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Citation

Eser, A., and Altiparmakogullari, Y. (2026) Changing Skills of Industrial Designers in the Age of GenAI: A Systematic and Practice Based Study, in Simeone, L., Gray, C. M., Verhoeven, A., de Götzen, A., Bakırlıoğlu, Y., Zohar, H., Stead, M., and Buwert, P. (eds.), *DRS2026: Edinburgh*, 8–12 June, Edinburgh, United Kingdom. https://doi.org/10.21606/drs.2026.868

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Changing skills of industrial designers in the age of genAI: A systematic and practice based study

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doi.org/10.21606/drs.2026.868

Abstract: This study explores the changing skills of industrial designers in the age of Generative Artificial Intelligence (GenAI). It combines a systematic literature review covering 2020–2025 with a practice based investigation involving six designers who actively use GenAI in their design processes. Focusing on both novice and expert designers, the study examines how GenAI influences skill development through the lenses of upskilling, reskilling, and deskilling. The findings show that while GenAI enhances creativity, idea generation, and visualization, it also brings challenges such as increased cognitive load, information reliability issues, and a decline in production awareness. Differences between novice and expert designers reveal that experience level plays a key role in how GenAI driven transformations affect design skills. Overall, the study demonstrates that GenAI not only accelerates creative processes but also reshapes the cognitive and practical dimensions of industrial design practice.

Keywords: generative artificial intelligence; industrial design process; design skills

1. Introduction

Artificial intelligence has rapidly become a technology that brings radical changes in many fields today. The impact of this transformation is not limited to technical areas but has also led to the emergence of new forms of application in creative processes. In this context, the reflection of artificial intelligence in creative fields is referred to as Generative Artificial Intelligence (GenAI) and is used as an effective tool in areas such as design, art, text, visual, or 3D model generation (Buonamici et al., 2020; Saadi & Yang, 2023). These artificial intelligence algorithms, capable of producing various ideas or solutions within seconds from complex geometries to visual details that would take hours to create manually, offer both significant opportunities and new challenges for creative disciplines. This situation has caused GenAI to evolve from being merely a production tool into an active component of the design process. Indeed, beyond its contributions to visual and content generation, GenAI has begun to transform workflows and designer roles in the field of Industrial Design. In design processes, it is used by designers in many stages such as idea exploration, brainstorming (Ong et al., 2021; Fang et al., 2023), concept development (Camburn et al., 2020; Tang et al.,

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2024), generating alternatives (Saadi & Yang, 2023; Wand et al., 2024; Shukla et al., 2025), prototyping (Buonamici et al., 2020; Liu et al., 2022), and production related details (Primo et al., 2017). With GenAI, designers can produce many ideas in a short time, visualize alternative ideas, create diversity in concept and form, and generate solutions from different perspectives (Camburn et al., 2020; Ong et al., 2021; Fu et al., 2012). In addition to providing significant advantages for designers by offering fast and systematic solutions, it can be said that it also has the potential to change well known design habits and structures. This situation redefines the designer's role in the production process and brings up which skills have come to the forefront and which have undergone transformation. Therefore, within this new design approach shaped by artificial intelligence, the professional role of the designer and the required competencies have become a current research area that needs to be examined comprehensively. The aim of this study is to examine the changes in the skills of industrial designers with the inclusion of GenAI in the design process. In this context, it aims to reveal which new skills have emerged in designers, which skills have developed, transformed, or lost their significance.

2. Industrial Design and Generative AI

Industrial design is a discipline that has continuously evolved in its scope, role, and structure, shaped by changing technological, economic, and social dynamics. These shifts have redefined how designers approach problems, use methods, and create value, leading to a more multilayered way of thinking within design processes. In this sense, design is viewed not merely as a means of producing formal outcomes but as a dynamic mode of inquiry and decision making that includes stages of research and exploration (Cross, 1982; Lawson & Dorst, 2009). The design process can be defined as an activity in which research is conducted, ideas are generated, discussed, evaluated, and gradually refined into a final outcome (Cross, 1982). It emerged to provide a framework for understanding how designers generate ideas and translate them into tangible solutions. Actions within this process such as problem solving, creating alternatives, and materializing concepts have been modeled over time to guide both design education and practice. Among the established frameworks, the Double Diamond Design Process, developed by the Design Council (2004), is one of the most recognized. It operates through two main phases divergence and convergence structured across four stages: discover, define, develop, and deliver. While the first two focus on exploring and defining problems, the latter two involve developing and realizing solutions. However, in practice, the process rarely follows a linear path; it remains a dynamic and iterative structure filled with uncertainty and complex decision making (Cross, 1990; Dorst & Dijkhuis, 1995). Consequently, design requires not only technical knowledge but also cognitive abilities such as intuition, visual thinking, and the capacity to deal with ambiguity.

2.1 GenAI in the Design Process

In the literature, there are various approaches to integrating GenAI into industrial design workflows. In the most comprehensive framework, Windl et al. (2022) examine this through four different models (Figure 1). The first model, "A Priori", positions AI as the creator of design inputs and contexts, while designers act as regulators who adjust the outcomes according to these contexts.

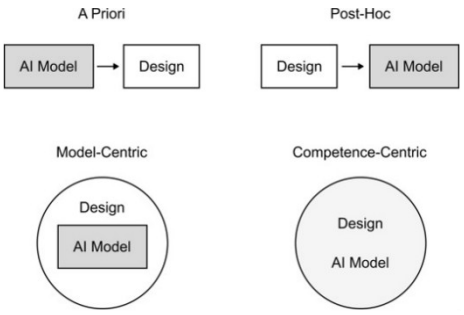


Figure 1 Four approaches to integrating AI in the design process (Windl et. al. 2022)

This approach may turn the designer into an operational moderator but may also result in a loss of flexibility in design. In the "Post hoc" model, the design is completed first, and then the AI model takes a supportive position afterward. Compared to the previous approach, this allows human control to remain central to the essence of design, positioning AI as an assistant. The "Model centric" model, on the other hand, places AI at the center of the design process, where the designer consults AI on every aspect, fostering a collaborative system. At this point, it can be said that the designer uses AI as a tool. Finally, the "Competence centric" model removes AI from the center, creating a synchronized, parallel collaboration between AI and the designer. Here, AI acts as a collaborator or creative partner. Although the debates around these four approaches continue, the model centric and competence centric models have been the most widely adopted (Windl et al., 2022). The other two models are often dismissed because they suggest that AI could act independently of human intervention, which contradicts the inherently relational and human dependent nature of design. Likewise, the post hoc model has become less accepted since the algorithmic and technological structure of AI does not naturally align with such a role.

Within this framework, as also explained by Windl et al. (2022), the model centric approach is regarded as a tool based relationship, similar to traditional computer aided design (CAD) software, where AI produces technical outputs in response to the designer's specific inputs (Mayers, 2024; Ozdemir, 2022). The concept of a tool can be defined as an element that facilitates human action toward a particular goal an entity that does not perform the action itself but enables its realization (Verbeek, 2005); in this sense, CAD/CAM programs, production machinery, and AI-based systems used in the design process can likewise be considered tools. The relationship established with design tools brings with it a human centered notion of control. However, this perspective has begun to be questioned in the face of more autonomous systems such as GenAI. This shift directs the designer GenAI relationship toward the second approach. One of the key discussions in contemporary design theory concerns whether GenAI should be regarded merely as a "tool" or as a "creative collaborator" actively contributing to the design process (Lee et al., 2024; Gao et al., 2024; Briscoe et al., 2023; Tholander & Jonsson, 2023). In contrast to the first view, the second approach positions GenAI as a co working partner or creative collaborator that participates actively in the design process. Within this framework, interactions between GenAI and designers are described through concepts such as "a stakeholder in the design process" (Briscoe et al., 2023), "digital partner" (Tholander & Jonsson, 2023), "hybrid collaboration" (Lee et al., 2024), or even "a group of young designers working simultaneously" (Mayers, 2025). It is considered a creative partner that develops ideas with the designer, proposes

alternatives, and contributes to overcoming both the defined and undefined aspects of the design process.

A significant part of recent research does not limit the potential of GenAI in design processes to technical support; instead, it situates it within a human machine collaboration, emphasizing hybrid and interactive design practices. Therefore, the contribution of GenAI to industrial designers is increasingly viewed as offering not merely functional facilitation but also a collaborative environment for creative decision making. GenAI actively participates in the design process, contributing both positively and negatively. It is involved in various stages, such as idea generation, developing design solutions, conducting online research, creating visuals, and extracting technical information for production from those visuals (Tang et. al. 2024; Fu et. al. 2024) In this respect, Shukla et al. (2025) warn that GenAI poses a potential risk of de-skilling among designers, as it may lead to a decline in certain traditional design skills. On the other hand, as in every technological transformation, it is also possible for new skills to replace the ones that have become obsolete. In this context, concepts such as re-skilling and up-skilling offer an important framework for understanding and evaluating the changing structures of competencies.

3. Method

This study examines the changes in designers' skills that have occurred alongside the integration of GenAI into the industrial design process. The research is based on a two stage methodological structure consisting of a systematic literature review and semi structured interviews. In the first stage, studies published between 2020 and 2025 were collected from the Scopus, Web of Science, Google Scholar, and TR Dizin databases. The keywords "industrial design," "generative artificial intelligence," "artificial intelligence in the design process," and "design skills" were used in the search, with the presence of the term "generative artificial intelligence" defined as a mandatory criterion. Studies that included at least one of the other keywords were also considered. From over 200 studies obtained, duplicates and those outside the scope of the research were eliminated, and 40 key studies most relevant in terms of content and method were examined in detail. These studies were classified according to the four main stages of the Double Diamond Design Model (discover, define, develop, and deliver) developed by the Design Council (2004), to determine in which phases GenAI is involved in the design process and which skills it affects. The primary aim of this classification is to demonstrate that GenAI is not used with the same intensity or function across all stages of the design process, and to identify the stages where it plays a more decisive role. To interpret the nature of skill transformations, the selected studies were analyzed using a content analysis approach under three main themes: up-skilling, re-skilling, and de-skilling. The up-skilling theme covers aspects of GenAI that strengthen or enhance existing skills; re-skilling focuses on how GenAI redefines or changes the way certain skills are approached; and de-skilling includes expressions that indicate a weakening or loss of skill relevance. This framework aims to interpret skill transformation through discourses in the literature and comparatively reveal how designers perceive these changes. Thus, the study provides an overview of GenAI's position in the design process and its influence on skill domains.

This study serves as a preliminary investigation based on a limited number of interviews, aiming to establish an initial understanding of how GenAI driven transformations affect design skills. The skill levels of industrial designers are determined not only by the knowledge they possess but also by how they apply it. Significant distinctions emerge between novice and expert designers, particularly in their approaches to problem definition, information gathering, and decision making processes. Participants were therefore categorized according to Dreyfus and Dreyfus's (1986) skill acquisition model: novice designers, with 0–5 years of professional experience, and expert designers, with more than five years of experience. This grouping enabled a comparative understanding of how experience influences the adaptation of new technologies and the transformation of core design competencies within the context of GenAI.

4. Findings

4.1 Literature Review

In the first phase of the study, studies from 2020 to 2025 examining the relationship between GenAI, the industrial design process, and changes in design skills were reviewed. As shown in Figure 2, the position and influence of GenAI across these stages are presented in a holistic manner, with its impact on the process and skill transformation categorized into three groups: up-skilling, re-skilling, and de-skilling.

Design Process	Impact Type	Skills	Publications
Discover (32)	△ Up-skilling (17)	*Data Integration, Contextualization, Analytical Thinking, and Problem-Solving*	Liao et al. (2020); Figoli et al. (2022); Tholander & Jonsson (2023); Wang et al. (2024); Berni et. al. (2024); Luo (2024); Hikmawati & Mohammad (2025); Chompunuch & Lubart (2025)
		Conceptualization, Brainstorming, and Needs Identification	Fang et al. (2023); Tholander & Jonsson (2023); Wu et al. (2024); Choudhury et al. (2025)
		Inductive Thinking	Sattele et al. (2024)
		Creative Thinking	Baidoo Anu & Ansah (2023); Kim & Maher (2023); Wang et al. (2024)
		Formulating the Right Questions	Dagli et al. (2025)
	↻ Re-skilling (13)	*Working Routine*	Figoli et al. (2022); Tang et al. (2024); Tholander & Jonsson (2023); Barrett et al. (2024); Fu et al. (2024); Luo et al. (2024); Takaffoli & Makela (2024); Wu et al. (2024); Chen et al. (2025); Sattele et al. (2024); Shukla et al. (2025)
		Diminished Subconscious Development and Creative Decline	Shukla et al. (2025)
		Transformation in Brainstorming and Problem Framing	Shukla et al. (2025)
	▽ De-skilling (22)	*Increased Cognitive Load and Dependency*	Woinaroschy (2020); Baidoo Anu & Ansah (2023); Guo et al. (2023); Zhai et al. (2024); Chen et al. (2025); Zuhra (2025)
		Being Constrained by AI Frameworks	Tang et al. (2024)
		Biased Information, Reliability, and Accuracy	Hikmawati & Mohammad (2025); Chompunuch & Lubart (2025)
		Social or Algorithmic Complacency	Gmeiner et al. (2023); Sattele et al. (2024)
		Technological Literacy and Challenges of Control	Jonsson & Tholander (2022); Liu et al. (2022); Berge & Plessis (2023); Smolansky et al. (2023); Tholander & Jonsson (2023); Gao et al. (2024); Lee et al. (2024)
		Critical Thinking and Creativity	Guo et al. (2023); Wang et al. (2024); Shukla et al. (2025); Zuhra et al. (2025)
Define (37)	△ Up-skilling (25)	*Creativity, Lateral Thinking, Inspiration, Rapid Alternative Generation, Problem-Solving, Analytical Thinking, and Decision-Making*	Liao et al. (2020); Verganti et al. (2020); Baidoo Anu & Ansah (2023); Guo et al. (2023); Tang et al. (2024); Tholander & Jonsson (2023); Gmeiner et al. (2023); Kim & Maher (2023) Palani & Ramos (2024); Wu et al. (2024); Luo et al. (2024); Wang et al. (2024); Berni et al. (2024); Chandrasekera et al. (2024); Fu et al. (2024); Chompunuch & Lubart (2025); Choudhury et al. (2025); Shukla et al. (2025); Chaca Espinoza (2025); Yu, (2025)
		Visualization and Conceptual Development	Liao et al. (2020); Baidoo Anu & Ansah (2023); Fang et al. (2023); Wu et al. (2024); Bartlett & Camba (2024); Chompunuch & Lubart (2025)
	↻ Re-skilling (17)	*Working Routine*	Figoli et al. (2022); Tang et al. (2024); Tholander & Jonsson (2023); Barrett et al. (2024); Fu et al. (2024); Luo et al. (2024); Takaffoli & Makela (2024); Wu et al. (2024); Chen et al. (2025); Sattele et al. (2024); Shukla et al. (2025)
		Diversity of Ideas	Kim & Maher (2023)
		Design fixation	Baidoo Anu & Ansah (2023); Chaca Espinoza (2025); Chen et al. (2025); Sattele et al. (2024)
		Critical Thinking and Responsibility	Verganti et al. (2020); Shukla et al. (2025)
	▽ De-skilling (25)	*Feasibility and Superficial Idea Generation*	Tholander & Jonsson (2023); Barrett et al. (2024); Luo et al. (2024); Chompunuch & Lubart (2025); Shukla et al. (2025);
		Increased Cognitive Load and Dependency	Woinaroschy (2020); Baidoo Anu & Ansah (2023); Guo et al. (2023); Zhai et al. (2024); Chen et al. (2025); Zuhra (2025)
		Outcome Uncertainty	Yang et al. (2020)
		Social or Algorithmic Complacency	Gmeiner et al. (2023); Sattele et al. (2024)
		Technological Literacy and Challenges of Control	Jonsson & Tholander (2022); Liu et al. (2022); Berge & Plessis (2023); Smolansky et al. (2023); Tholander & Jonsson (2023); Gao et al. (2024); Lee et al. (2024)
		Critical Thinking and Creativity	Guo et al. (2023); Wang et al. (2024); Shukla et al. (2025); Zuhra (2025)

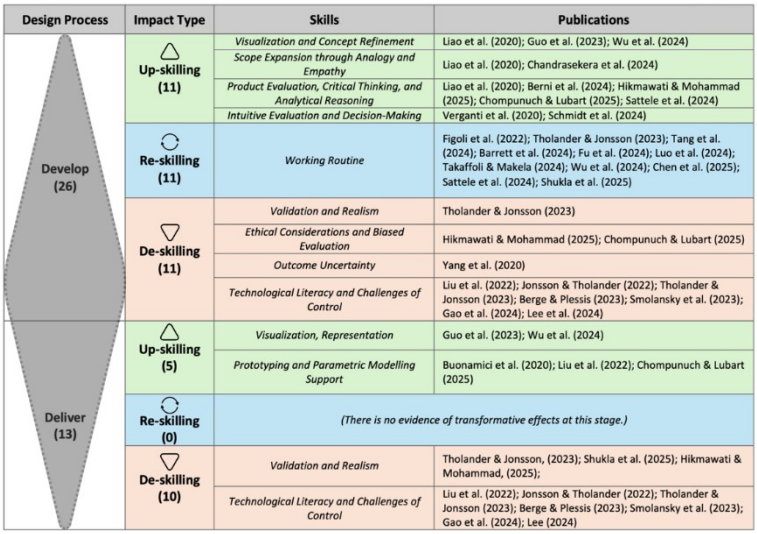
Figure 2 Publications on GenAI's Impact on Skills in the Discover and Define Stages

In the discover stage, 32 of the 40 analyzed articles included statements regarding the use of GenAI. Among these, 17 studies indicated that GenAI supports existing skills, while 22 suggested that some skills may weaken.The up-skilling findings were grouped into five main themes: data synthesis, contextual reasoning, analytical thinking and problem solving; conceptualization, brainstorming and need identification; inductive reasoning; creative thinking; and forming the right questions. The most emphasized themes were data synthesis, analytical thinking, and problem solving. The reskilling category included 13 studies showing that GenAI changes how designers define problems and conduct research. These studies revealed shifts in design routines, a decrease in unconscious development and creativity, and transformations in brainstorming and problem framing. Deskilling effects were identified in 22 studies, describing challenges such as increased cognitive load and dependency, limited reasoning within AI frameworks, biased or unreliable information, social or algorithmic laziness, lack of technological literacy and control, and a decline in critical thinking and creativity. These findings highlight the risk of designers becoming overly dependent on GenAI and losing control over their creative and analytical abilities.

In the Define stage, 37 out of 40 studies discussed the influence of GenAI on idea generation skills. Within the up-skilling dimension, 25 studies noted that GenAI strengthens creativity, lateral thinking, rapid idea generation, problem solving, decision making, visualization, and conceptual development. 17 studies were classified under reskilling, emphasizing how GenAI transforms designers' work routines, sources of inspiration, the novelty and diversity of ideas, and their sense of responsibility in critical decision making. Finally, 25 studies revealed deskilling effects, indicating risks such as superficial idea generation, lack of practical applicability, cognitive overload, dependency, output uncertainty, social and algorithmic laziness, limited technological literacy and control, and a decline in creativity and critical thinking.

Following these stages, the analysis proceeds with the Develop and Deliver phases, where GenAI's impact on design development, visualization, and implementation becomes more evident (Figure 3). In the Develop stage, 26 of the 40 reviewed publications discussed how GenAI relates to skills in this phase. The results show that supportive and limiting effects appear in similar numbers. Supportive findings from 11 studies indicate that GenAI helps with visualization, concept refinement, expanding ideas through analogy and empathy, product evaluation, analytical thinking, and intuitive decision making.

Transformative findings from another 11 studies note that GenAI changes work routines by reshaping designers' habits and ways of making decisions. Under constraining effects, 11 studies mention risks such as verification and accuracy problems, ethical concerns, output uncertainty, low technological literacy, and weaker critical thinking. Overall, GenAI supports analytical and evaluation skills but also creates limits in verification and control processes. In the Deliver stage, 13 studies referred to GenAI's influence in the final part of the design process. Among the supportive findings, 5 studies report that GenAI helps with visualization, prototyping, and parametric modeling. No transformative effects were found, while 10 studies under constraining effects point to verification, reliability, technological literacy, and control challenges.



Design Process	Impact Type	Skills	Publications
Develop (26)	△ Up-skilling (11)	*Visualization and Concept Refinement*	Liao et al. (2020); Guo et al. (2023); Wu et al. (2024)
		Scope Expansion through Analogy and Empathy	Liao et al. (2020); Chandrasekera et al. (2024)
		Product Evaluation, Critical Thinking, and Analytical Reasoning	Liao et al. (2020); Berni et al. (2024); Hikmawati & Mohammad (2025); Chompunuch & Lubart (2025); Sattele et al. (2024)
		Intuitive Evaluation and Decision-Making	Verganti et al. (2020); Schmidt et al. (2024)
	⟳ Re-skilling (11)	*Working Routine*	Figoli et al. (2022); Tholander & Jonsson (2023); Tang et al. (2024); Barrett et al. (2024); Fu et al. (2024); Luo et al. (2024); Takaffoli & Makela (2024); Wu et al. (2024); Chen et al. (2025); Sattele et al. (2024); Shukla et al. (2025)
	▽ De-skilling (11)	*Validation and Realism*	Tholander & Jonsson (2023)
		Ethical Considerations and Biased Evaluation	Hikmawati & Mohammad (2025); Chompunuch & Lubart (2025)
		Outcome Uncertainty	Yang et al. (2020)
		Technological Literacy and Challenges of Control	Liu et al. (2022); Jonsson & Tholander (2022); Tholander & Jonsson (2023); Berge & Plessis (2023); Smolansky et al. (2023); Gao et al. (2024); Lee et al. (2024)
Deliver (13)	△ Up-skilling (5)	*Visualization, Representation*	Guo et al. (2023); Wu et al. (2024)
		Prototyping and Parametric Modelling Support	Buonamici et al. (2020); Liu et al. (2022); Chompunuch & Lubart (2025)
	⟳ Re-skilling (0)	*(There is no evidence of transformative effects at this stage.)*	
	▽ De-skilling (10)	*Validation and Realism*	Tholander & Jonsson, (2023); Shukla et al. (2025); Hikmawati & Mohammad, (2025);
		Technological Literacy and Challenges of Control	Liu et al. (2022); Jonsson & Tholander (2022); Tholander & Jonsson (2023); Berge & Plessis (2023); Smolansky et al. (2023); Gao et al. (2024); Lee (2024)

Figure 3 Publications on GenAI's Impact on Skills in the Develop and Deliver Stages

4.2 Interview Findings

To compare and interpret the findings obtained from the literature review, semi structured interviews were conducted with six participants who actively use GenAI in their design processes. Participants were divided into two groups based on their level of experience: three novice designers (N1, N2, N3) and three expert designers (E1, E2, E3). During the interviews, participants were first asked questions about their professional background and frequency of GenAI use to collect demographic information (Table 1). The case study focuses on understanding how industrial designers with different levels of experience engage with GenAI in their professional practice. According to the demographic data presented in Table 1, all designers have been actively using GenAI tools in their design processes for at least two years. The participants described their current level of GenAI use in two ways: as "intensive users," who regularly and deeply integrate these tools into their workflows, and "occasional/low users," who engage with them more selectively or experimentally. All participants are currently working as professional industrial designers.

Table 1 Demographic Profile of Participants

Participant Profile	**Experience (Years)**	**Duration of GenAI Use (Years)**	**Frequency of Use**
N1	1	2	Occasional / Low
N2	2	3	Intensive
N3	1	3	Intensive
E1	12	3	Intensive
E2	11	3	Intensive
E3	8	2	Occasional / Low

Participants were then asked to retrospectively describe a project in which they used or collaborated with GenAI. During these narratives, they shared information about the types of GenAI tools they used, their purposes, the stages of the design process in which they were applied, and their overall experiences throughout these processes. In the following part of the interviews, participants were asked which skills were influenced by GenAI, how these effects appeared as supportive, transformative, or limiting, and how they were reflected in the final design outcomes. To enable comparison with the literature, a structure similar to the analytical framework used in previous studies was adopted. Accordingly, the statements were associated with different stages of the design process and categorized under three main themes: up-skilling, re-skilling, and de-skilling. Each participant's responses were coded and represented alongside the themes they supported, as shown in Table 2.

Table 2 Participants' Reflections on GenAI's Impact on Design Skills

Design Process	**Impact Type**	**Insights from Novice Designers**	**Insights from Expert Designers**
Discover	Up-skilling	Deepening research (N1) Expanding the problem area (N1; N3) Time management (N2)	Data validation and missing information detection (E1; E2; E3)
	Re-skilling	Stimulating exploration (N1)	Critical think ing and consultation (E3)
	De-skilling	Original idea generation (N1) Imagination (N2) Incorrect or incomplete information (N1; N2; N3)	Interpretation errors and gaps in meaning (E2; E3) Incorrect or incomplete information (N1; N3)
Define	Up-skilling	Creativity (N1; N2; N3) 3D Form Perception (N1; N2; N3) Time Management (N1; N2; N3) Generating alternative ideas (N1; N2; N3)	Problem definition (E3) Generating alternative ideas (E1; E2; E3) Analytical thinking and critical thinking (E1; E2) Time Management (E2; E3)
	Re-skilling	Critical thinking with feedback (N1; N3)	Interactive dialogue (E2; E3) Creating sketches and idea alternatives (E2; E3)
	De-skilling	Addiction (N1) Imagination (N1; N2) Rapid production (N3) Design Management (N1; N2; N3)	Evaluation of the idea (E1) Interpretation errors and gaps in meaning (E2; E3)
Develop	Up-skilling	Form alternatives (N1; N2; N3) Material experimentation (N2) 3D Form Perception (N1; N2; N3)	Creativity (E3) Form alternatives (E1; E; E3) Material experimentation (E1; E2) Analytical and critical thinking (E1) Design Management (E1; E2; E3)
	Re-skilling	Form creation (N1; N3) Critical thinking with feedback (N1; N3)	Creating sketches and idea alternatives (E3)
	De-skilling	Creativity and imagination (N1) Always the same visual output (N1; N2)	Cognitive load and decision making (E1; E3)

		Cost and Time (N1)	
Deliver	Up-skilling	Technical information (N1) Visualization (N1; N3) Text editing (N1; N2; N3)	Visualization (E1; E2; E3) Data validation (E1)
	Re-skilling		Expression Quality (E1; E2)
	De-skilling	Data incompatible with production (N1; N3)	Data incompatible with production (E1; E2; E3)

4.3 Up-skilling

All participants reported using GenAI during the discover stage. Novice designers used it to expand the problem space and gather ideas, while expert designers valued its speed in accessing relevant information. Overall, GenAI was seen not as a replacement for traditional research but as a supportive tool that fills information gaps and deepens understanding.

> "After conducting research, I consult AI to get some ideas. It usually provides information about international sources much faster; I often struggle to access these myself." (N1)

In the define stage, both groups noted that GenAI supported idea generation and time management, enhancing idea diversity and overall efficiency. Novice designers found it boosted their creativity and 3D form perception, while expert designers highlighted improvements in analytical and critical thinking, leading to a more systematic problem solving approach.

> "Through AI, I was able to generate alternative sketches and quickly visualize different forms. Ideas that would normally come to mind weeks later appeared at the very beginning of the process." (E3)

In the develop stage, participants emphasized expanded opportunities for material exploration and experimental thinking, while the earlier focus on idea variety evolved into exploring form alternatives. Expert designers noted a shift from time management toward design management, highlighting the growing importance of managing the process holistically rather than simply saving time.

> "Seeing product suggestions through material alternatives accelerates me and helps me think more about form and surface quality." (N2)

Finally, in the deliver stage, both groups emphasized the significance of visualization skills. However, novice designers stated that they relied on GenAI tools not only for visualization but also to improve their verbal and written expression, as they often felt less confident in articulating their project outcomes effectively.

4.4 Re-skilling

In the discover stage, most participants reported no major transformation in their skills. In the define stage, however, both groups especially expert designers observed shifts in idea development, sketch based work, and communication, noting that GenAI's interactive dialogues reshaped how they developed ideas. In the develop stage, novice designers

indicated that GenAI transformed their form generation methods and encouraged new ways of thinking through feedback driven interaction. By the deliver stage, expert designers highlighted that GenAI's enhanced visual and presentation capabilities had redefined their routines, improving both confidence and communication quality in project presentation.

4.5 De-skilling

At this stage, participants expressed concerns that using GenAI for visual ideation or concept generation rather than for research at the beginning of the design process might limit creativity and imagination. In the discover phase, both participant groups also noted that when used for research, GenAI could sometimes produce inaccurate or distorted information. Moreover, participants stated that relying entirely on GenAI for idea generation might lead to gaps in meaning and a weakened design context, potentially hindering the designer's individual development.

> "AI is like a baby that knows everything but doesn't understand you; if you don't describe clearly enough, it can distort the task based on its own assumptions." (E1)

> "…Sometimes it presents general statements without citing sources, so I had to take my own notes and verify them with reliable references." (N2)

In later stages of the process, novice designers reported difficulty in managing their workflow while using GenAI. Specifically, they found it challenging to maintain control when form variations changed continuously during sketch uploads. Expert designers, on the other hand, emphasized that GenAI sometimes generated irrelevant or meaningless ideas. Although many participants acknowledged that GenAI brought speed and efficiency to the process, some particularly novices pointed out that excessive speed could become a disadvantage.

> "In some parts of the process, I also experienced the downside of 'too much speed.' The system works fast, but I still think slowly. So, I can't always analyze the results immediately." (N3)

During the develop phase, novice designers noted that when the process was not well managed, GenAI tended to produce repetitive or similar outcomes. They also stated that the constant generation of visual alternatives forced them into continuous evaluation, which increased cognitive load and made decision making more difficult. In the final deliver phase, all participants emphasized that since GenAI does not provide production oriented outputs, it may lead to challenges in implementation during the final stages of the design process.

5. Discussion

In this section, a comparative analysis of the literature review and interview findings was conducted to illustrate how skills evolve throughout the design process. Accordingly, Figure 4 was developed, presenting the stages of the design process together with three main categories of skill influence: up-skilling, re-skilling, and de-skilling. These categories are visually distinguished in the graphic through specific color codes and icons.

Design Skills	Discover	Define	Develop	Deliver
Creativity and Inspiration	Expanding ideas, exploring different directions. ▲	Generating alternative ideas, thinking quickly ▲	Experimental form searches, visual diversity. ↻	Limited effect
Analytical Thinking and Problem Solving	Data synthesis, information fusion. ▲	Systematic decision making. ▲	Reformulating process management skills ↻	Verification and control difficulties. ▼
Visualization and Expression	Limited effect	Visual idea generation. ▲	Variations in form, surface and material. ▲	Presentation quality and narrative power ▲
Critical Thinking	Biased information, accuracy issues. ↻	Superficiality, cognitive laziness. ▼	Obligation to comment on recurring results ▲	Limited effect
Time and Process Management	Quick access to information. ▲	Increasing the speed of idea generation. ▲	Difficulty managing alternatives ▼	Limited effect
Empathy and Contextual Thinking	Understanding user needs ▲	Reframing the problem ↻	Detachment from production reality. ▼	Limited effect
Communication Skills	Limited effect	Limited effect	Change in visual language quality. ↻	Increasing the power of verbal and visual presentation. ▲

up-skilling ▲ re-skilling ↻ re-skilling ▼

Figure 4 Comparative Overview of Skill Changes in Literature and Interview Findings

5.1 Supporting Access to Information and Creativity

In the initial discover stage, findings from both the literature and interviews show a notable level of consistency both indicate that GenAI tools are mainly used to broaden the research scope, speed up information access, and support conceptual thinking. Participants similarly noted that these tools help collect data and explore the problem space more efficiently. At this findings GenAI, supports creativity, analytical thinking, empathy, and time management, yet it requires a careful balance with critical reflection. Without this balance, creativity risks becoming superficial and uniform. Studies also warn that issues of information reliability and bias can increase cognitive load and weaken critical reasoning (Hikmawati & Mohammad, 2025). Interview findings partly confirm these concerns. Novice designers showed more hesitation and concern, not overreliance, as their limited experience made them less confident in using GenAI effectively. Experienced designers, by contrast, approached it with greater control, seeing it as a supportive assistant rather than a risk. This indicates that designers' attitudes toward GenAI largely depend on their level of experience and confidence.

5.2 Idea Development and Process Transformation

In the Define and Develop stages, both the literature and interview findings reveal that GenAI has significantly transformed how designers generate, evaluate, and manage ideas. Previous studies indicate that it enhances creativity, analytical reasoning, and decision making, while enabling the development of diverse ideas in a shorter time (Tang et. al., 2024; Luo, 2024). Participants similarly emphasized that GenAI increases idea diversity and makes problem solving more systematic. Notably, the ability to produce and vary visuals emerges as the most influential factor in skill development across both sources. However, while high quality visuals can strengthen 3D perception, they may also lead designers to become captivated by the image itself. This "visual fixation" poses a risk, particularly for novice designers whose critical thinking skills are still developing, as they may grow overly attached to generated outputs and struggle to evaluate them objectively. The literature also warns that continuous idea generation can increase cognitive load and lead to superficial thinking (Shukla, 2025). Interviews support this, as participants reported that the abundance

of alternatives made evaluation and decision making more challenging. Expert designers noted difficulties in managing the process when vast numbers of related or unrelated visuals were generated, creating additional cognitive pressure and affecting both creativity and critical reasoning. Conversely, and unlike the literature, novices appeared to adapt better to the process through 3D form generation and material experimentation, which acted as a catalyst for their self efficacy and critical thinking. For experts, GenAI provided a means to save time and focus more deeply on product and experience oriented decision making.

5.3 Visualization and Production Reality

In the Deliver stage, the influence of GenAI is most evident in visualization, presentation, and communication skills. Both the literature and interview findings indicate that GenAI enables designers to represent their ideas more effectively (Wu, 2024; Liu, 2022). High resolution visuals and rapid prototyping tools enhance expressiveness while saving time in the presentation phase. However, this stage also presents certain limitations. Participants noted that GenAI generated visuals often fail to fully correspond with real world production constraints, leading to difficulties in verification and practical implementation. This mismatch may weaken decision making and technical evaluation abilities, particularly among novice designers. Overall, the findings suggest that while GenAI strengthens presentation and communication capabilities, it may simultaneously reduce designers' awareness of production context and practical feasibility.

6. Conclusion and Limitation

This study examined the influence of GenAI on the evolving skills of industrial designers across different stages of the design process. The findings reveal that the impact of GenAI varies significantly depending on the designer's level of experience. Novice and expert designers approach and utilize GenAI in distinct ways, which in turn shapes both the nature and direction of skill development. Expert designers tend to perceive GenAI as a research assistant that optimizes processes and accelerates decision making, whereas novice designers view it more as a mentor or instructor that supports learning and provides guidance throughout the process. The comparative analysis of literature and interview data suggests that GenAI may support creativity, analytical reasoning, and visualization in design processes, while also potentially influencing designers work routines and cognitive strategies. However, despite its potential to accelerate processes and generate alternatives, GenAI also introduces challenges such as increased cognitive load, information reliability issues, and a reduced awareness of production context.

This study serves as a preliminary investigation based on a limited number of interviews. Future research should conduct in depth studies with both novice and expert designers to gain a more comprehensive understanding of how GenAI driven transformations influence skill development and professional identity.

Acknowledgements: The author used OpenAI's ChatGPT (GPT-5, 2025) to assist with grammar editing and improving the clarity of English expression. No part of the paper's content, analysis, or conclusions was generated by AI; all intellectual contributions, interpretations, and arguments are entirely the author's own.

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