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Applied Artificial Intelligence
An International Journal

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/uaai20

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To cite this article: Younjung Hwang, Seokjun Jeong & Yi Wu (2025) Artificial Intelligence in Design Process: An Analysis Using Text Mining, Applied Artificial Intelligence, 39:1, 2453782, DOI: 10.1080/08839514.2025.2453782

To link to this article: https://doi.org/10.1080/08839514.2025.2453782

Published online: 19 Jan 2025.

APPLIED ARTIFICIAL INTELLIGENCE
2025, VOL. 39, NO. 1, e2453782 (22 pages)
https://doi.org/10.1080/08839514.2025.2453782

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Artificial Intelligence in Design Process: An Analysis Using Text Mining

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ABSTRACT
The progress of Artificial Intelligence (AI) offers modern designers opportunities to explore innovative design processes. Particularly, generative AI that creates images and other content through text can contribute to the creative processes in various design fields such as graphics, industrial design, UX, and fashion. However, there is a lack of comprehensive research on AI's role and applications throughout the entire design process, and current papers often employ qualitative methods such as interviews and case studies. Therefore, this paper aims to quantitatively analyze experts' views on AI's utilization in the whole design process through text mining of literature. The researchers selected 126 papers through scientific databases such as ScienceDirect, Web of Science, and utilized the keyword matching method to extract the frequency of keywords for each stage of the design process – Research, Ideation, Mock-up, Production, and Evaluation. Through text mining, research findings indicate that AI is predominantly discussed in the later stages of design, particularly in the production process, while its use in the mock-up stage is perceived to be low. Additionally, distinct differences in AI use across design disciplines were identified: graphics focusing on ideation; UX on evaluation; and fashion on production.

ARTICLE HISTORY
Received 27 February 2024
Revised 26 June 2024
Accepted 9 January 2025

Introduction

The advancement of Artificial Intelligence (AI) offers modern designers opportunities to explore new creative methods and collaborate more effectively (Verganti, Vendraminelli, and Iansiti 2020). AI is transforming design problem-solving approaches by automating traditional tasks (Xuan 2023); reducing defects in the production stage; and efficiently accelerating production speed (Bhagat 2023). In particular, the recent emergence of generative AI, capable of learning patterns from databases and generating results based on user demands (Saadi and Yang 2023), exhibits the ability to create diverse forms of data like text, images, voice, and video. Such innovative technology has the potential to transform traditional design

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processes in various fields such as graphics, industrial design, UX, fashion, and more. The design process involves various stages including research, ideation, prototyping, evaluation, and encompasses the development of products, systems, services, or experiences (Chen and Terken 2022). Currently, AI has the potential to assist in such design creation processes, enabling the development of superior products that surpass initial performance levels (Abukmeil et al. 2021; Gui et al. 2023). Researchers have utilized generative AI, including large language models like Chat GPT, as a research and brainstorming tool in the design process' research and data collection stages (Abdallah and Estévez 2023). These tools provide diverse product stylings based on customer emotions during the prototype creation and production phases (Bilgram and Laarmann 2023). Additionally, such models prove useful in creating automated frameworks for optimizing various design options for engineering performance (Oh et al. 2019). Other studies have explored the potential of generative AI as an evaluation model for collaborative concept measurement with designers in the early stages of the design process (Demirel et al. 2023).

While individual studies explore the functionalities and potential contributions of AI in design, there is a lack of comprehensive research on AI's role and applications throughout the entire design process. Existing studies often concentrate on the early stages of design, employing methods such as literature reviews, expert interviews, and case studies. While these approaches offer in-depth insights, they may be influenced by researchers' biases or experiences, limiting the objectivity of analyzing and validating the ongoing discussions about AI utilization.

To address this dearth, this study aims to comprehensively analyze expert discussions on the utilization of AI throughout the entire design process with the use of text mining. Text mining involves a range of NLP techniques to extract insights from textual data, extending beyond traditional NLP boundaries. It focuses on deriving valuable information from unstructured or semi-structured text formats, utilizing AI technologies like machine learning to automate data processing and generate actionable insights (Akilan 2015, Naik, Mythreyan, and Seema 2022). This has proven to be an effective new approach for macroscopically analyzing the existing research landscape (Antons et al. 2020). Given the current state of individual research on AI-driven design methodologies in various fields, this research method can provide a more comprehensive framework for understanding the role and potential applications of AI in the creative process of design. The research addresses the following questions:

RQ1. How is AI technology discussed in the design creation process?

RQ2. Are there differences in AI utilization methods across different design disciplines in the design creation process?

RQ3. How is the role of AI required in the design process of each discipline?

The paper is structured as follows: a) Section 2 reviews existing research on the design process, and discusses the significance of this study; b) Section 3 introduces the research method -text mining- used in this paper, specifically the keyword matching method; c) Section 4 presents the analysis, results, and discussion; and d) Section 5 summarizes the study's limitations, contributions of the approach, and implications.

Literature Review

Stages of the Design Process

The design process represents the stage undertaken by creators to develop and concretize a product, service, or idea. This process encompasses systematic planning and execution to achieve the creator's goals and vision, outlining a series of steps in bringing creative ideas to fruition. Perspectives on the procedural realization of design, however, vary among researchers. Nevertheless, a common initial stage identified by most researchers is the "Research" phase, where designers explore problems that require resolution (Arntson 2011). In this stage, problems are analyzed, recognized, and defined (Asimow 1962; Hanks, Belliston, and Edwards 1977), and consumer demands and needs are accurately understood (French 1999). Researchers in this phase primarily collect data, information, and materials (Archer 1968; Schenk 1991), appropriately analyze them (French 1999; Snider, Culley, and Dekoninck 2013). This research process is commonly referred to as the initial design stage within the design process (Lawson et al. 2016), or the first concept generation stage (Hitchcock, Haines, and Elton 2004).

The subsequent step, the "Ideation" process, is also an early stage in design. In this procedure, designers aim to solve problems through the generation of numerous ideas and concepts (Cross 1997). Many researchers have defined this as conceptualization, wherein designers create design concepts appropriate for problem-solving during this stage (French 1999; Howard, Culley, and Dekoninck 2008). Designers may engage in drawing or sketching (Bonnardel et al. 2018) or freely generate ideas through thumbnail creation (Arntson 2011).

The mid-stage of design, the "Mock-up" process, can be explained as the creation stage of a prototype, involving the direct testing and fabrication of concretized ideas into tangible samples (Nini 2006). In this stage, the produced samples are reevaluated (Hitchcock, Haines, and Elton 2004), modified (Schenk 1991), and solutions to identified issues are sought (De Rooij et al. 2021).

Upon completion of the Mock-up process, the subsequent post-design stage is the "Production" phase (Bonnardel et al. 2018; De Rooij et al. 2021). In this stage, product manufacturing is executed (Howard, Culley, and Dekoninck 2008; Snider, Culley, and Dekoninck 2013), and ideas materialize through physical media (Mader and Eggink 2014). During this phase, designers enhance details (Arntson 2011; French 1999), explore collaborative partners and suppliers (Schenk 1991), and address numerous issues inherent in the actual production process (Schenk 1991).

The final stage of the design process is the "Evaluation" phase. This involves reviewing the produced product and undergoing a review process to receive feedback (Archer 1968; Cross 1997; French 1999). If issues arise, rapid redesign is necessary (Hitchcock, Haines, and Elton 2004), and efforts are made to modify, advance, and improve the next design through continuous communication with customers (Asimow 1962; Cross 1997).

A comprehensive assessment of the literature review from previous researchers yielded similarities in the creative design process. As such, it can be fundamentally classified into five stages: research, ideation, mock-up, production, and evaluation. Each design stage involves specific tasks, objectives, and requirements. The design process may also be broadly classified into the early stages (research, ideation); the mid-stages (mock-up); and the later stages (production, evaluation). These processes iterate and interconnect, visually materializing products, services, and experiences. In this study, however, analysis is based on the utilization status of AI in design through the five stages of the design process as described above.

AI Applied to the Design Process

Generative AI, centered around large language models (LLMs) like ChatGPT, is currently being practically utilized across various industries to generate new content such as images, audio, text, and videos (Brynjolfsson, Li, and Raymond 2023). For example, in ChatGPT 4, integration with DALL-E 3 enables the conversion of text to images, and through the Text-to-Video model, SORA, it is possible to create realistic video clips with prompts only (Qin et al. 2024). Such technologies are involved in various creative content generation applications, including advertising campaign creation for marketers (Bulut and Arslan 2024), sound generation for composers (Patil et al. 2023), arrangement of color painting for artists (Lu et al. 2023), and content creation for educators (Leiker et al. (2023). In the field of design, generative AI is emerging as an innovative technology that has the potential to revolutionize design tools. Researchers are exploring the effective integration of AI and design by rapidly integrating data and streamlining the design process to stimulate creative activities (Lai, Chen, and Yang 2023). For instance, researchers have utilized Generative Pre-trained Language Models (GPT) to derive concepts and ideas in design (Vlah, Žavbi, and Vukašinović 2020; Zhu and Luo 2023; Zhu, Zhang, and Luo 2023), or conduct research on design solutions (Gill 2023). The role of AI in the early stages of design has been explored diversely. Furthermore, in the later stages of design, AI has been employed to develop work frames that automatically evaluate designs (Yoo et al. 2021) or to enhance digital prototypes through feedback (Bilgram and Laarmann 2023).

Text Mining: Structural Analysis of the Design Process

There are indeed many studies that have examined the detailed applications of AI in various design processes. However, as mentioned previously, there is a current inadequacy in the structural analyses of the role of AI throughout the entire design process. While there exist studies exploring the integration of design processes with AI, they often focus on specific disciplinary areas, such as investigating the role of AI in the early stages of design processes (Jana, Yang, and Saadi 2023); exploring the role of AI in idea generation processes within the field of UX (Hwang 2022); or researching the application of AI in engineering design and product conceptualization processes (Yüksel et al. 2023). These studies primarily concentrate on specific disciplinary areas in the early stages of the design process. Furthermore, most of these studies have derived research findings through qualitative research methods such as case studies, literature reviews, and expert interviews. While such research methods allow for an in-depth understanding of various discussions related to AI, there exists a limitation where research results can be influenced by researchers' experiences and biases.

To address such inadequacies, this research aims to analyze existing studies with the use of text-mining techniques to extract more objective and structural research results. Text mining utilizes various NLP techniques to extract insights from textual data, extending beyond traditional NLP boundaries, and employs AI technologies to automate data processing (Akilan 2015, Naik, Mythreyan, and Seema 2022). Text mining refers to the process of extracting interesting and non-trivial patterns or knowledge from text documents (Akilan 2015), and it is a research method that involves transforming text documents into an intermediate form to deduce patterns or knowledge from that form (Tan 1999). Furthermore, text mining is increasingly being utilized in systematic literature reviews (SLRs) to automate various stages, including research selection, quality assessment, data extraction, and synthesis. One practical application is using TF-IDF to automatically classify document relevance across multiple documents. This involves considering both the frequency of words within documents and their frequency across other documents, enabling automated systematic literature reviews (Van Dijk et al. 2023). These methodologies enable researchers to validate the potential applications and possibilities of AI, while also providing new perspectives to complement existing research, which has mainly focused on the initial stages of design.

As a first step in identifying foundational document collection, researchers gather relevant papers and databases on AI from sources such as ScienceDirect, Scopus, Mendeley, ProQuest, SAGE Journals, SpringerLink, and Google Scholar. Subsequently, text mining techniques are applied to comprehensively analyze discussions in the research, ideation, mock-up, production, and evaluation stages. Finally, the perspectives of each design discipline expert (Visual, Industrial, Fashion, UX) are examined to compare and integrate relevant discussions.

Methodology

The focus of this study is to analyze, through text mining, how design experts perceive the utilization of generative AI in design. Specifically, the objective is to understand the extent (frequency) of mentions in expert-generated content related to generative AI with regard to the five stages of the design process. For instance, a high frequency of mentions in expert-authored content about generative AI for a specific stage indicates that the application of generative AI is relatively more crucial in that stage. The technical process of analyzing the mention frequency for each stage in design experts' writings can be illustrated in Figure 1.

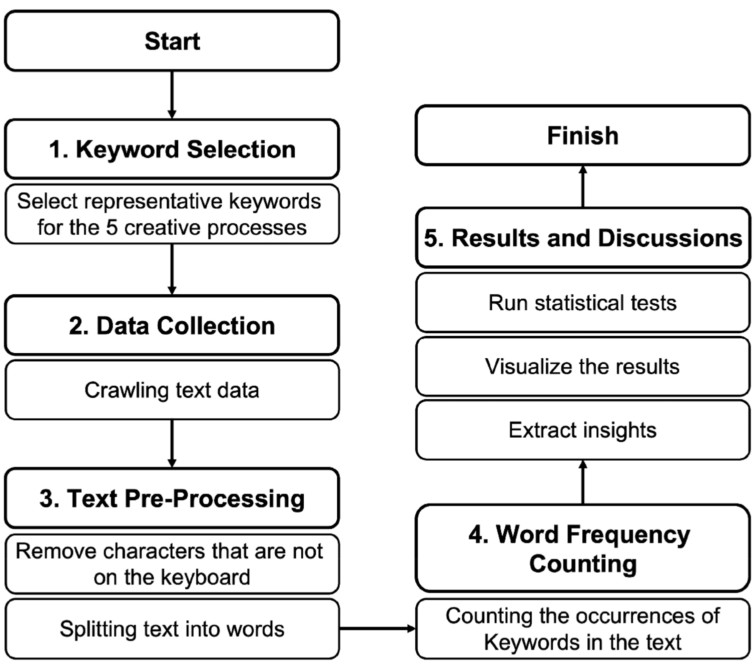

Figure 1. Workflow of overall analysis.

This study utilized Python, incorporating libraries that offer state-of-the-art NLP technology for analysis. The analysis was conducted in November 2023, and the data and source code used in this analysis can be accessed at https://github.com/8orrin9/textmining/tree/Design-AI (verified on April 20, 2024).

Creating a Keyword List

To select the keywords, the authors followed a three-stage process. First, the authors read papers related to the design process and refined the keywords through brainstorming. Then, the authors formed a group of experts to evaluate the chosen keywords. Finally, the experts cross-verified the keywords to derive the final set of keywords. The keyword selection process is shown in Figure 2.

The specific process is as follows. In the first process, three of our authors collected data from papers available on ScienceDirect, SpringerLink, Web of Science, Scopus, IEEE Xplore, ACM Digital Library, and Google News up to 2023. Specifically, the authors selected 69 papers related to the creative process in the arts, 35 papers on the overall design process, and 126 papers on the creative processes in graphic, industrial, UX, and fashion design, totaling 230 papers. Then, the authors read these papers and refined the keywords for each design stage (Research, Ideation, Mock-up, Production, Evaluation) through brainstorming. As a result, 30 keywords were selected for the Research stage, 33 for the Ideation stage, 32 for the Mock-up stage, 33 for the Production stage, and 30 for the Evaluation stage. This represents the initial set of automated keyword extraction.

In the second process, the authors formed a new expert group consisting of two experts from each of the fields of graphic, industrial, fashion, and UX design, totaling eight experts, to conduct a cross-verification process. The expert group was made up of professionals from academia and the design

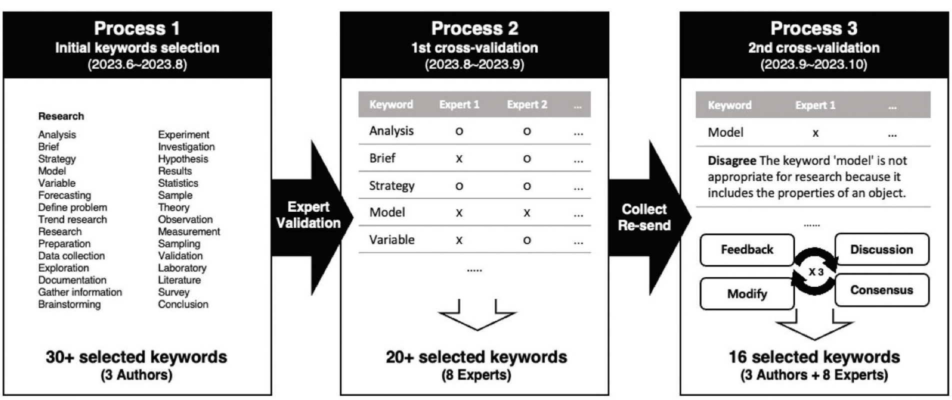

Figure 2. Process of the keyword selection.

industry, each with over five years of experience in their respective fields and sufficient experience in the design process. The authors presented the initial list of keywords to the experts in writing. And the experts marked the keywords they believed were related to the respective design stages based on their experience and subjective judgment. The authors then received the checklists from the experts, collecting all keywords that were marked at least once. As a result, 22 keywords were extracted for the Research stage, 21 for the Ideation stage, 25 for the Mock-up stage, 26 for the Production stage, and 20 for the Evaluation stage.

In the third process, experts conducted a secondary cross-validation of opinions using the Delphi Method, exchanging written feedback. This method involves gathering opinions from at least five experts over 2–3 rounds, synthesizing feedback to unify the expert group's perspectives and achieve consensus (Linstone and Turoff 2002). The authors re-sent the list of keywords collected in the second stage to the experts. If experts disagreed the keyword of the design process, they were instructed to mark it as "disagree" and provide reasons for their decision. When experts' opinions did not align, the authors compiled the keywords and justifications and forwarded them to all experts. This process was repeated three times. During the written discussions, keywords that continued to fail consensus were either removed or revised. As a result, consensus among experts was achieved for 16 keywords at each stage, as depicted in Table 1.

Data Collection and Pre-Processing

The materials selected for analysis using the keywords identified for each stage of the design process were extracted from papers, newspaper articles, and interviews in the graphic, industrial, fashion, and UX fields. This was deemed necessary to comprehensively understand the application of AI in the design

Table 1. Keywords for each of the 5 sub-factors of the design process model.

1. Research	2. Ideation	3. Mock-up	4. Production	5. Evaluation
Forecasting	Idea development	Prototype	Realization	Verification
Planning	New idea	Modeling	Industry	Feedback
Define problem	Incubation	Sample	Embodiment	Revision
Trend research	Synthesis	Simulation	Manufacturing	Refinement
Research	Ideation	Mock-up	Production	Evaluation
Analysis	Problem-solving	3D model	Mass-production	Validation
Preparation	Conceptualization	Blueprint	Automation	Examination
Data collection	Insights	Render	Explication	Judgment
Scoping Documentation	Illumination	Wireframe	Optimization	Review
Gather-information	Solution	Rough	Sales	Monitoring
Brainstorming	Imagination	Dummy	Streamline	Testing
Strategy	Mind mapping	Demo	Market	Prove
Survey	Inspiration	CAD	Distribution	Reflection
Construction	Generation	Heatmap	Output	Grading
Organization	Inventing	Thumbnails	Print	Score
	Intuition	Draft	Supply	Assessment

process from various perspectives. It was considered valid to include both expert qualitative interviews from newspaper articles and quantitatively analyzed data. Hence, this study extracted papers from ScienceDirect, SpringerLink, Web of Science, Scopus, IEEE Xplore, ACM Digital Library, and Google News up to 2023. Consequently, a total of 126 studies were analyzed, comprising 23 papers related to the creative process of graphic design; 36 related to industrial design; 31 related to fashion design; and 36 related to UX design.

Afterward, text pre-processing tasks were performed. It is a crucial step that can significantly impact the final results of text mining. The collected text data had all non-alphabetic characters replaced with spaces. Special characters, numbers, and punctuation were removed, leaving only alphabetic characters. The text was then tokenized into words based on whitespace. A frequency-based matching method was later employed for text analysis after the pre-processing stage. This method counts the frequency of appearance of prepared keywords in the text.

The pre-processing procedure was uniformly applied to the text data collected from the graphic, industrial, fashion, and UX fields. A total of 4006 sentences were obtained for vectorization in the graphic design field; 3251 sentences in the industrial design field; 4043 sentences in the UX design field; and 3020 sentences in the fashion design field. Tables 2, 3, 4, and 5 display the first five and last five sentences of the sentence lists. Subsequently, researchers analyzed the text using the frequency-based matching method.

Matching Keyword Method

The keyword matching method is one of the most fundamental analysis methods for comparing texts, where a score of 1 point is counted if the words in the document match exactly with the keywords in the keyword list. In this study, the words obtained through the text pre-processing were arranged as rows, and the design-stage keywords were arranged as columns to form a dataset filled with zeros for all values. Programming was then

Table 2. Pre-processing sentences from the “AI for graphic design process” articles.

No	Article	Before Pre-processing	After Pre-processing
0	The Impact of AI on the Graphic Design Industry	Graphic design is one of the fields that has been most impacted by the development of artificial intelligence.	graphic design is one of the fields that has been most impacted by the development of artificial intelligence
1		According to statistics provided by Forbes, AI is expected to see an annual growth rate of 37.3% from 2023 to 2030.	according to statistics provided by forbes ai is expected to see an annual growth rate of from to
...	...	...	...
4005	Future implications of AI in graphic design	Expands the boundaries of traditional graphic design.	expands the boundaries of traditional graphic design
4006		Complex designs, interactive visuals, and immersive experiences.	complex designs interactive visuals and immersive experiences

Table 3. Pre-processing sentences from the “AI for industrial design process” articles.

No	Article	Before Pre-processing	After Pre-processing
0	How AI is changing the game for Industrial Designers	AI is an umbrella term used to describe a range of technologies that enable machines to perform tasks that would typically require human intelligence.	ai is an umbrella term used to describe a range of technologies that enable machines to perform tasks that would typically require human intelligence
1		It involves using computer algorithms to simulate intelligent behavior and decision-making based on large sets of data.	it involves using computer algorithms to simulate intelligent behavior and decision making based on large sets of data
. . .	. . .	. . .	. . .
3250	The Role of AI in Modernizing Industrial Design and Manufacturing	Issues such as data privacy, security, and ethical considerations must be carefully addressed to ensure that the benefits of AI are realized without compromising the values and principles that underpin our society.	issues such as data privacy security and ethical considerations must be carefully addressed to ensure that the benefits of ai are realized without compromising the values and principles that underpin our society
3251		By working together, businesses, governments, and educational institutions can harness the power of AI to drive sustainable growth and prosperity for all.	by working together businesses governments and educational institutions can harness the power of ai to drive sustainable growth and prosperity for all

Table 4. Pre-processing sentences from the “AI for UX design process” articles.

No	Article	Before Pre-processing	After Pre-processing
0	AI in User Interface Design and Evaluation	The task of designing and testing user interfaces (UIs) has seen significant changes in the past years.	the task of designing and testing user interfaces uis has seen significant changes in the past years
1		Even when user-aware methods, like user-centered development,1 have been around for decades, the switch to these methodologies is relatively recent.	even when user aware methods like user centered development have been around for decades the switch to these methodologies is relatively recent
. . .	. . .	. . .	. . .
4042	The Power of AI in Enhancing the UX Design Process	AI and User Experience design inevitably interlink.	ai and user experience design inevitably interlink
4043		We hope this article has given you a clear overview of these issues and how UX may evolve thanks to the advances in AI.	we hope this article has given you a clear overview of these issues and how ux may evolve thanks to the advances in ai

Table 5. Pre-processing sentences from the “AI for fashion design process” articles.

No	Article	Before Pre-processing	After Pre-processing
0	Revolutionizing Fashion Design with AI	AI and its Impact on Fashion Design	ai and its impact on fashion design
1		AI has become increasingly prevalent across various industries, including the fashion industry.	ai has become increasingly prevalent across various industries including the fashion industry
. . .	. . .	. . .	. . .
3019	Enhancing Creativity in Fashion: The Role of AI Fashion Design Generator	It is expected that within the next decade, there will be various advanced technologies paving their way into this field.	it is expected that within the next decade there will be various advanced technologies paving their way into this field
3020		Fashion companies can leverage such tools to bring out more exceptional and exclusive designs personalised according to individual preferences while also being environmentally sustainable at large-scale production levels.	fashion companies can leverage such tools to bring out more exceptional and exclusive designs personalised according to individual preferences while also being environmentally sustainable at large scale production levels

implemented to replace 0 with 1 in each cell if the word listed in the corresponding row and column matched. Table 6 displays the results of applying the keyword matching method to the text in the graphic field.

Next, the sum of the ones listed in each dataset was calculated for each stage. In other words, the total number of occurrences of keywords for a specific stage in the text was computed. Formula (1) represents the equation for calculating the frequency for each stage in the text using the keyword matching method.

$$F_j = \sum_{i=1}^{in} \sum_{k=1}^{kn} Count_{ijk} (\mathrm{i} = 1, \ldots, \mathrm{in}, \mathrm{j} = 1, 2, 3, 4, 5, \mathrm{k} = 1, 2, \ldots, \mathrm{kn}(13\mathrm{or}14)) \tag{1}$$

In this equation, $\mathrm{Count}_{\mathrm{ijk}}$ represents the result (0 or 1) of applying the "matching keyword method" to the graphic field text, indicating each cell's elements in Table 2. **Fj** refers to the sum of matching frequencies of keywords belonging to the jth stage. The ***k*** signifies the keywords belonging to each stage, and the number of these keywords is ***kn*** (13 or 14). Finally, ***i*** represents a word in the text of each area, and its quantity is denoted as ***in***. The calculation in equation (1) is repeated in the same manner, not only in the graphic area but also in the industrial, fashion, and UX areas.

Results and Discussion

To assess how the selected keywords for each stage of the design process were mentioned in the design domain, the keyword matching method was applied. However, there was a need to address the concern that the amount of text crawled from each design field varied. This discrepancy posed a challenge as the frequency of matched keywords inevitably increased with a larger amount of text. To ensure more accurate analysis results, we applied a simple standardization process. Initially, the total number of words composing the text collected for each field was calculated. Next, the ratio of the total number of words in each field to the existing analysis results was computed and then adjusted to a natural number range. The standardized results are presented in Table 7.

Table 6. Graphic-dataset for matching keyword method.

Graphic	Research Forecasting	Research Brief	… …	Production Streamline	… …	Evaluation Prove	Evaluation Reflection
how	0	0	…	0	…	0	0
is	0	0	…	0	…	0	0
…	…	…	…	…	…	…	…
and	0	0	…	0	…	0	0
streamline	0	0	…	1	…	0	0
routine	0	0	…	0	…	0	0
…	…	…	…	…	…	…	…
graphic	0	0	…	0	…	0	0
design	0	0	…	0	…	0	0

Table 7. Standardized keyword occurrence frequency by design process.

	Research	Ideation	Mock-up	Production	Evaluation
Graphic	560	738	25	3232	305
Industry	271	451	120	3697	1232
UX	544	163	245	1687	2667
Fashion	1315	554	35	8724	0

In the Graphic field, the occurrence frequency of keywords appears in the following order: Production – Ideation – Research – Evaluation – Mock-up. In the Industry field, the sequence is Production – Evaluation – Ideation – Research – Mock-up, while in the UX field, it is Evaluation – Production – Research – Mock-up – Ideation. In the Fashion field, the sequence is Production – Research – Ideation – Mock-up – Evaluation. These findings differ from the contents of previous research, which focused mainly on the early stages of design (Ideation, Research) for the utilization of AI. The actual results from text mining analysis emphasize the application of AI in the later stages of design (Production, Evaluation). To effectively compare the occurrence frequency of keywords across design disciplines, the frequencies listed in Table 7 were normalized for each field. This normalization involved dividing the frequency of each process in a field by the total frequency of that field. The normalized occurrence frequency of keywords is illustrated in Bar Plot format in Figure 3.

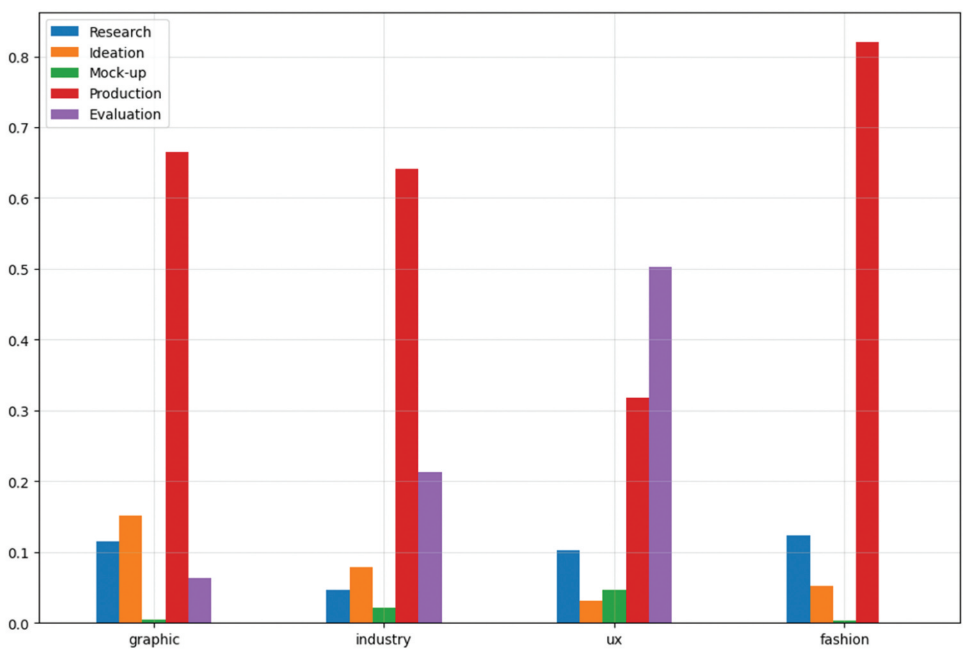

Figure 3. Standardized keyword occurrence frequency by design process.

Thus, based on the above results and subsequent analysis, the research questions initially raised can be answered as follows.

Q1: Firstly, the findings indicate that AI is predominantly focused on the later stages of the design process (Production and Evaluation), with significantly fewer mentions (Independent two-sample t-test, $\bar{X}_{later} = 2693$, $\bar{X}_{initial} = 574.5$, $S_{later} = 2771.63$, $S_{initial} = 349.15$, p-value = .034) in the initial design stages (Research and Ideation). This is evident from examining the graphs, where the production stage, representing the later design phase, is recorded with the highest frequency across the Graphic, Industry, and Fashion disciplines. Similarly, in the UX field, the evaluation stage, followed by the production stage, is most frequently mentioned. Therefore, the text mining-based analysis indicates a broad discussion of AI in the production-based later stages of design. This contradicts previous research which predominantly focused on the early design process and the use of AI. These keyword analysis results significantly suggest a demand for the role of AI in the efficient automation of design production and manufacturing, highlighting the need for further in-depth research on AI-based later-stage design processes in the future.

Secondly, AI has been extensively discussed in the Production stage, while the necessity of the Mock-up stage is found to be the lowest. The high frequency of discussion in the Production stage aligns convincingly with the characteristics of generative AI and is consistent with previous research findings. In the product manufacturing phase, designers can automatically generate designs and create suitable models using AI's deep learning technology. This automation of the design process can also be applied in marketing and sales processes. For instance, AI can efficiently distribute designs in the market and shorten production lines. In contrast, the Mock-up stage generally shows low frequencies, particularly in the Graphic and Fashion fields, with only a few comments in the Mock-up stage. This is because generative AI programs used in the Mock-up stage still require human intervention for manual creation, making it challenging for AI alone to implement complex forms desired by human designers. Although AI can generate numerous variations of simple drafts, producing meaningful prototypes for innovation is still limited (Mountstephens and Teo 2020). These challenges, however, are expected to be gradually addressed alongside the development of AI for generating high-quality prototypes (Bilgram and Laarmann 2023).

Thirdly, in the Ideation and Research stages, a relatively even distribution was observed across fields. This indicates active discussions on AI's role in concept finalization and decision-making during the initial design stages, irrespective of the discipline. Designers in each field aim to establish design goals and methods using AI's rapid computations and various analysis methods. Moreover, there is a trend toward incorporating AI in the initial design stages, such as automatically generating design concepts and deriving various ideas using language training models (Jana, Yang, and Saadi 2023; Vlah, Žavbi, and Vukašinović 2020; Zhu and Luo 2023).

In summary, current discussions on AI usage in design predominantly focus on the later stages, particularly the Production process, while the necessity of the Mock-up stage is perceived to be the lowest. This trend is closely related to the technological capabilities of AI currently being employed in practice. AI is predominantly discussed for maximizing productivity through automation in straightforward production processes, while its preference is lower in the Mock-up stage, which requires precise creativity and complex drafts due to technical reasons.

Q2: Results regarding the utilization of AI reveal significant variations across different design disciplines. For example, in the UX field, the Evaluation stage showed a significantly higher level of AI utilization compared to other stages (z-test, $\bar{X} = 2667$, $\mu = 1051$, $\sigma = 1197.96$, z-score = 2.7, p-value = .003). Conversely, in the fashion design field, it exhibited considerably lower figures compared to other stages (z-test, $\bar{X} = 0$, $\mu = 1051$, $\sigma = 1197.96$, z-score = −1.75, p-value = .04). These stark differences stem from the challenge for AI to meet the need to assess products in real-world contexts (Verganti, Vendraminelli, and Iansiti 2020). In the UX domain, AI can develop digital prototypes and test various modules based on virtual platforms where actual materials or substances are not utilized (Stige et al. 2023). However, in other fields such as graphic design, fashion design, and industrial design, actual materials need to be used, which imposes limitations on evaluating products solely through AI. Particularly in fashion design, where producing samples with actual fabric and materials is necessary, testing and measuring results through AI become challenging (Evangelista 2020). Moreover, generative AI possesses the attribute of reinforcing learning through feedback from humans, suggesting that in the evaluation stage, continual human intervention is required rather than solely relying on AI-generated outcomes.

Q3: Hypothesis Setting and Testing on the Use of AI in Each Design Process are as Follows (Table 8). In this section (Q3), as in the previous section, all statistical tests conducted are z-tests (Significance Level = 0.05).

Table 8. Hypothesis setting on the use of AI in each design process.

Hypothesis 1	In the Graphic field, the proportion of AI-related mentions during the Ideation stage will be higher than in other fields.
Hypothesis 2	In the Graphic field, the proportion of AI-related mentions during the Mock-up stage will be lower than in other fields.
Hypothesis 3	In the Industry field, the proportion of AI-related mentions during the Mock-up stage will be higher than in other fields.
Hypothesis 4	In the Industry field, the proportion of AI-related mentions during the Research stage will be lower than in other fields.
Hypothesis 5	In the UX field, the proportion of AI-related mentions during the Evaluation stage will be higher than in other fields.
Hypothesis 6	In the UX field, the proportion of AI-related mentions during the Ideation stage will be lower than in other fields.
Hypothesis 7	In the Fashion field, the proportion of AI-related mentions during the Production stage will be higher than in other stages.
Hypothesis 8	In the Fashion field, the proportion of AI-related mentions during the Mock-up stage will be lower than in other stages.

In the field of graphic design, there is a focus on the initial creative process of ideation, deriving ideas from imagination and concepts (Hutchinson 2018). Therefore, researchers anticipated that AI would be relatively more discussed in the ideation process of graphic design compared to other areas (Hypothesis 1). Additionally, considering that some designers simultaneously engage in both thumbnails and rough drafts corresponding to the mock-up stage during the ideation phase (Arntson 2011), it was expected that mock-up processes would receive the least mention (Hypothesis 2) (Table 9).

The results indicate that in the field of graphic design, there is a broader discussion during the ideation process compared to other areas ($\bar{X} = 738$, $\mu = 476.25$, $\sigma = 240.36$, z-score = 2.18, p-value = .015). However, significant results were not found in the hypothesis of the mockup process ($\bar{X} = 25$, $\mu = 106.25$, $\sigma = 101.85$, z-score = −1.59, p-value = .055). It is important to note, however, that blindly rejecting the alternative hypothesis and accepting the null hypothesis solely because the p-value is greater than 0.05, given a significance level of 5%, may lead to a "Type II error (beta error)." For Hypothesis 2, the p-value is very similar to the significance level, thus requiring careful interpretation. This is interpreted as discussions on obtaining suitable mock-up samples through modifying and inputting prompts into generative AI taking place, although the scope of such discussions is not extensive. According to the above results, discussions in the initial creative process within the field of graphic design appear to be more diverse compared to other academic disciplines. This is attributed to the nature of graphic design, which aims to create creative images based on innovative and original ideas.

In the field of industrial design, researchers anticipated that discussions on AI would be most active during the prototyping stage, as AI can automatically generate numerous prototypes through style learning modules (Oh et al. 2019) (Hypothesis 3). Moreover, in the field of industrial design, there is a tendency to focus more on identifying and resolving issues with existing products rather than on research areas (Jana, Yang, and Saadi 2023), leading to the anticipation of relatively fewer discussions in the research domain (Hypothesis 4) (Table 10).

In the results of the testing, it was observed that the utilization of AI in the research process is relatively less discussed compared to other domains ($\bar{X} = 271$, $\mu = 672.5$, $\sigma = 448.4$, z-score = −1.79, p-value = .037). However, the hypothesis

Table 9. Results of the z-test of AI usage in the field of graphic design.

Hypothesis	z-score	p-value (significance)	Decision
Hypothesis 1	2.18	0.015	Accept
Hypothesis 2	−1.59	0.055	Reject

Table 10. Results of the z-test of AI usage in the field of industrial design.

Hypothesis	z-score	p-value (significance)	Decision
Hypothesis 3	0.27	0.39	Reject
Hypothesis 4	−1.79	0.037	Accept

regarding the mock-up process in industrial design did not reveal significant results ($\bar{X} = 120$, $\mu = 106.25$, $\sigma = 101.85$, z-score = 0.27, p-value = .39). Nevertheless, the mock-up process in industrial design emerged higher than in other two fields (graphic and fashion) excluding UX, indicating relatively more active discussions during this stage. This suggests that in the field of industrial design, due to the high production costs per unit of product compared to other disciplines, there is a relatively greater demand for utilizing AI in mock-up processes.

In the field of UX, obtaining feedback and integration regarding the usability of web (mobile) pages before launching the actual platform is crucial (Earnshaw, Tawfik, and Schmidt 2017). Therefore, researchers anticipated that AI would be most frequently mentioned in the evaluation stage of UX (Hypothesis 5). Conversely, since the UX field prioritizes improving existing modules based on usefulness, usability, findability, and accessibility rather than developing new modules based on creative ideas (Morville 2005), it was expected to be least discussed during the ideation stage (Hypothesis 6) (Table 11).

The analysis revealed that in the actual UX field, AI is overwhelmingly mentioned in the evaluation domain ($\bar{X} = 2667$, $\mu = 1051$, $\sigma = 1197.96$, z-score = 2.7, p-value = .003). However, it was observed that discussions were relatively scarce during the ideation stage compared to other fields ($\bar{X} = 163$, $\mu = 476.5$, $\sigma = 240.36$, z-score = −2.61, p-value = .005). This suggests that in the UX field, the role of AI is primarily discussed for practical purposes, such as complementing designs and exchanging feedback, rather than for creating new designs. Particularly, AI can be effectively utilized during the feedback stage as it can analyze user tests and provide useful development solutions at the final stage of development (Earnshaw, Tawfik, and Schmidt 2017). However, due to the nature of the UX field focusing on practical problem-solving, there appears to be some limitations in using AI to derive new ideas and inspiration.

Lastly, in the field of fashion design, it was anticipated that the most discussions would occur during the production process, as AI enables the prediction of user preferences, sales, and market demand (Jain 2020) (Hypothesis 7). Additionally, since AI has limitations in producing and evaluating samples using fabric, materials, and textiles (Evangelista 2020), it was expected to be scarcely mentioned during the mock-up stage (Hypothesis 8) (Table 12).

Table 11. Results of the z-test of AI usage in the field of industrial design.

Hypothesis	z-score	p-value (significance)	Decision
Hypothesis 5	2.7	0.003	Accept
Hypothesis 6	−2.61	0.005	Accept

Table 12. Results of the z-test of AI usage in the field of fashion design.

Hypothesis	z-score	p-value (significance)	Decision
Hypothesis 7	3.96	3.76E–05	Accept
Hypothesis 8	−1.254	0.105	Reject

The analysis revealed that in fashion design, discussions are primarily widespread during the production process ($\bar{X} = 8724$, $\mu = 2125.6$, $\sigma = 3726.75$, z-score = 3.96, p-value = 3.76E–05), but no significant results were found in the validation of the mockup process ($\bar{X} = 35$, $\mu = 2125.6$, $\sigma = 3726.75$, z-score = −1.254, p-value = .105). This reflects the latest industry trend of producing mock-up samples based on consumer preferences, sizes, and color choices through 3D printing by AI (Elran, Harel, and Zoran 2023). These findings demonstrate that AI is being actively discussed in the production process, encompassing supply chain management and mass production, facilitated by automation technology. Moreover, the emergence of discussions surrounding virtual digital samples suggests a broadening of the scope of AI mockup processes within the realm of fashion design (Table 13).

Table 13. Findings, challenges, and potential of AI in the design process.

Research Design filed	findings	challenges	Potential of AI
All design filed	• The later stages of design (production, evaluation) are the most extensively discussed. • Relatively less discussion occurs during the early stages of design, particularly during mockup creation.	• Technical limitations are encountered during the mockup stage, which demands precise creativity and intricate designs. • Meaningful output for innovation through designs is restricted.	• Potential for utilization in the efficient production and automation aspects of design. • Ability to test various modules through feedback.
Visual Design	• The ideation process is discussed relatively more than other processes.	• The lack of clear distinction between mockup and ideation may impose limitations on the utilization of the mockup process.	• Effective idea brainstorming. • Rapid image draft generation from keywords.
Industrial Design	• The mock-up process is discussed relatively more than two other processes. • Lack of discussion in the research process.	• The simultaneous conduct of the concept generation process and the research process poses challenges for applying AI to the research phase.	•Prototype generation through AI 3D Printing. • Reduce production costs by creating numerous prototypes before production
UX Design	• The evaluation process is discussed relatively more than other processes. • Lack of discussion in the ideation process.	• The practical use of AI focused on improving existing modules, thus limiting the development of creative ideas.	• Valuable feedback on designs during the evaluation stage. • Providing development solutions by analyzing usability test data.
Fashion Design	• The production process is discussed relatively more than other processes.	• AI may have limitations in the mockup process due to its inability to perform actual physical fabrication.	• AI supply chain management and inventory control systems. • Predicting user preferences and forecasting sales and demand in the market.

Conclusion

Generative AI, a technology that generates text, images, audio, video, and more based on prompts, is currently being researched for its application in the creative processes of diverse design fields, including visual arts, industry, UX, and fashion. However, discussions on this topic are fragmented across different design domains and mainly focus on the initial stages of design, making it challenging to fully understand the potential applications of AI in the design process. To address these issues, this study collected discussions from experts and structurally analyzed how AI is discussed at each stage of the design process using text-mining methods.

The research findings indicate that discussions about AI primarily occur in the later stages of the design process, particularly during the production phase, with the least amount of discussion happening regarding the prototype stage. Furthermore, distinct differences in AI usage were observed across each field: graphic design primarily in ideation, UX design in evaluation, and fashion design in the production stage. These findings differ from the contents of previous qualitative studies, which mainly emphasize AI utilization in the early stages of the design process. Quantitative analysis of the collected data indicates that designers primarily demand AI integration for efficiency in design generation and automation processes, particularly in production and manufacturing aspects. Additionally, they anticipate that the optimization of market distribution will be enhanced through AI-assisted production processes. This underscores the need for future research to thoroughly examine both the early and later stages of the design process regarding AI utilization.

This study expands upon previous discussions primarily focused on the initial stages of design, offering new insights through quantitative research results visualized via text mining. However, data analyzed through text mining may have limitations in generalizing within broad theoretical frameworks as it applies to specific contexts or limited timeframes. Therefore, in future research, researchers aim to refine specific timeframes and research fields to derive AI utilization strategies tailored to the requirements of each domain.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

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Data Availability Statement

The data and the source code that support the findings of this study are openly available at https://github.com/8orrin9/textmining/tree/Design-AI.

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