent tools that support design students to keep abreast of rapidly-changing technology and collaborative education programs that connect with industry and other design institute will be helpful learning resources. Based on the result of expert interview and the preliminary model (see Section 2.6) generated after the literature review, a general model indicating the trend of design education was developed (see Section 4.5.3).

Secondly, 50 leading design institutes according to the 2020 QS World University Rankings specializing in Art and Design were analyzed to obtain detailed information of design education, on the aspects of program positioning, design methods, intelligent tools for learning, collaborative educational programs, stakeholders etc. To summarize the findings, a refined model for future design education was developed, informing a complete list of multidimensional education aims and learning resources (see Section 5.5.8). At this stage, the model is (1) holistic and comprehensive; (2) reflecting the changes of industrial design; (3) based on empirical data in the real world; and (4) provides operable teaching strategies for educators. The definitions and implications of each influencing factor were discussed in Section 5.6.1.

Thirdly, the questionnaire involving the front-line educators in China was implemented to gain more firsthand information about design education. The study compared the influencing factors in current situation and future vision from the educators' perspectives to further refine the theoretical model. Through regression analysis, a structural equation model (see Section 6.7.8) was build based on the quantitative data, which confirmed that cause and effect relationships between stakeholders and education aims, collaborative environments and design-learning process, intelligent tools and design-learning process, design-learning process and education aims. Through paired T test, the study identifies the gap between current situation and future vision of design education. The final model (see Section 6.8.6) highlights the directions of improvement for design institutes and design educators.

In conclusion, the research has proposed a new education model that fits the opportunities and challenges of future design education to answer the second research question. The model has several features, that are: (1) holistic and comprehensive; (2) reflecting the changes of industrial design; (3) based on empirical data in the real world; (4) provides operable teaching strategies for educators; and (5) indicates the gap between current situation and future vision of design education.

10.2.3 The Case Study with AI-supported Collaborative Learning Strategy

Research Question 3: How to enhance design education based on the proposed theoretical model?

The proposed theoretical model demonstrates the influencing factors of design education with significant increasing importance for future, where the design educators should make more efforts to explore and improve. Eisner (1997) said that the development of educational curriculum is a process of transforming the vision for education into a process. To address the research question, the study ticks the boxes of some important influencing factors of design education to propose the AI-supported learning strategy. The study outlines the cross-cultural collaborative design-learning process (see Section 7.5) to facilitate design teams with diverse cultural backgrounds. The study also develops a new AI-supported design tool (see Section 7.6). The case study is used to evaluate the proposed learning strategy in educational practice. The result proves that the proposed strategy can improve participants' learning experience, facilitate the idea generation and prototyping phase of cross-cultural design process, and enhance the communication quality in design collaboration. Regarding the education aims, the participants' cultural awareness has increased significantly. It makes contributions to cultural studies, collaborative learning and AI-supported strategy.

10.3 Reliability and Validity

This research considers the issues of reliability through the use of triangulation (Robson, 2002). It collected data at a variety of times and from a number of participants and sources with diverse cultural backgrounds. If findings replicate, this supports their reliability (Miles & Huberman, 1984). For example, the expert interview collected subjective opinions of 37 design experts representing 36 organizations from 26 countries and international organizations. The Top 50 design institute analysis collected data of 40 effective sample institutes from 14 countries with 259 design education programs. The questionnaire collected and analyzed quantitative data of 126 design educators from 21 provinces in China. The research also applied standardized data collection and analyzing methods to yield more validated data. It employed a variety of standard research methods including literature review, interview, systematic review, questionnaire, case study and theory development. In analyzing qualitative data, at least two researchers work independently to avoid bias.

The validity of the findings is also improved by triangulation. By using both qualitative data and quantitative data generated from different types of methods (interview, systematic review and questionnaire), this study improved the validity of the proposed theoretical model. For example the relationships among the influencing factors of design education were revealed in the literature review and expert interview, and were further validated by questionnaire.

10.4 Limitations and Future Work

Design education is a complex issue, with many aspects to be considered and the proposed theoretical model is only a general framework; however, it contributes to an understanding of the trend of industrial design and design education while providing several potential strategies for educators. The model needs to be refined in future studies and more firsthand information in the design education practices is needed, rather than the general introductions published on official websites. Among the top 50 design institutes, 5 institutes were because they did not have English descriptions, which means that the samples are not sufficiently representative.

There are also some limitations for developing the AI design tool. First, there was a limitation to the number of images used for the cultural image dataset. Owing to a limited amount of data, a model specifically for the cultural image style transfer function has not been trained. Future studies should expand the cultural image dataset to validate the classification accuracy and include more cultural elements. Following the construction of a large dataset is constructed, an important future work is designing and training an end-to-end deep learning model for culture image elements analysis and style transfer. Besides the used Residual Neural Network model (He et al., 2016) in this study, other networks such as SENet (J. Hu, Shen, & Sun, 2018) and DenseNet (Huang, Liu, Van Der Maaten, & Weinberger, 2017) are also suitable for this style classification task. Further studies can focus on identifying which one will have a better performance. Second, the case study was conducted only based on the Dutch culture, meaning future studies should research whether or not our method would be applicable for other cultures. Furthermore, there was a limited number of participants involved in the study, although after interviewing the participants it was observed that new data seems not to contribute to the findings owing to its repetition of comments. Future studies should test with more participants to draw more valuable and general conclusions.

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APPENDICES

Appendix 5A: Top 50 Design Institutes of 2020 QS World University Rankings in Art and Design

QS Ranking	Country	Design Institute	English	Design Program
1	UK	Royal College of Art	●	●
2	UK	University of the Arts London	●	●
3	USA	Parsons School of Design at The New School	●	●
4	USA	Rhode Island School of Design	●	●
5	USA	Massachusetts Institute of Technology	●	●
6	Italy	Politecnico Milano	●	●
7	Finland	Aalto University	●	●
8	UK	The Glasgow School of Art	●	●
9	USA	School of the Art Institute of Chicago	●	●
10	USA	Pratt Institute	●	●
11	Australia	Royal Melbourne Institute of Technology University	●	●
12	USA	Art Center College of Design	●	●
13	China	Tongji University	●	●
14	UK	Goldsmiths, University of London	●	●
15	China	The Hong Kong Polytechnic University	●	●
16	USA	Stanford University	●	●
17	USA	Carnegie Mellon University	●	●
18	Netherlands	Design Academy Eindhoven	●	●
19	China	Tsinghua University	●	●
20	USA	California Institute of the Arts	●	●
21	Denmark	The Royal Danish Academy of Fine Arts	●	●
22	France	ENSCI Les Ateliers	French	Not applicable
23	Australia	University of Technology Sydney	●	●
24	UK	Loughborough University	●	●
25	USA	California College of the Arts	●	●
26	Sweden	Umea University	●	●
27	France	Ecole Nationale Superieure des Arts Decoratifs	●	●
28	China	China Central Academy of Fine Arts	●	●
28	USA	School of Visual Arts	●	●
30	Singapore	National University of Singapore	●	●
30	Argentina	Universidad de Buenos Aires	Spanish	Not applicable
30	UK	University of Oxford	●	None
33	Sweden	Konstfack University College of Arts, Crafts and	●	●
34	USA	Columbia University	●	None
34	USA	Yale University	●	None
36	USA	Savannah College of Art and Design	●	●
37	Singapore	Nanyang Technological University	●	●
38	Korea	Seoul National University	●	●
39	USA	University of California, Los Angeles (UCLA)	●	●
40	Canada	Emily Carr University of Art + Design	●	●
40	Mexico	Universidad Nacional Autónoma de México	Spanish	Not applicable
40	Germany	Universität der Künste Berlin	Germany	Not applicable
43	Australia	Swinburne University of Technology	●	●
44	USA	New York University	●	●
45	Switzerland	Zurich University of the Arts	●	●
46	UK	University College London	●	None
46	Italy	Universidad de Palermo	Italian	Not applicable
48	Australia	The University of New South Wales	●	●
49	Australia	The University of Melbourne	●	●
50	Italy	Politecnico di Torino	●	None

Appendix 5B: Titles of Education Programs

Appendix 6A: Questionnaire for Design Educators

The aim of the questionnaire is to understand the current situation of design education in the university and explore the future. It acquires information in the perspective of design educators about education aims, design-learning process and learning resources. The questionnaire may take you 5-10 minutes. All your data will be anonymized such that your name and data cannot be recognized within all the data collected from all our participants. The collected results will be used for publication in academic conferences or journals and for future research.

1. What is your position?

   □ Design teacher

   □ Director of design school or design department

   □ Sorry you are not suitable for this questionnaire
2. What is your age range?

   □ Less than 20 years □ 21-25 years □ 26-30 years □ 31-35 years □ 36-40 years

   □ 41-45 years □ 46-50 years □ 51-55 years □ 56-60 years □ More than 60 years
3. What is your gender?

   □ Male □ Female □ Secrecy
4. How many years of working experience do you have? ______________
5. Which school do you affiliate to?

   □ Design School □ Mechanics School □ Business School

   □ Art School □ Computer Science School □ Others ___________
6. What design-related education programs do your university offer?

   □ Industrial design □ Product Design □ Others ________________
7. Have you educated design students in multidisciplinary program?

   □ Yes □ No
8. Have you educated design students in cross-cultural program?

   □ Yes □ No
9. What education programs do your university offer?

   □ Exchange program

   □ Double-degree program

   □ In-course internship

   □ Activities organized by international platforms (e.g. DESIS, CIRRUS and CUMULUS)

□ Others__________

10. Among all the stakeholders below, please select the stakeholders currently involved in design education programs and rate the importance. 1 means not important at all, 5 means very important. If the stakeholder is not involved, please choose “no participation”.

    □ Educator

    □ Peer

    □ User

    □ Client

11. Among all the design tools below, please select the tools currently involved in design education programs and rate the importance. 1 means not important at all, 5 means very important. If the tool is not involved, please choose “unused”.

    □ Modeling tools (e.g. traditional machinery for model making with foams and plastics and facilities for plastic vacuum forming, plastic casting, rubber mold making, painting, and finishing. Materials include wood, metal, plastics, foam, clay, wax, and many types of casting materials such as plaster, resin, rubber, latex, and liquid plastic)

    □ Digital fabrication tools (e.g. laser cutting, CNC milling and lathing, 3D printing, rapid prototyping)

    □ Interaction prototyping tools (e.g. interaction prototyping, Arduino platform, Raspberry Pi)

    □ Mixed reality tools (e.g. Virtual Reality, Augmented Reality)

    □ AI tools (e.g. image recognition, machine learning, deep learning tensorflow)

12. What skills are your current design courses aiming to? please rate the importance for the selected one. 1 means not important at all, 5 means very important. If the education aim is not involved, please choose “unused”.

    □ Creativity

    □ Technology integration

    □ User perspective

    □ Social and cultural awareness

    □ Commercial awareness

    □ Communication skills

    □ Teamwork and leadership

    □ Problem-solving skills

13. What career options do your students have after their graduation?

□ Product Designer □Industrial Designer □ Interaction Designer □ Product Manager □ Engineer □ Artist □ Entrepreneur □ Social activist □ Others __________

Thank you for your answers about the current situation of design education in your university. According to a report from the World Economic Forum, 42% of required skills in today's workforce will change and 75 million jobs will be displaced over the 2018-2022 period. This trend challenges the education domain to prepare the students for jobs and markets that do not yet exist. Now, please imagine the form of design education in 10 years.

14. What education programs do you think will support future designers?

□ Exchange program

□ Double-degree program

□ In-course internship

□ Activities organized by international platforms (e.g. DESIS, CIRRUS and CUMULUS)

□ Others__________

15. Among all the stakeholders below, please select the stakeholders involved in design education and rate the importance. 1 means not important at all, 5 means very important:

□ Educator

□ Peer

□ User

□ Client

16. Among all the design tools below, please rate the importance for future designers. 1 means not important at all, 5 means very important.

□ Modeling tools (e.g. traditional machinery for model making with foams and plastics and facilities for plastic vacuum forming, plastic casting, rubber mold making, painting, and finishing. Materials include wood, metal, plastics, foam, clay, wax, and many types of casting materials such as plaster, resin, rubber, latex, and liquid plastic)

□ Modeling tools (e.g. traditional machinery for model making with foams and plastics and facilities for plastic vacuum forming, plastic casting, rubber mold making, painting, and finishing. Materials include wood, metal, plastics, foam, clay, wax, and many types of casting materials such as plaster, resin, rubber, latex, and liquid plastic)

□ Digital fabrication tools (e.g. laser cutting, CNC milling and lathing, 3D printing, rapid prototyping)

□ Interaction prototyping tools (e.g. interaction prototyping, Arduino platform, Raspberry Pi)

□ Mixed reality tools (e.g. Virtual Reality, Augmented Reality)

□ AI tools (e.g. image recognition, machine learning, deep learning tensorflow)

17. How important do you think multidisciplinary program for design students in future? please rate the importance. 1 means not important at all, 5 means very important.

    □ Not important at all □ Not important □ Neutral □ Important □ Very important

18. How important do you think cross-cultural program for design students in future? please rate the importance. 1 means not important at all, 5 means very important.

    □ Not important at all □ Not important □ Neutral □ Important □ Very important

19. What skills do you think are important for future designer? please rate the importance for each one. 1 means not important at all, 5 means very important.

    □ Creativity

    □ Technology integration

    □ User perspective

    □ Social and cultural awareness

    □ Commercial awareness

    □ Communication skills

    □ Teamwork and leadership

    □ Problem-solving skills

20. What career options do you think that the future design students will have after their graduation?

    □ Product Designer □Industrial Designer □ Interaction Designer □ Product Manager □ Engineer □ Artist □ Entrepreneur □ Social activist □ Others __________

Appendix 6B: Provinces of Samples

Province	Number	Percentage
Zhejiang	49	38.89%
Jiangsu	19	15.08%
Beijing	7	5.56%
Hunan	7	5.56%
Guangdong	6	4.76%
Hubei	6	4.76%
Heilongjiang	5	3.97%
Shanghai	3	2.38%
Sichuan	3	2.38%
Hebei	3	2.38%
Fujian	3	2.38%
Anhui	3	2.38%
Henan	2	1.59%
Liaoning	2	1.59%
Shandong	2	1.59%
Shanxi	2	1.59%
Guangxi	1	0.79%
Macao	1	0.79%
Gansu	1	0.79%
Chongqing	1	0.79%

Appendix 8A: Participant Information Collection Form

This is a cross-cultural design study supported by the University of Nottingham Ningbo. The aim of the study is to evaluate an innovative AI tool that facilitates the cross-cultural design process. You will make groups with two designers online for completing design tasks. The study takes 1.5-2 hours, and you will get 10 euros for reward. During the study, you will collaborate with other two designers collaborate and design a product for Dutch users. You will communicate remotely via Skype with them. The study has two design tasks, that are carried out with and without the assistance of the AI tool. Each design task takes 30 minutes. After completing each task, you will fill out a questionnaire about your experience. At the end of the study, you will have a short interview. The whole process of this study will be video recorded by Skype. And the design outcome, answers of questionnaires and interview will also be collected as experimental data. The data collected are only used for scientific analysis and kept confidential. Your identity will not be disclosed in any use of the information. All your data will be anonymized such that your name/data cannot be recognized within all the data collected from all our participants. Please fill in the following information if you accept to participate this study. We really appreciate your support!

1. What is your gender?
   □ Male □ Female □ Secrecy
2. What is your age? _______
3. What is your grade?
   □ Bachelor year 1 □ Bachelor year 2 □ Bachelor year 3 □ Bachelor year 4
   □ Bachelor year 5 □ Master year 1 □ Master year 2 □ Master year 3 □ PhD
4. Have you passed any English test?
   □ CET-4 □ CET-6 □ ILETS □ TOFEL □ Others_______
5. Please self-evaluate your English skills.
   □ Very bad (I cannot speak directly in English. I need an interpreter to help me communicate)
   □ Bad (It’s difficult for me to speak English. Basically I can only communicate through words and gestures)
   □ Average (I can speak basic English sentences. I cannot communicate my ideas efficiently)

□ Good (I can speak English fluently. Though sometimes there may be stabilization, I can communicate my ideas efficiently)

□ Very good (I can speak English freely and fluently like native language)

6. Have you used any AI-supported design tool before?

   □ Yes____________ □ No

7. What's your understanding of the typical color in Dutch culture?

   □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with □ Understand very well

8. What's your understanding of the typical material in Dutch culture?

   □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with □ Understand very well

9. What's your understanding of the typical pattern in Dutch culture?

   □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with □ Understand very well

10. What's your understanding of the typical form in Dutch culture?

    □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with □ Understand very well

11. What's your available time slot for the experiment?

    □ 2020.12.23 10:00-12:00 □ 2020.12.23 13:00-15:00

12. What's your Skype account?

Appendix 8B: Questionnaire of Participants

Please answer the following questions based on your experience during this design session. The data filled in this questionnaire will be processed anonymously.

1. What's your understanding of the typical color in Dutch culture?
   □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with
   □ Understand very well
2. What's your understanding of the typical material in Dutch culture?
   □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with
   □ Understand very well
3. What's your understanding of the typical pattern in Dutch culture?
   □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with
   □ Understand very well
4. What's your understanding of the typical form in Dutch culture?
   □ Do not understand at all □ Not familiar with □ Neutral □ Familiar with
   □ Understand very well
5. During which phase of design process did you use this AI-supported tool?
   □ Design research □ Idea generation □ Prototyping □ Evaluation and testing
   □ Design communication
6. How do you think of the communication quality during the collaborative design process of this design task?
   □ Very bad □ Bad □ Average □ Good □ Very good
7. How is the relationship between team members during the collaborative design process of this design task?
   □ Very bad □ Bad □ Average □ Good □ Very good