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ABSTRACT

As artificial intelligence (AI) technology is gradually put into application in the design industry, higher requirements have been imposed on the competence of industrial designers in the market. This study explored the application of AI technology in the design field and its future development direction on the basis of literature research in order to figure out the competency factors of industrial designers under the background of AI technology. Expert research and interview were used to obtain expert reliability, followed by a questionnaire survey of designers and data analysis to verify the effectiveness of the competency model, based on which the competency model of industrial designers in the AI context has been finalized. The result shows that it is necessary for designers to be capable of integrating and reserving cross-domain knowledge due to high demands on the degree of recognition to innovation ability, knowledge, and professional capability, and on the innovation of both design thinking and design method. Under the background of AI, industrial designers are required to understand the basic background knowledge of AI, and to have the ability to finish information sorting and provide assistance in designing applying AI software, and the ability to cooperate with AI engineers. This competency model will not only promote the development of AI technology in the industrial design trade by imposing new demands on industrial designers but also point out the direction for the cultivation of design talents in institutions of higher learning.

Keywords: Artificial intelligence, industrial designer, competency model, design education.

INTRODUCTION

As artificial intelligence (AI) technology being applied in-depth in a variety of fields, it will greatly change our lives in the foreseeable future, as a result of which a number of policies have been issued successively by state and local governments of China to promote AI to a national strategic level while many experts and scholars are successively involved in the research and discussion on the AI technology from the perspective of their own disciplines. Although the industrial design field is characterized by innovation as one of its strengths, an extensive range of AI design software has already become popular in the market quietly. Examples are the software name Banner which is able to accomplish the design of 8,000 posters within a second, the software ARKie and Adobe Sensei capable of quick design of all variety of posters, Tailor Brands, and Logojoy, which are able to design various logos within 1.5 seconds, and the software name of AutoDraw and Prisma which make it possible for a new hand of painting to become a master of art in a minute; More examples are Philippe Starck who designed the first AI seat using AI software in 2019 and Designer Philip Schmitt who designed the first seat with soul by applying generative adversarial networks (GAN). In the face of the in-depth application of AI in the design field, the question is whether designers will be replaced by a machine in the future, what industrial designers need to be capable of in order to deal with this occupational crisis, and what institutions of higher learning should do to reform their design education in order to cultivate students adaptive to the new wave of technology.

Based on the competency factors of industrial designers figured out through literature research, the preliminary construction and revision of designer competency model have been accomplished through expert survey, and then the effectiveness of this model was verified by way of a questionnaire survey of designers and data analysis in this dissertation, and then built up the industrial competencies model under AI Technology. This competency model not only impose new requirements for the competence of designers, but also it divides the professional level of industrial designers in a scientific way, which points out the direction for the cultivation of industrial design talents of higher education while providing significant theoretical support for the establishment of a professional qualification evaluation system for industrial designers.

REVIEW OF RELEVANT RESEARCH

Research on the Competency of Industrial Designer

As proposed by David McClelland from Harvard University in 1973, the concept of competency refers to the comprehensive competence of knowledge, motivation, self-image, characteristics, skill, and social role (McClelland & Boyatzis, 1980), which

was then divided into three dimensions including occupation, behavior, and strategic integration which respectively represent the skills to deal with specific and routine tasks, the skills to deal with non-specific and random tasks, and the management skills in the organizational situation (Marrelli, 1998).

An investigation of the industrial design graduates from the University of Canberra in Australia in 1998 showed that the elements for survival in an enterprise include ten skills such as hand painting, model construction, drawing software, expression ability, etc. (Liu Tao, 2006). In 1999, a research was conducted by the Industrial Design Department of Japan concluding the competence requirements of designers and the weight as shown below: planning capability (0.3), modeling ability (0.25), thinking (0.2), coordination (0.12), expression (0.08) and computer operation (0.05). Researcher (Xiao, 2006) divided the basic competence of an industrial designer into six capabilities, including thinking, connection in mind, analysis, problem-solving, observation, and practice. Yan (2009) believed that a professional designer must have the capability to identify and solve problems, innovation ability, and teamwork. Researcher Hu and Zhao (2009) analyzed the competence an industrial design talent should have from three aspects, including education in institutions of higher learning, design contests, and business market, and proposes 13 points for evaluation. Lecler and Horan (2018), by deeply exploring the core competence and psychological features of designers, concluded that creativity, exploration, and initiative are gatekeepers of designers' abilities.

In summary, the competency of industrial designers refers to the knowledge, skills, values, appreciation ability, and creativity as necessary to successfully accomplish design tasks, and an industrial designer is required to not only have the professional ability to deal with specific, routine tasks, and the behavioral ability to deal with non-specific, random tasks, but also have the management capability to deal with the organizational situation.

Research on the Competence Model of Industrial Designer

Chen (2011), thorough investigation on the competence and quality features of creative talents, summarized five level-1 indexes including knowledge, personality traits, motivation, innovation, and general ability, as well as 20 level-2 indexes. Duan (2011) divided the competence of industrial design talents into three level-1 abilities, including basic public knowledge, specialty, and innovation, as well as five level-2 abilities. The researcher McLaughlin proposed the competence iceberg model dividing competency features into five categories: knowledge, traits, motives, self-concept, and skill, which reflected the hidden potential motivation and characteristics of ability (McLaughlin et al., 2012). Duan (2012) thought that innovation, professionalism, analytical thinking, communication skills, customer awareness, and market analysis should be included in the competency model of industrial designers. Cao (2013) deduced a competence structure model of industrial designers by applying the component sub-theory of competence to conclude three level-1 abilities, ten level-2 abilities, and 16 level-3 abilities, and identifies the weight of evaluation indexes for the competence of senior, middle-level, and junior industrial designers. Nieminen (2015) used the quantitative analysis of questionnaire and model validation to construct a user-centered designer competence model based on 12 abilities of designers such as user advantage, soft skill, hard skill, designer advantage, etc. Lee (2016) developed an evaluation scale for the industrial design ability index (IDAI) through quality function deployment (QFD) and grey relation analysis (GRA) and then verified the effectiveness of the evaluation scale by testing 211 university students. Moreover, Bi, Wang, and Liu (2018) constructed a design competence evaluation system under the cloud manufacturing mode from perspectives of meta-competency and the competency on industry technology, design tasks, and learning ability.

New Competence Demands Imposed by AI Technology

With the continuous penetration of AI technology in the field of design, some scholars have begun to think about the demands for the competence of designers. For example, Yang (2018) pointed out that in the era of AI, designers were required to have the ability to integrate interdisciplinary knowledge, reserve cross-domain knowledge, and transform the design direction from functionality into emotional beauty. Another example is Ning Fang, who believed that industrial design was moving towards a more complex inter-discipline and that industrial design talents should have a higher ability of innovation by integrating professional knowledge and the ability to deliver innovative design with the help of a network (Ning, 2018). Moreover, the researcher Zhang (2020) conducted an investigation on the necessity and feasibility of AI basic education for the development of design discipline and design education, and a discussion on the potential risks incurred due to AI education in design and their coping strategies.

Looking back to the existing literature, it’s not difficult to find that current researches on the competency model of industrial designers are characterized by the following: firstly, while the researches on competency are relatively mature both at home and abroad, the researches on competency model specific to industrial designers are low in number and the theory not systematic enough. Secondly, the division of competency factors of industrial designers is ambiguous, lacking scientific criteria for selection and evaluation. Thirdly, the researches on the evaluation of abilities of industrial designers are mainly focusing on the composition of competency factors rather than the analysis of the weight of each factor. Fourthly, the impact of new technology on the ability of industrial designers was not taken into consideration. As a consequence, this research is innovative by systematically sorting out the competence structure of industrial designers using scientific, statistical methods and by constructing a systematic theoretical system for the competence structure of industrial designers on the basis of AI technology.

PRELIMINARY CONSTRUCTION OF COMPETENCY MODEL

The selection of competency factors is critical to ensure the authenticity and effectiveness of the entire competency model and that whether the selected index and the design of its weight are scientific will have a direct influence on the reliability and validity of the evaluation result of the competence model. This section selected the competency factors of industrial designers by summarizing the competency factors and their frequency present in the existing researches and combined the new demands for the competence of designers under AI technology. Then, this research revised the model based on the results from the questionnaire and interviews with experts.

Selection of Competency Factors and Frequency Statistics

With the keywords of "industrial designer & competency" and "artificial intelligence & competence of industrial designers," 20 papers with citation times high than ten times were selected from CNKI. Based on an in-depth study, the competency factors of industrial designers were figured out. Due to differences in the expression of competency factors of industrial designers, these statistics combined and reorganized the competency factors appropriately.

Since the existing AI software has participated in product design and preliminary research which can sort out design data, product modeling, evaluation of the functional structure, and production of renderings, industrial designers under the background of AI are required to have the background knowledge of AI, abilities of interdisciplinary integration, the abilities of data statistics and research using AI software, and even the capability of programming to guide the design of AI software. A preliminary model and specific content of competency factors for industrial designers were formed, as shown in Table 1 below.

Table 1 Preliminary model and specific content of competency factors for industrial designers under the background of AI

Level-1 Competency Factor	Level-2 Competency Factor	Specific Content
A Knowledge	A1 General Education Knowledge	With linguistic, mathematical, literary and artistic, historical and cultural ability and the ability of social analysis and moral thought and other capabilities
	A2 Professional Industrial Design Knowledge	Master basic and professional knowledge on industrial design
	A3 Humanistic Knowledge and Literacy	Possess humanistic knowledge, attitude and spirit, and the ability for penetration of culture and art to science and technology
	*A4 Interdisciplinary Knowledge	Able to integrate interdisciplinary knowledge and the reserve of cross-domain knowledge
	*A5 Background Knowledge of AI	Master the basic background knowledge of AI and big data
	*A6 Lifelong Growth Oriented Knowledge Structure	The ability to acquire and supplement new knowledge by self-study to meet the needs of social development and work
B Professional Capability	B1 Design Research Ability	Able to access, process and express design information
	B2 Design Expression Ability	The ability of design expression including expression by hand painting, plane and 3D software
	B3 Professional Aesthetic Ability	Master aesthetic principles and understand others' aesthetic views
	B4 Product Comprehensive Design Ability	Able to provide solutions to the issues existing in the appearance, function and structure of products
	B5 Ability of Teamwork, Project Planning and Management	Able to communicate with team members, make a reasonable schedule, organize personnel, allocate property and solve the problems encountered in the process of design
C Innovation	C1 Innovation of Design Thinking	The ability to creative thinking and transform from functionality into emotional beauty
	C2 Innovation of Design Methods	Able to mobilize resources to optimize allocation
*D Ability to Apply AI Technology	*D1 Ability to Apply AI Design Software	Master more than one AI design software, and provide quick assistance for the design process by computer aided engineering and reinforcement learning
	*D2 Ability to Sort Out Information with AI	Master more than one AI information process software to improve design efficiency
	*D3 Combination of Designers with Machine Trainers	Able to master an AI programming language, design data model and algorithm to guide the machine how to design (teach the machine how to design)
Note: *The competence factors of designers under the background of AI as proposed by the author		

Expert Survey and Revision of the Model

In order to improve the scientific nature of the competency model for industrial designers under AI technology, the questionnaire and interview were used in this section to obtain expert reliability and revise the model.

Design of Questionnaire and Selection of Experts

The questionnaire used for the expert survey was designed to list the competency factors and the specific content. In the questionnaire, scoring criteria were divided into three levels, 3 points for appropriate one, 2 points for appropriate after revision, and 1 point for inappropriate, the last of which should be accompanied by recommended modifications. For the purpose of the survey, 15 experts were selected, 9 of which were professors engaged in design education for a number of years in universities, 4 were designers from well-known design companies with more than ten years of experience in design, and the remaining were experts with experience in AI technology. This survey includes not only a questionnaire to be completed but also a one-on-one interview to acquire more comments from experts on the revision.

Analysis of the Survey Result

A data model was used to analyze the survey result with the help of Mean, Standard Deviation (SD), and Coefficient of Variability (CV), wherein Mean was used for determining the concentration of experts' opinions on a competency factor while the latter two are used for identifying the discreteness of experts' recognition to a competency factor and to the description of behavioral features.

Known: and， xi and yi presents a single sample and represents a set of samples. The formula is as follows:
Mean: Represents a concentrated trend of a random variable or set of data:

$$\mathrm{mean}_X = \frac{\sum_{i=1}^{n} x_i}{n}; \tag{1}$$

SD: The degree of discreteness when measuring random variables or a set of data is absolute difference quantity:

$$D1_X = \frac{\sum_{i=1}^{n} (x_i - \mathrm{mean\_x})^2}{n}; \tag{2}$$

CV: A measure of the degree of dispersion of a group of data, belonging to the number of relative differences (difference variance):

$$SD1_X = \sqrt{D1_X}; \tag{3}$$

If CV lower than 0.15 refers to balanced data distribution and CV higher than that refers to significantly unbalanced data distribution. Table 2 shows the analysis of results from the Level-1 factor. Moreover, the experts' comments on the revision are shown in detail in Table 3 below as supplementary to the factor.

Table 2 The analysis of the result from Level-1 factors

A	CV	Mean	SD	B	CV	Mean	SD
	0.23	2.77	0.62		0.24	2.72	0.65
C	CV	Mean	SD	D	CV	Mean	SD
	0.20	2.80	0.55		0.41	2.45	0.97

From Table 2, the mean of 2.77, 2.72, 2.80, and 2.45 and the CV of 0.23, 0.24, 0.20, and 0.41, which respectively corresponds to A- knowledge, B-professional Capability, C-innovation, and D-Application of AI Technology. It can be seen that experts had a high degree of recognition in innovation, knowledge, and professional capability, instead of the application of AI technology, to which they hold different views. With regard to the AI technology factor, the Mean is 1.52 for the nine professors from universities, 2.83 for the four designers, and 3 for experts with experience in AI technology, which shows that professors from universities had Low recognition of AI technology.

Table 3 The analysis of the result from Level-2 factors

	CV	Mean	SD	Recommended modifications
A1	0.26	2.73	0.704	A5 should be modified as having the background knowledge and partial professional basic knowledge on AI
A2	0.18	2.87	0.516	
A3	0.18	2.87	0.516	
A4	0.27	2.67	0.724	
A5	0.28	2.60	0.737	
A6	0.18	2.87	0.516	
B1	0.28	2.60	0.737	None
B2	0.20	2.80	0.561	
B3	0.28	2.60	0.737	

B4	0.18	2.87	0.516	
B5	0.26	2.73	0.704	
C1	0.18	2.87	0.516	None
C1	0.18	2.87	0.516	
D1	0.42	2.33	0.976	D1 should be modified as the ability to know about AI software
D2	0.22	2.73	0.594	
D3	0.59	2.29	1.356	D3 should be modified as the collaboration between designers and AI engineers

From Table 3, Among the six level-2 competency factors under A-knowledge, the recognition of A2- professional knowledge on industrial design, A3- humanistic knowledge, and A6-lifelong growth-oriented knowledge structure were high, while that A5-background knowledge of AI was lower. In the opinion form experts, the background knowledge of AI is wide and difficult, so it is difficult for students to master it. The students can understand the basic knowledge and application of artificial intelligence than master the knowledge.

Among the five level-2 competency factors under B-professional capability, the recognition to each competency factor was high, and B2-design expression ability and B4-product comprehensive design ability were highest.

Among the two level-2 competency factors under C-innovation, C1-innovation of design thinking and C2-innovation of design methods had higher value of Mean, showing that experts were unanimous, shared a high degree of recognition and believed the importance for industrial designers to have innovative thinking and ability under the background of AI.

In terms of D-Ability to apply AI technology, the value of Mean of D1- ability to apply AI design software, D2- ability to sort out information with AI, and D3- a combination of designers with machine trainers were 2.33, 2.73, and 2.29, and the CV of them is 0.42, 0.22 and 0.59 respectively. The experts had more different opinions and discussed lots in this section. The experts recommend that the degree of mastery D1 should be modified from application to understanding. And they believed it was quite high demanding for designers to master an AI programming language, and the D3 should be revised as the collaboration between designers and AI engineers.

VERIFICATION OF THE COMPETENCE MODEL

Design and Distribution of Questionnaire

Based on the feedback of the experts on the competency model, another questionnaire was formulated, and verification was conducted by having more designers complete it. A five-point scale was used in the questionnaire where options and respective scoring were shown as follows: highly inconsistent (1 point), inconsistent (2 points), moderate (3 points), consistent (4 points), and highly consistent (5 points). The questionnaire was distributed online via www.wjx.cn. The questionnaire sent out 180 and 156 effective, which the effective rate was 86.7%. The survey subject consists of a young population aged from 18 to 25 making up 83.3%, a group aged from 26 to 30 occupying 7.7% and the rest aged from 31 to 40 accounting for 8.3%, of which people with working experience in design up to 1-3 years take up 31.4%, and more than three years design experience proportion was 11.5%.

Analysis and Test of Questionnaire Results

The questionnaire analysis not only used the Mean, which formula is (1) but also added the reliability test, which can reflect the reliability of the questionnaire. The reliability test refers to the degree of consistency of the results obtained by repeated measurement of the same research object using the same method. This article used Corrected Item -Total Correlation (CITC) and Cronbach's α：

CITC: Corrected item-total Correlation, It is generally represented by the letter r, which is used to measure the linear relationship between two variables:

$$r(X,Y)=\frac{\mathrm{Cov}(X,Y)}{\sqrt{D1_X * D1_Y}}; \tag{4}$$

Cronbach's α：it refers to the average value of the split-half reliability coefficient obtained by all possible item division methods of the scale:

$$\alpha=\frac{K}{K-1}\left(1-\frac{\sum_{i=1}^{K} D_{C_i}^2}{D_C^2}\right) \tag{5}$$

C $\{C_1, C_2, \ldots, C_K\}C_i$ $\{c_{i1}, c_{i2}, \ldots, c_{im}\}$ K is the number of items on a scale, is the variance of the total sample, is the variance of the observed sample.

The analysis and test of questionnaire results are shown as Table 4. The relation of the mean of each level-2 competency factor as shown as Figure 1.

Table 4 The analysis of results from the questionnaire survey

L1	L2	Mean	CITC	α
A Mean= 3.58	A1	3.74	.653**	.929
	A2	3.83	.863**	.924
	A3	3.58	.551**	.931
	A4	3.44	.678**	.928
	A5	3.23	.575**	.930
	A6	3.64	.715**	.927
B Mean= 3.90	B1	3.95	.813**	.926
	B2	3.92	.642**	.929
	B3	4.07	.654**	.929
	B4	3.82	.767**	.927
	B5	3.90	.709**	.928
C Mean= 3.85	C1	3.88	.754**	.927
	C2	3.81	.607**	.930
D Mean= 3.31	D1	3.34	.485**	.934
	D2	3.29	.698**	.927
	D3	3.29	.579**	.932

Note: **significant correlation at 0.01 (bilateral), *significant correlation at 0.05 (bilateral); it is required for CITC≥0.400, and Cronbach α=0.933

From Table 4, analysis was performed to study the correlation between each item and dimensions, the strength of which was represented by the Pearson correlation coefficient. From table 4, it can be seen that there was a significant positive correlation between each item from A1 to A6 and the knowledge dimension (A), of which the positive correlation between A2- professional knowledge on industrial design and the knowledge dimension (A) was most significant. The same situation occurred when it comes to each item from B1 to B5 and the professional capability (B), between C1, C2 and the innovation (C), and between each item from D1 to D3 and the ability to apply AI technology (D). In each case, a significant positive correlation existed between them, and the most significant one occurs respectively between B1- design research ability and the professional capability (B), between C2- innovation of design methods and the innovation (C), and between D2- the ability to sort out information with AI software and the ability to apply AI technology (D).

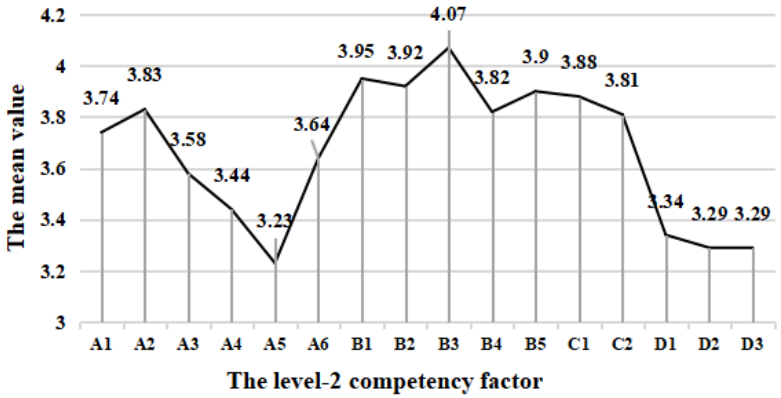

Figure 1: The relation of the mean of each level-2 competency factor

Reliability analysis was used to study the accuracy of quantitative data, in which generally the correction item-total correlation (CITC) higher than 0.400 is desirable, and Cronbach's α exceeding 0.8 represents high reliability, from 0.7 to 0.8 is good reliability, from 0.6 to 0.7 is acceptable reliability, and if less than 0.6 is poor reliability. Where the value of Cronbach's α if the item is significantly higher than Cronbach's α, then re-analysis upon deletion of the item may be considered. As we see from Table 4, the reliability coefficient is 0.933, higher than 0.9, demonstrating high reliability of the survey data. In

accordance with the "Cronbach's α if item deleted," the reliability coefficient will increase significantly if D1- ability to apply AI design software is deleted. As a result, this item may be revised or deleted. The CITC of all items as analyzed is higher than 0.4, which not only showed that there was a good correlation among them but also demonstrated sound reliability.

Revised Competency Model of Industrial Designers under AI Technology

Based on experts's comments and the result from the questionnaire survey of designers, for the purpose of the A- knowledge dimension, the modification was made to A5- background knowledge of AI and big data of which mastering was revised as understanding with reference to experts' comments. For the purpose of C- innovation, a high degree of recognition fell on this part as concluded from both the expert interview and the questionnaire survey of designers. Therefore it remained unchanged. In terms of D-ability to apply AI technology, an expert discussion was concentrated on D1-ability to apply AI design software which, as recommended, should be modified as the ability to know about AI design software, as well as D3- a combination of designers with machine trainers for which they believe that it is quite demanding for designers to master an AI programming language and that it is necessary to strengthen the collaboration between designers and AI engineers. Given the above, the competency model of industrial designers under the background of AI was finalized, as shown in Figure 2.

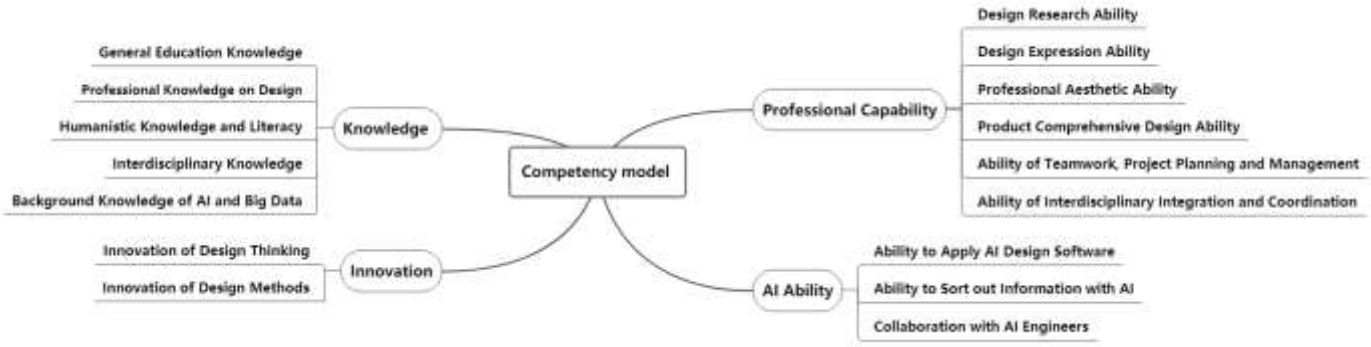

Figure 2: Competency model of industrial designers under the background of AI

CONCLUSION

As AI technology is altering with each passing day, the influence in AI education is changing accordingly. AI applications emerge in an endless stream, and each of them has differed a lot from others. For the purpose of design, industrial designers need to take on a series of processes including preliminary survey, data analysis, sketch design, computer modeling, and post-processing of scheme, of which many a process is tedious and inefficient, taking a very long time to complete and requiring designers to repeat a piece of simple work for a long-term, such as a preliminary survey that needs a lot of time to access to and sort out information, and post-processing of scheme that requires designers to adjust all parameters through a computer. However, by completing the preliminary data sorting and production of renderings with high efficiency, the AI information processing software and design software will help designers save most of their time, and thus making it possible for designers to spare more time to do innovative design.

In order to keep up with the development of artificial intelligence technology, designers should not only have the basic design professional ability and design professional knowledge, but also have the ability of interdisciplinary integration and coordination, the knowledge structure of interdisciplinary and lifelong growth, the basic knowledge of artificial intelligence and big data background, and the ability to use artificial intelligence software to assist design information collation and improve the design process. At the same time, higher-level designers need to be able to master AI programming language, design data models and algorithms to guide the machine on how to design. So it is necessary to update the demands for the competency of a designer in real-time with the development of AI technology.

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