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DETERMINANTS OF AI ADOPTION INTENTION IN FASHION DESIGN: A REVIEW

Luan Xiaoli[1], Nooraziah Ahmad[2*], Mohd Zaimmudin Mohd Zain[3]

[1] Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan, Malaysia;
School of Fashion Design, Jiangxi Institute of Fashion Technology, Nanchang, Jiangxi, China;
Nanchang Key Laboratory of Clothing Digital System Design, Jiangxi Institute of Fashion Technology, Nanchang, Jiangxi, China
Email: c20e0287f@siswa.umk.edu.my
[2] Institute for Artificial Intelligence and Big Data, Universiti Malaysia Kelantan, Malaysia;
Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan, Malaysia
Email: nooraziah@umk.edu.my
[3] Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan, Malaysia
Email: zaimmudin@umk.edu.my
[*] Corresponding Author

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Abstract:

Artificial intelligence (AI) is increasingly applied across diverse fields, emerging as a frontier in fashion design research and practice. The use of AI tools has significantly advanced innovation and sustainability in the fashion design industry. However, user adoption intentions toward AI tools remain unclear, and systematic literature integration is lacking. This research primarily aims to comprehensively explore the factors that influence users' willingness to adopt AI tools in the fashion design industry. This study strictly adheres to the PRISMA guidelines, conducting systematic literature searches and screening in Google Scholar and the CNKI database. Through a comprehensive analysis of the included studies (encompassing research theories, adoption variables, and findings), it was found that a multi-layered, complex system of factors influences the willingness to adopt AI tools in the fashion design industry. This study overcomes the limitations of single-theory models by identifying and evaluating determinants of adoption intention within the specific context of fashion design creation. By synthesising a more comprehensive, contextualised theoretical framework, this study extends the application of the Technology Acceptance Model in the field of fashion design. It not only offers new perspectives on understanding designer-technology interactions but also provides user-centred design directions for AI developers, effective technology promotion strategies for fashion enterprises, and guidance for educational institutions in cultivating human-machine collaboration capabilities. This research integrates relevant studies to fill a critical gap in understanding the adoption intentions of AI tools within the fashion design industry.

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Keywords:

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Introduction

Artificial intelligence (AI) is rapidly advancing in the fashion industry. This trend is driven by rapidly advancing technologies in the Fourth Industrial Revolution. This transformation has accelerated with the recent wave of automation and digitalisation (Faghih et al., 2025). In the current era, AI has undergone rapid development, propelling numerous industries in new directions (Li et al., 2024). It continues to disrupt and reshape traditional creative industries, bringing new opportunities and challenges to fields such as media, education, and design (Cao et al., 2023).

The fashion industry is a highly creative industry with rapid product iterations. Traditionally, the fashion industry has relied more on practitioners' intuition in design and decision-making during the innovation process (Karpova et al., 2013). Nevertheless, the advancement of society and emerging technologies is now propelling the fashion sector into a phase of innovative transformation, fuelled by artificial intelligence. By leveraging AI, the industry can streamline and enhance multiple stages of garment manufacturing (Agrawal et al., 2018; Pournader et al., 2021). The rapid advancement of AI technology has prompted fashion industry professionals to integrate new tools into traditional design and production processes. In fashion design, the widespread adoption of AI tools provides businesses with powerful creative support and entirely new ways of working. (Tao et al., 2023). The fashion industry is expected to continue evolving and advancing creatively in design, driven by the use of artificial intelligence tools. Designers will be able to create more diverse creative designs in less time.

AI tools are helping designers create a broader range of creative ideas in less time. They not only improve the quality and speed of the design process but also encourage designers to move beyond the boundaries of traditional fashion, exploring fresh styles and concepts that may not have been possible before (Lee et al., 2025). Due to this growing influence, it’s essential to understand what motivates designers to incorporate these tools into their work.

Despite global technology companies and fashion giants continuing to invest resources in developing advanced AI design tools, applying them in design still faces the challenge of user acceptance (Kurniawan et al., 2024). By researching and analysing these influencing factors, developers can more effectively refine tool functionality and user experience to ensure better alignment with user needs. This approach has significantly increased the penetration rate of AI tools in fashion design. Furthermore, it speeds up the sector's shift toward digitalisation and supports the achievement of innovation-led growth objectives (Li et al., 2024).

Currently, although scholars have begun to focus on this interdisciplinary field, the existing research landscape still exhibits significant limitations. First, most relevant studies are based on a single theoretical framework (e.g., the Technology Acceptance Model, TAM), lacking systematic integration. Second, the adoption of relevant variables is mainly based on a single theoretical framework. However, fashion design, as a specialised field that highly relies on intuition and creativity, may have significant differences in its adoption-driving mechanisms

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from conventional information technology, which have not been fully explored. In addition, current research lacks a comprehensive analysis and summary of the findings and various influencing factors. Current research has not yet explored the challenges and barriers that users encounter when integrating new technologies into their workflows (Zhou & Lee, 2024), primarily due to a lack of comprehensive understanding of the factors influencing user acceptance and willingness to adopt AI tools in the fashion design field.

Therefore, in response to the current state of research that lacks systematic summarisation, this study aims to provide a comprehensive identification, screening, and assessment of the existing literature through a literature review. This research investigates the primary factors influencing users' willingness to accept and utilise AI tools. In terms of theory, this research will transcend the limitations of a single theory and is committed to integrating fragmented knowledge, thereby constructing a comprehensive, multidimensional factor framework applicable to the specific creative context of fashion design. This approach will lay a more solid theoretical foundation for future research. On the practical level, the results of this research will provide AI tool developers with profound user insights, guiding them to design humanized tools that better meet the needs of designers; simultaneously, it will also provide a scientific basis for fashion companies and educational institutions to formulate effective technology promotion strategies, training programs, and organizational change plans, thus facilitating the integration of AI technology and human creativity more efficiently and harmoniously.

Methodology

This review adopts the PRISMA protocol, which provides a structured and widely recognised framework for systematically identifying, evaluating, and integrating research in the field (Page et al., 2021a; Page et al., 2021b).

The need for review has been addressed in the Introduction Section. As for research questions, three questions are proposed based on the objectives in the Introduction section, which are:

1. What does the existing literature utilise the main theoretical frameworks in exploring the willingness to adopt AI tools in the fashion design domain?
2. What are the main adoption variables that influence users' behavioural willingness to adopt AI tools?
3. Based on the current research, what are the key research gaps and future directions that scholars should further explore?

Eligibility Criteria

To ensure academic quality, we followed the methodology proposed by Shen et al. (2021), with Table 1 clearly defining the inclusion and exclusion criteria for this review.

Table 1: Literature Inclusion/Exclusion Criteria

Inclusion criteria	Exclusion criteria
Journal articles	Books, manuals or reports
Research focused on fashion design, AI tools, and behavioural intentions.	Research that is not related to the topic of the study
Studies published between 2020 and 2025	Research not published between 2020 and 2025
The title contains at least one keyword.	The title does not contain a keyword.

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Abstract contains at least one keyword per topic	Abstract does not contain keywords for each topic
The study employs a transparent methodology, a clearly defined target population, a specified sample size, a research theory, selected variables, and well-drawn conclusions.	The study lacks a methodology, population, sample size, research theory, adopted variables, and conclusions.
Studies published in peer-reviewed journals	Studies not published in peer-reviewed journals.
Full-text accessible studies	Full-text inaccessible studies
	Duplicate publications

Search Strategy
The first stage involves identifying the literature, and Google Scholar and China National Knowledge Infrastructure (CNKI) databases are selected for searching. Our literature review exclusively included peer-reviewed journal publications and proceedings from academic conferences, spanning the period from 2020 to the present. Specific online literature sources are listed in Table 2.

Table 2: Online Sources Used in This Work

No.	Source	Website Address
1	Google Scholar	https://scholar.google.com/
2	CNKI	https://www.cnki.net

When searching for literature, we constructed search strings based on the aforementioned inclusion criteria. The search strategy was structured to intersect three specific dimensions. The keyword "fashion design" was used to limit the application domain to the apparel industry, while the keyword "artificial intelligence" was grouped to represent the technological constructs. Furthermore, the keyword "technology acceptance" was used as a theoretical filter to isolate studies focusing on user adoption and behavioural intent. The search results were collected from 2020 to 2025. Specific filtering details are shown in Table 3.

Table 3: Filters And Specifications for Searching Online Sources

Source	Search string	Filters
Google Scholar	"Fashion design" AND "Artificial intelligence" AND "technology acceptance"	Year(s): 2020–2025
CNKI.	"Fashion design" AND "Artificial intelligence"	Article type: Research article Year(s): 2020–2025

Selection Process
First, all primary selected articles were manually reviewed to exclude duplicates. Subsequently, Literature titles and abstracts were screened based on the Eligibility Criteria. After excluding inaccessible documents, full-text evaluations were conducted. The Eligibility Criteria were continuously applied during the evaluation process to filter the literature. Ultimately, documents meeting the eligibility assessment were included in this review.

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Information Extraction

To achieve the research objectives, we analysed and summarised the literature included in the review, extracting the following core information: authors, publication year, journal name, research methods, research subjects, sample size, research focus, theoretical framework, adopted variables, and relevant research results.

Results

Initially, we constructed a search string based on the inclusion criteria and identified 626 documents among the selected online resources. According to the results, the relevant documents were primarily in English, with a relatively small number of Chinese documents. Second, we checked the duplication rate of the identified 626 papers, eliminated duplicates (58), and finally retained 568 documents for the next screening step. Again, guided by the set criteria, we performed an initial screening of the fetched documents by reviewing their titles and abstracts. Literature that did not share a common criterion (507) was eliminated, and finally, 61 literatures were subjected to the complete text acquisition stage. Next, no-access literature (13) was excluded from the 61 articles, and finally, 48 articles proceeded to the full-text review stage. By evaluating whether the references met the inclusion criteria, the non-compliant literature (33) was excluded. Ultimately, a total of 15 literature entries entered the data extraction and analysis stage. Figure 1 illustrates the entire screening process.

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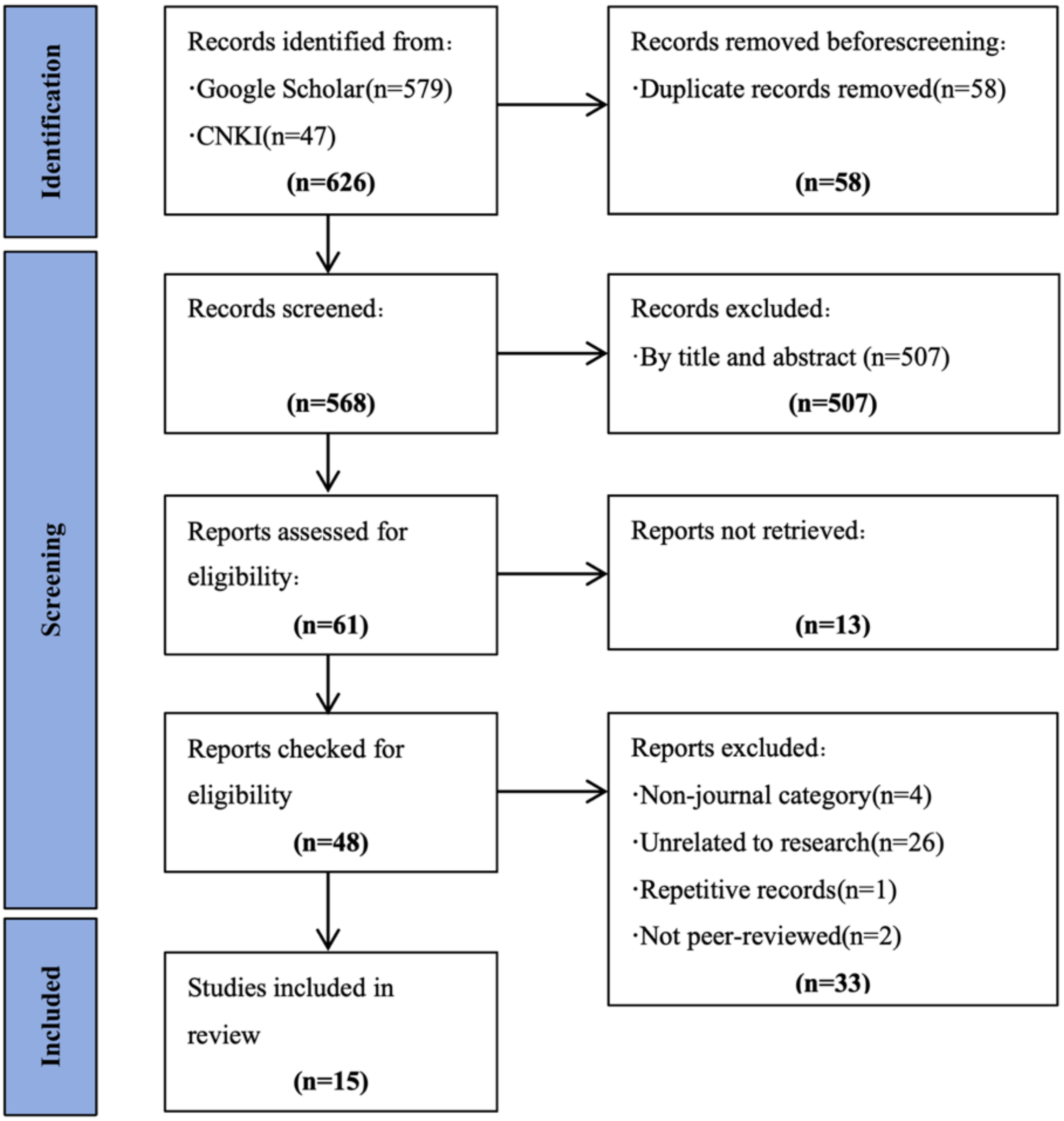

Figure 1: PRISMA Flow Diagram for Selection of Sources

This study focuses on the literature between 2020 and 2025. As shown in Figure 2, the annual quantities of relevant literature collected in our search are depicted. It is noteworthy that relevant publications showed a significant growth trend between 2024 and 2025. Fourteen of the papers (93%) were published during this period. This upward trend is mainly attributed to the revolutionary advances in AI technology, a result that highlights the trend in this research area and emphasises the need for reviews.

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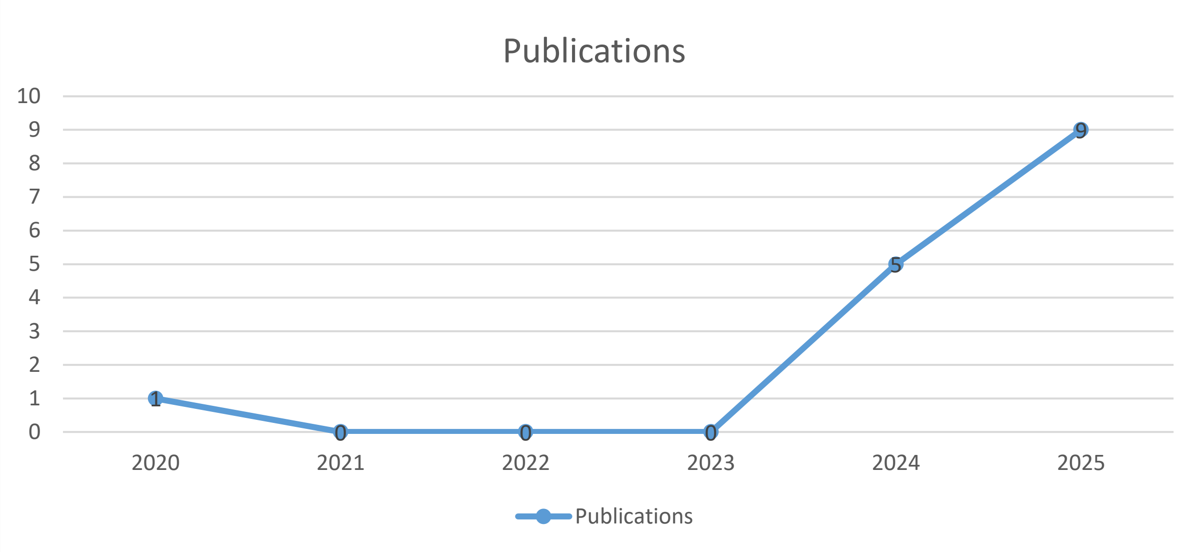

Figure 2: Based on the Distribution of Articles by Publishers

Given the different fields involved in this study, the results of such research are published in a variety of journals. Table 4 lists the 15 different journals involved in this study, with the same percentage in each journal. This result reflects the widespread interest in the relevant research.

Table 4: Distribution of Articles Based on Publisher

Publisher	Amount
International Journal of Human–Computer Interaction	1
International Conference on Intelligent Cybernetics Technology & Applications	1
Clothing and Textiles Research Journal	1
Young Consumers	1
Scientific Reports	1
Current Psychology	1
International Journal of Human–Computer Interaction	1
European Journal of Management Studies	1
Interactive Learning Environments	1
Education and Information Technologies	1
Journal of Applied Learning and Teaching	1
IEEE Access	1
Proceedings of the 2025 4th International Conference on Big Data, Information and Computer Network	1
Frontiers in Computer Science	1
International Review of Research in Open and Distributed Learning	1

The research approaches employed in this paper were categorised into three types: quantitative, qualitative, and mixed methods. According to the data illustrated in Fig. 3(a), after analysing the research methods of 15 documents, it was found that 11 papers used quantitative research (73.3%), zero papers used qualitative research (0%), and four papers used mixed research (26.7%). It can be observed that most relevant studies are quantitative, with data collection primarily conducted through questionnaires. A moderate volume of mixed-method research

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was also employed, which combined quantitative data collection via questionnaires with qualitative approaches, including focus groups and semi-structured interviews.

In terms of the category of the research population, five of the literatures contained student populations, which is related to the easier and more convenient collection of questionnaires by the researcher's profession. Additionally, four documents feature designers as research subjects. Three documents contain consumers as research subjects, and two papers contain educators as research subjects. Four documents contain other research subjects, such as related practitioners, freelancers, and individuals with experience in using or an interest in AI tools. Some of these studies employed multi-group analyses, and the distribution of the number of research subjects is illustrated in Figure 3(b).

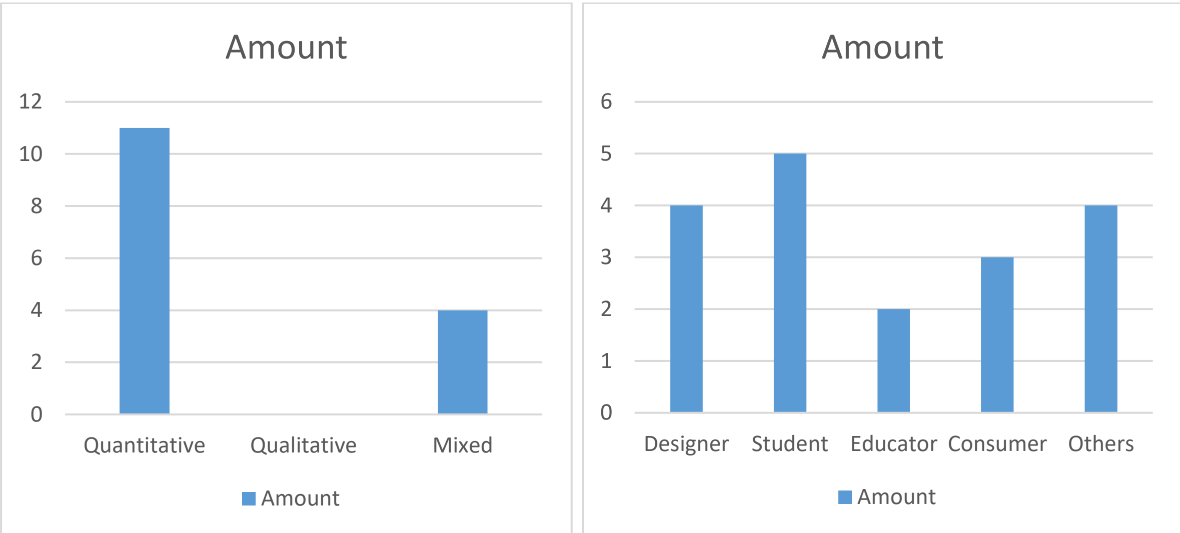

Figure 3(A) And 3(B). Distribution Of Research Methods and Distribution of Research Subjects, respectively.

In terms of sample size, out of the 15 papers, 0% (n= 0) of the studies had a sample size of 1-200 people, 20.0% (n= 3) had a sample size of 200-300 people, 40.0% (n= 6) had a sample size of 300-400 people, 20.0% (n= 3) had a sample size of 400-500 people, 6.7% (n= 1) had a sample size of 500-600, and 13.3% (n= 2) of the studies had a sample size of 600 or more, as shown in Fig. 4. Since the relevant studies were mainly quantitative and mixed, the sample size was mostly 200 or more. In these research findings, the sample size for mixed-method studies represents the combined total of quantitative and qualitative samples. Additionally, the studies found that the primary sample size typically ranges between 300 and 400 participants.

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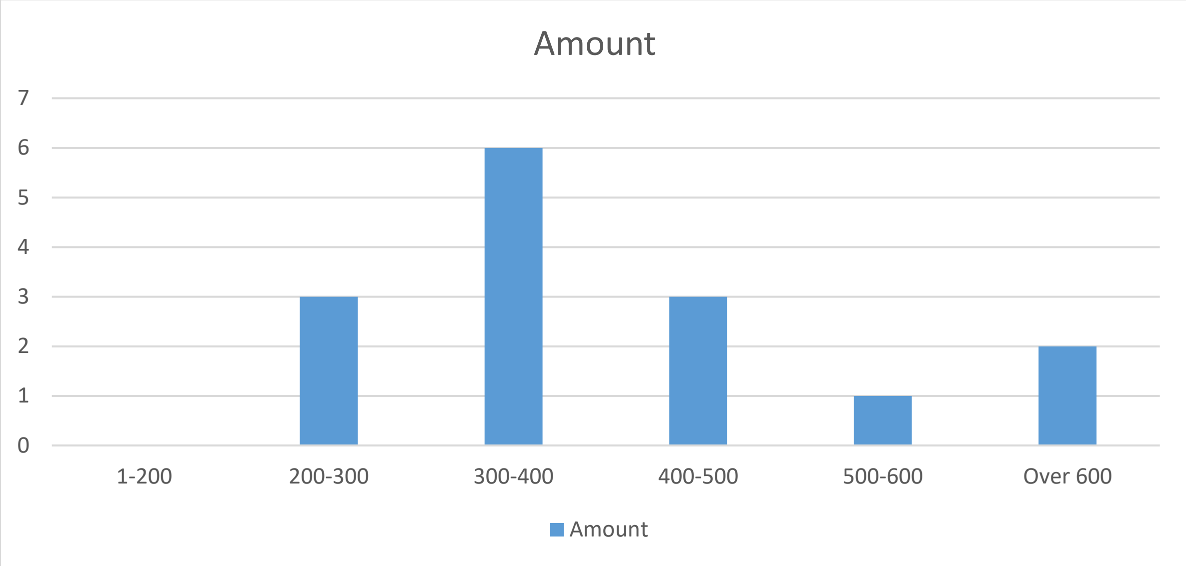

Figure 4: Sample Size Distribution

In addition to the above statistical analysis, this study focuses on the content analysis of the 15 papers included in the study. The focus consists of Research Focus, Research Theory, Adopted Variable and Research Results, as shown in Table 5. From the results, we can see that related studies mainly focus on AI, Artificial Intelligence Generated Content (AIGC), AI tools, fashion, design, the Technology Acceptance Model, and Behavioural intention, among others, which is consistent with the research purpose of this review. In terms of Research Theory, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are the primary models employed. Among them, nine documents used the TAM model, six documents used the UTAUT model, and two papers used both the TAM model and the UTAUT model. Research findings indicate that the TAM and UTAUT models provide the theoretical foundation for the adoption of AI tools in fashion design. The adoption of relevant variables is primarily governed by the core variables of these two models. For example, perceived usefulness (PU) and perceived ease of use (PEU) in TAM, performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC) in UTAUT. This review of 15 studies concludes that AI adoption intention in fashion design is primarily motivated by PE, EE, and SI, but is notably inhibited by risk perceptions and anxiety. Moreover, the influence of these factors is not fixed but is critically moderated by contextual conditions such as task applicability, creative requirements, specialised expertise, and cultural influences. This calls for a shift away from universal models to a more granular and contextually grounded approach to understanding technology acceptance in creative industries. This highlights the need to move beyond generic models and adopt a nuanced, context-sensitive approach to understanding technology acceptance in creative industries.

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Table 5: Literature Analysis

Literature	Research Focus	Research Theory	Adopted Variable	Research Results
(Li et al., 2024)	Behavioural intention; AIGC; UTAUT model; fashion industry	UTAUT	Performance Expectancy (PE), Effort Expectation (EE), Social Influence (SI), Facilitating Conditions (FC), Perceived Risk (PR), Commercial Value (CV), Correlation between job responsibilities and creativity, Years of working, Behavioural Intention (BI), Use Behaviour (UB)	PE, EE, SI, and FC all have significant positive effects on the intention to use, while PR have a substantial adverse effect on the intention. CV has a considerable positive impact on BI, UB, and PE. The correlation between job responsibilities and creativity can significantly moderate the effects of PE on BI, as well as the impact of PR on BI. The employment substantially interferes with the effect of PE on BI, and the length of employment significantly moderates the impact of PR on BI.
(Kurniawan et al., 2024)	AI, design processes, generative adversarial network, user acceptance	TAM UTAUT TTF	Perceived Usefulness (PU), Ease of Use (EU), Computer Anxiety (CA), Perceived Self-Efficacy (PSE), Social Influence (SI), Perceived Enjoyment (PcE), Task Technology Fit (TTF), Behavioural Intention (BI)	PU, EU, TTF, and CA do not have a positive influence on BI. In contrast, SI, PSE, and PcE show a significant effect towards BI.
(Liang et al., 2020)	fashion AI, technology attitudes, purchase intention	TAM	Perceived Usefulness (PU), Perceived Ease of Use (PEU), Performance Risk, Technology Attitudes, Attitude toward AI, Fashion Involvement (FI), Purchase Intention	PU, PEU, and Performance Risk were significant in influencing consumers' attitudes toward AI. Positive attitudes toward technology had a positive influence on the Purchase Intention. FI moderates the path from Technology Attitudes to PI.

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(Sharma & Sharma, 2024)	AI, Young consumers, Consumer lifestyles, Sustainable consumption, Environmental impact	UTAUT UTAUT2	Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), Habits, Environmental Awareness, Trust in AI, Personalisation Perception (PP), AI-Driven Behavioural Intentions (AIBI), Sustainable Consumption Behaviour (SCB)	PE, EE, SI, and others exert a substantial influence on AIBI, which in turn has a positive influence on SCB. All hypotheses in this study are supported.
(Hu et al., 2025)	digital media designers, AI drawing tools, Factors influencing	TAM UTAUT	Perceived Usefulness (PU), Perceived Ease of Use (PEU), Personal Innovation, Price Value (PV), Social Influence (SI), Perceived Trust (PT), Output Quality (OQ), Purchase Usage Intention (PUI),	PEU significantly influences both PU and PUI positively, and PU also positively impacts PUI significantly. OQ significantly enhances both PUI and PT's effectiveness, and PU mediates the relationship between PEU and PUI. SI and PV have a significantly positive impact on PUI. PT significantly positively influences PUI and mediates the relationship between OQ and PUI.
(Liu et al., 2025)	AI, Creativity support tool, Technology acceptance, BI, Human–	UTAUT	Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC),	PE, EE, SI, and the RE were positively related to intent to use, whereas Ethical Concern and Privacy Concern were negatively associated with intent to use. Interactivity and personalisation appear

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	computer interaction		Regulatory Environment (RE), Ethical Concern, Privacy Concern, Dependency Concern (DC), Interactivity, Personalisation, Intention to use AI-CSTs	to be critical predictors of EE. The relationship between FC, DC and intention to use did not seem to be significant.
(ElSayad & Mamdouh, 2025)	AI, Customisation, Word-of-Mouth (WOM) intention	TAM	Perceived Usefulness (PU), Trust, Customization, Perceived Performance Risk (PPR), WOM intention	PU and trust influence WOM intention and mediate the relationship between customisation and WOM intention. Customisation, PPR, and trust influence PU, which mediates the relationship between PPR and WOM intention.
(Arachchi & Samarasinghe, 2025)	AI, TAM, Technology readiness, Attitude to AI	TAM	Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Anthropomorphism, Perceived Intelligence (PI), Perceived Animacy (PAN), Attitudes toward AI, Technology Readiness (TR), Consumer Purchase Intention for fast-moving consumer goods (FMCGs)	PU, PEU, Perceived Anthropomorphism, PI, PAN, have a significant positive influence on attitudes toward AI. TR positively moderated the impact of the AI-related attitudes on consumer purchase intention for FMCGs.
(Shen et al., 2025)	Generative artificial intelligence image, Midjourney, TAM, art and design	TAM Self-Determination Theory (SDT)	Job Replacement Anxiety (JRA), Perceived Competence (PC), Perceived Relatedness, Original Privacy Concern (OPC), Perceived Usefulness (PU), Perceived Ease of Use (PEU),	Higher PC and Perceived Relatedness significantly reduce JRA and OPC. PU and PEU positively impact BI.

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			Behavioural Intention (BI)	
(Verano-Tacoronte et al., 2025)	Generative AI, Technology adoption, Higher education, Teachers	UTAUT	Performance Expectancy (PE), Effort Expectancy (EE), Anxiety about the Future of the Academic Profession, Anxiety about Misusing ChatGPT, Anxiety about Student Learning, Behavioural Intention (BI), Use Behaviour (UB)	Anxiety about student learning exhibits a significant adverse direct effect on BI and an indirect effect through PE. Anxiety is negatively associated with BI, with significant mediation through both EE and PE. Anxiety concerning the future of the academic profession does not show a statistically significant relationship with BI.
(Stroud & Du, 2025)	AI, ChatGPT, higher education, structural equation modelling, TAM, thematic analysis	TAM	Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude Towards Use (ATU), Behavioural Intention to Use (BIU), Actual Use, Perceived Benefits (PB), Concerns	Results indicate that students who perceive ChatGPT as applicable exhibit more positive attitudes, leading to stronger Behavioural Intentions and higher Actual Use for academic tasks outside the classroom. Additionally, open-ended responses and interviews highlighted both benefits and concerns. Key benefits included time savings, ease of information gathering, and enhanced creativity. Concerns focused on a lack of understanding of ChatGPT’s functionalities, fear of over-reliance, mistrust of generated content, and risks to academic integrity.
(Zhu et al., 2025)	AIGC, design content, user experience, workflow,	Technology-Organisation-Environment (TOE)	Technological Maturity (TM), Learning Cost (LC), Innovativeness, Output Availability (OA),	CP and IE exert the most significant positive impact on designers' behavioural intentions. OA and cross-functional collaboration demonstrate practical benefits in improving

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	and AI technology.		Organisational Context (OC), Cross-functional Collaboration, Career Path (CP), Social Construction (SC), Environmental Context, Industry Environment (IE), Ethics and Privacy (EP), Public Acceptance (PA), Behavioural Intention (BI), Action	content quality and team efficiency. TM and PA serve as key drivers of adoption, while SC and innovation underscore AI's capacity to foster creativity and design diversity. Ethics and privacy reflect user concerns over data security, whereas LC negatively affect adoption due to perceived complexity.
(Lai et al., 2025)	AIGC tools, AIDUA, Anthropomorphism, Design industry, Designer-AI collaboration	AIDUA, Task Technology Fit (TTF)	Social Influence (SI), Hedonic Motivation (HM), Anthropomorphism, Task Characteristics, Technology Characteristics, Task Technology Fit (TTF), Performance Expectancy (PE), Effort Expectancy (EE), Emotions, Willingness to Accept AIGC Tools, Objection to the Use of AIGC	The study reveals a significant impact of SI on PE. SI positively correlates with PE.SI does not significantly affect EE.HM has a positive impact on both performance and EE. The effect of anthropomorphism on PE was not significant. Both performance and effort expectations have a positive effect on emotions. The match between technology features and tasks has a substantial impact on designers' emotions.
(Wang & Chen, 2024)	AIGC, SOR, TAM, TPB, designer, usage behaviour	TAM, Theory of Planned Behaviour (TPB)	Subjective Norm (SN), Facilitating Conditions (FC), Technological Anxiety (TA), Self-efficacy, Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioural Intention (BI)	Users' FC significantly influence self-efficacy, which in turn determines their intention to adopt AIGC. Interviews revealed that factors hindering the widespread application of AIGC mainly encompass legal security, ethical risks, and fairness.
(Ma et al., 2024)	AI, higher education,	TAM	Perceived Usefulness (PU), Perceived Ease	Notable differences emerged between Chinese

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TAM, attitudes, BI	of Use (PEU), Attitudes Toward Use (ATU) Behavioural Intention (BI)	and international students in terms of adoption rates, perspectives, and willingness to use AI. A more substantial effect of perceived ease of use on both attitudes and behavioural intentions among international students compared with their Chinese counterparts. Cultural backgrounds and prior technological exposure play intricate roles in shaping perceptions of AI technology.

Discussion

Through a comprehensive review of the literature, we identified the following research theories as the primary frameworks employed in this study, as detailed below.

TAM

Davis (1989) proposed the TAM model. It is the cornerstone framework for how technology is accepted. The model emphasises Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as the key determinants of Behavioural Intention (BI), which in turn predicts Actual Use of the system (Davis, 1989). Venkatesh and Davis (2000) validate the predictive power of the TAM and establish its application in a variety of environments. As AI tools are increasingly integrated into fashion environments, the utility of TAM is growing.

UTAUT

Venkatesh et al. (2003) proposed the UTAUT model by integrating eight theories related to the Theory of Acceptance and Use of Technology. The four dimensions of this theory that influence behavioural intentions are: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC). Among them, PE, EE, and SI are the main determinants of usage behaviour, while FC and BI influence technology adoption behaviour (Venkatesh et al., 2003). UTAUT theory explains up to 70% of technology adoption and usage behaviour, indicating its effective applicability to research on technology adoption and usage behaviour (Chang et al., 2022; Toh et al., 2023). By studying the determinants of fashion practitioners' AI tool usage intentions, the UTAUT model establishes a theoretical framework that enables researchers to identify core influences on technology adoption, including those that may promote or impede consistent tool use by designers (Li et al., 2024).

Other Theories

In addition to the two leading theories, TAM and UTAUT, the TTF, TOE, and SDT theories are also used in the results.

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TTF is primarily used to assess the task-technology fit and to predict the performance of the technology further (Goodhue & Thompson, 1995). It suggests that the fit between task requirements and technology features contributes to user satisfaction and performance outcomes (Huang, 2021). Existing literature indicates that TTF can be integrated with other models. For example, TTF integrates with UTAUT2 (Latané, 1981), TTF integrates with TAM (Fryer et al., 2017), and TTF integrates with UTAUT (Lazarus, 1991). Integrating the TTF model with other research models helps us gain a more comprehensive understanding of the factors influencing user behavioural intent. (Lai et al., 2025).

The Technology-Organisation-Environment (TOE) model has broad applicability and can explain the process of technology adoption across various technological, industrial, and cultural contexts (Zhu et al., 2025). It has been used to analyse technology adoption across organisational systems, open systems, and enterprise systems, showing that technological, managerial, and environmental factors jointly influence organisational decisions. Using the TOE framework, the technology adoption analysis covers three dimensions: the technology dimension assesses the characteristics of the AIGC and its compatibility with existing workflows; the organisational dimension evaluates the resources, managerial support, and employee competencies; and the environmental dimension focuses on the external market, competition, and regulatory policies (Baker, 2011).

SDT theory focuses on the intrinsic drivers behind individual behaviours, which helps to reveal the psychological mechanisms and motivations behind user behaviours (Deci & Ryan, 2004). TAM and SDT can be combined to explore users' perceptions of AI. Combining TAM with SDT enables the exploration of users' attitudes toward AI tools and the factors that influence them (Shen et al., 2025).

With the proliferation of generative AI in the design industry, scholars commonly employ TAM, UTAUT, UTAUT2, and their extended models to explain user acceptance of AI tools. These theories are applicable to fashion design contexts due to the industry's heavy reliance on creativity, uncertainty surrounding new technologies, and emphasis on tool usability and workflow integration. The PU and PEU dimensions within TAM directly correspond to the creative enhancement and process efficiency concerns of apparel designers when evaluating AI tools. Consequently, multiple studies have confirmed these factors significantly influence attitudes and BI (Li et al., 2024; Shen et al., 2025; Hu et al., 2025). The PE, EE, SI, and FC proposed by UTAUT similarly reflect key factors such as collaborative team dynamics, managerial support, and tool output quality, demonstrating clear predictive power for the fashion industry (Li et al., 2024; Liu et al., 2025; Sharma & Sharma, 2024). Furthermore, the UTAUT2-emphasized hedonistic motivation (HM), price value (PV), and habit formation align with designers' emphasis on inspiration, user enjoyment, and cost-effectiveness of tools. Concurrently, extended variables such as Innovativeness and Output Availability (Arachchi & Samarasinghe, 2025; Hu et al., 2025; Wang & Chen, 2024; Liu et al., 2025) further elucidate the unique psychological mechanisms at play in creative professionals' aesthetic judgments and cross-technology collaboration. Collectively, these theoretical models and their extended constructs comprehensively cover the three most critical considerations for fashion users adopting AIGC tools: creative efficacy, technological uncertainty, and tool-workflow fit. Consequently, they are widely employed to explain fashion users' willingness to use AI tools (Kurniawan et al., 2024; Liang et al., 2020; Zhu et al., 2025).

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In conclusion, most of the literature exploring the influencing factors of the application of AI tools in fashion design mainly adopts general theories such as TAM and UTAUT for research, and supplements other theories in a timely manner according to the specific research needs. Provide a clear conceptual overview of the core structure and extended variables of TAM and UTAUT. This study summarizes the main concept summary table, as shown in Table 6. In addition, we also calculated the support rates among these structural relationships. First, we summarize the number of documents that have proposed this hypothesis from the 15 documents in Table 5. Then we divide the number of documents supporting this hypothesis by the number of those proposing it. Ultimately, it received support rate.

Table 6: Conceptual Summary of Core and Extended Variables

Theoretical	Construct	Definition	Relationship	Support Rate
TAM	Perceived Usefulness	The degree to which an individual believes that using a specific system will maximize their performance. (Davis,1985).	PU→BI	67%
TAM	Perceived Ease of Use	The degree to which an individual believes that using a system requires minimal effort reflects their expectation that the new technology will be easy to learn and use.	PEU→BI	50%
UTAUT	Performance Expectation	The degree to which an individual subjectively believes that using a particular product or technology can enhance their performance and experience (Venkatesh et al., 2012).	PE→BI	100%
UTAUT	Effort Expectation	Users' perception of system usability. Factors such as the time and effort required to master the technology directly influence users' willingness to adopt it (Venkatesh et al., 2012).	EE→BI	100%
UTAUT	Social Influence	The degree to which users perceive the external environment's attitude toward their adoption of new products or technologies (Venkatesh et al., 2012).	SI→BI	100%
UTAUT	Facilitating Conditions	Facilitating conditions refer to the perceived support and promotion of new products or technologies from both internal and external environments (Venkatesh et al., 2012).	FC→BI	50%
UTAUT 2	Hedonic Motivation	The pleasure or enjoyment derived from using technology (Venkatesh et al., 2012).	HM→BI	100%
UTAUT 2	Price Value	Consumers' cognitive trade-offs between the perceived benefits of artificial intelligence technology and its economic costs (Venkatesh et al., 2012).	PV→BI	100%

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UTAUT 2	Habit	Habit measures the extent to which people transform behaviors into automatic patterns (Venkatesh et al., 2012).	HB→BI	100%
TTF	Task Technology Fit	The degree of alignment between technical features and task requirements, specifically the suitability of technology in supporting user task execution(Goodhue & Thompson 1995).	TTF→BI	0%
Expansion	Trust	Individuals are willing to rely on the technology based on their belief in its capabilities, good faith, and integrity (Gefen et al., 2003).	Trust→ BI	100%
			Trust→PU→BI	100%
Expansion	Perceived Risk	Potential losses that users perceive may result from using new technologies or products (Bauer, 2001).	PR→BI	100%
			PR→PU→BI	100%
			PR→Trust→BI	0%
Expansion	Perceived Self-Efficacy	An individual's capacity to achieve desired outcomes through personal effort (Kurniawan, Chau & Gui, 2024).	PS→BI	100%

Although studies vary considerably in their settings, the substantial recurrence of similar variables points to both a shared fundamental explanatory framework across the discipline and the identification of distinct contextual factors.

Positive factors : The core constructs of TAM: PU and PEU, and the core constructs of UTAUT: PE, EE, SI, and FC were found to be the most stable in explaining BI, the most pervasive drivers. This confirms the strong explanatory power and generalizability of the TAM and UTAUT models in AI adoption research (Hu et al., 2025; Kurniawan et al., 2024). whereas intrinsic motivation is shaped by hedonic motivation and creativity (Hu et al., 2025; Lai et al., 2025). These findings indicate that, for designers, AI tools must be not only functional but also engaging and creatively stimulating.

Obstacle factors : In addition to TAM and UTAUT, this review also identified other barrier variables particularly relevant to creative industries such as fashion design. Emotional resistance often arises from Perceived Risk (PR) and Technological Anxiety (TA) (Kurniawan et al., 2024; Li et al., 2024).

Mediating and Moderating Variables : this study reveals the complexity of the influence of pathways. Rather than directly influencing behavioural intention, several variables are indirectly influenced by mediating variables (e.g., attitudes) (Stroud & Du, 2025), or conditioned by moderating variables (e.g., years of experience, personal innovativeness) (Hu et al., 2025; Li et al., 2024).

The evolution of variables reflects the broadening of research perspectives. From the initial focus on the technology itself (PU & PEU) to the incorporation of social and environmental

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factors (Zhu et al., 2025), to the in-depth exploration of the HCI experience (Liu et al., 2025), suggests that the academic community has shifted from a purely technological perspective to a systemic perspective of the triad of techno-human-social interaction. Compared to sectors like education, retail, or manufacturing, the fashion industry places greater emphasis on aesthetic sensitivity, personal expression, and intuitive workflows. These industry characteristics alter users' evaluation criteria for AI tools. or fashion design professionals, judgments of "perceived utility" typically center on creative quality and stylistic consistency rather than mere efficiency (Hu et al., 2025). Simultaneously, a fluid interactive experience is crucial for maintaining creative momentum (Gao et al., 2023). Social influence exhibits stronger bidirectionality, as users frequently navigate between team expectations and personal expression (Mårtensson & Norma, 2025). Moreover, the importance of inspiration and pleasurable experiences for creative thinking makes hedonic motivation a more powerful predictor (Arachchi & Samarasinghe, 2025). Collectively, these industry characteristics reinforce the role of the TAM/UTAUT theoretical framework in explaining AI tool adoption intentions within the fashion sector.

In summary, the discussion suggests that future research addressing AI adoption in the field of fashion design should abandon a single, universal model in favour of a contextualised, integrated theoretical framework.

Key Findings

First, the core drivers are highly consistent. PE and EE are the most stable and powerful positive predictors of BI in the vast majority of studies (Li et al., 2024; Sharma & Sharma, 2024). This suggests that users are most concerned with the "PU" and "PEU" of AI tools. SI is also frequent, indicating that the perceptions of people around them (coworkers, classmates, superiors, social trends) have a significant impact on personal decision-making (Kurniawan et al., 2024; Liu et al., 2025).

Second, risk and anxiety are the main barriers. A higher level of perceived risk considerably reduces the intention to adopt. (Shen et al., 2025; Verano-Tacoronte et al., 2025). Users fear that AI is wrong, ineffective, or leads to data leakage. Anxiety is a significant psychological barrier that directly or indirectly diminishes the willingness to use. This study reveals that technological anxiety exerts a more pronounced influence within creative industries. Design professionals' concerns regarding job displacement, compromised originality, or tool complexity directly diminish their willingness to adopt AI tools (Li, 2025). Research indicates that transparent system feedback and step-by-step training effectively alleviate such anxiety, enhancing users' sense of control over AI tools (Gera, 2024).

Again, beyond traditional models, emotional and experiential factors are increasingly important. In addition to rational "usefulness" and "ease of use", emotional factors play an essential role. HM is a key driver (Lai et al., 2025). Positive emotions and attitudes have been repeatedly shown to be key mediating variables in influencing behavioural intentions and actual use. Additionally, the motivation for enjoyment serves as a key driver in promoting user adoption of AI tools. Systems that enhance the pleasure of creative exploration and strengthen inspiration triggers are more readily embraced (Allam, 2025). Related research indicates that enriching interactive experiences and visual feedback helps amplify this sense of enjoyment, thereby increasing willingness to use such tools (Elmashhara et al., 2024).

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Finally, complex mediating mechanisms. Many studies have found that effects are not direct but are realised through a range of mediating variables. For example, PU and attitude are the most common mediating variables. PEU does not usually affect willingness directly, but works indirectly by influencing PU first. This suggests that the user's decision-making process is a complex, multi-step psychological chain.

Contribution

Theoretical Contribution: This study systematically reviews the literature on AI tool adoption in fashion design. It confirms the foundational role of traditional technology acceptance models in fashion contexts while also identifying their limitations in explaining the actual behaviors of design communities. Building upon this, the study integrates multiple key variables to outline critical factors for AI tool adoption that better align with the characteristics of the fashion industry. For instance, it expands to include emotional barriers (e.g., anxiety) and creative drivers (e.g., hedonic motivation). This framework offers a more explanatory theoretical perspective for future research on AI tool acceptance within the fashion industry.

Practical Contribution: The findings provide clear actionable directions for fashion brands, fashion designers, and AI tool developers. Understanding "how to reduce anxiety" and "how to enhance the creative experience" is key to increasing willingness to use AI. This helps companies strengthen clear feedback, improve interaction comfort, and add inspiration-boosting features in tool design, making it easier for design users to integrate AI tools into their daily workflows.

Methodological Contribution: Employing the PRISMA systematic review methodology, this study systematically synthesizes existing research on AI tool adoption in fashion design. It establishes a literature screening and evaluation framework for future scholars to reference. This approach not only enhances the transparency of the review but also provides a reliable research pathway for comparing AI adoption mechanisms across different creative fields.

Impact

The outcomes of this research are expected to have a broad impact across three key areas: academic, industrial, and social. From an academic perspective, this study transcends the limitations of traditional technology adoption theory by exploring additional factors, including emotion and innovation. It contributes to expanding the theoretical framework of technology acceptance within the creative industries.

From an industry perspective, this research is expected to have a profound impact on the development of AI tools. It provides a user-oriented development strategy that will facilitate technological innovation in AI tools. Furthermore, this research offers insights for fashion business leaders and aims to accelerate collaboration between users and AI tools. For instance, AI anxiety suppresses users' intention to use, while hedonistic motivation effectively enhances their behavioral intention. For industry practice, this implies that when promoting AI tools, efforts should simultaneously reduce users' uncertainty (eg. by alleviating anxiety through clearer processes and transparent data mechanisms) and enhance the tool's pleasurability and inspiration-triggering capabilities to boost hedonistic motivation. This finding aligns with existing research concluding that "anxiety reduces technology adoption" (Venkatesh, 2000) and "hedonic motivation increases behavioral intention" (Venkatesh et al., 2012), providing actionable guidance for AI tool implementation in the fashion industry.

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At the societal level, this research advances the sustainable development of artificial intelligence in fashion design. It propels fashion design toward more efficient, intelligent, and eco-friendly models. At the same time, by emphasising human-computer collaboration rather than substitution, this study helps to alleviate career anxiety caused by technological change. It provides insights for creative workers to plan for their professional future in the age of AI, thus generating positive socio-economic benefits.

Conclusion

Through a literature review, this study delves into the key factors influencing the behavioural intent to adopt AI tools in the field of fashion design. Through a comprehensive analysis of 15 studies, this study reveals the specificity and complexity of technology acceptance behaviour in the creative industries. The main findings suggest that PE, EE, SI, and FC constitute the core underlying factors influencing adoption intentions, while perceived risk, technology anxiety, and career replacement anxiety form the primary barriers to adoption. More importantly, this study identified influential factors that are particularly important in creative work environments, including perceived pleasure, task-skill matching, and the correlation between job content and creativity.

The theoretical significance of this study lies in its expansion of the application boundaries of the traditional Technology Acceptance Model in the context of fashion design. It proposes a more comprehensive and contextually relevant theoretical framework, offering new perspectives for understanding the interaction between designers and technology. At the practical level, this study provides user-centred design directions for AI tool developers, effective technology promotion strategies for fashion business managers, and guidance for educational institutions to cultivate human-computer collaboration skills among future designers.

Although this study provides valuable insights for the fashion design industry, several limitations remain. First, the research is constrained by the scope of the databases used. Second, the number of relevant literature sources is limited. Ultimately, the current literature requires further exploration of cultural contexts and professional variations.

Future research should adopt long-term tracking and multi-methodological approaches to gain a deeper understanding of the phenomenon. It should investigate the dynamics among key variables through more extensive studies. Concurrently, comparative research across cultures and regions should be conducted.

Furthermore, shifting academic focus from adoption motives to sustained usage patterns and their enduring impact on design outcomes would deepen understanding of technology adoption behaviours in creative fields.

In summary, this study not only systematically integrates factors influencing the adoption of AI tools in fashion design but also establishes a research foundation for academic and industrial advancement in this field, while providing critical recommendations for technology-driven and intelligent design.

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References
Arachchi, H. D. M., & Samarasinghe, G. D. (2025). Perceived attributes of artificial intelligence (AI) toward consumers' AI attitudes and purchase intention in an AI-powered retail. *European Journal of Management Studies*, 30 (3-4), 243-267.

Allam, H. (2025). Hedonic Systems: Integrating Motivation, Usability, and Sociotechnical Contexts in Smart Systems. *The Artificial Intelligence Business Review*, *1*(1).

Baker, J. (2011). The technology-organisation-environment framework. *Information Systems Theory: Explaining and Predicting Our Digital Information, Vol. 1*, 231-245.

Bauer, R. A. (2001). Consumer behavior as risk taking. In Marketing: Critical perspectives on business and management (Vol. 2, p. 568). Routledge.

Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P. S., & Sun, L. (2023). A comprehensive survey of AI-generated content (AIGC): a history of generative AI from GAN to ChatGPT. *arXiv preprint arXiv:2303.04226*.

Chang, M., Walimuni, A. C., Kim, M.C., & Lim, H.S. (2022). Acceptance of tourism blockchain based on UTAUT and connectivism theory. *Technology in society*. *71*, 102027.

Davis, F. D. (1985). A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results. (Ph.D in Management Disertation), Massachusetts Institute of Technology, Sloan School of Management.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.

Deci, E. L., & Ryan, R. M. (2004). *Handbook of self-determination research*. University of Rochester Press.

Elmashhara, M. G., De Cicco, R., Silva, S. C., Hammerschmidt, M., & Silva, M. L. (2024). How gamifying AI shapes customer motivation, engagement, and purchase behavior. Psychology & Marketing, 41(1), 134-150.

ElSayad, G., & Mamdouh, H. (2025). The Power of AI in Retail E-Commerce: What Drives Online Customer Word-of-Mouth Intention Toward AI-Powered Shopping Applications?. *International Journal of Human-Computer Interaction*, 1-13.

Faghih, E., Saki, Z., & Moore, M. (2025). A Systematic Literature Review-AI-Enabled Textile Waste Sorting. *Sustainability*. *17*(10), 4264.

Fryer, L. K., Ainley, M., Thompson, A., Gibson, A., & Sherlock, Z. (2017). Stimulating and sustaining interest in a language course: an experimental comparison of Chatbot and Human task partners. *Computers in human behavior*. *75*, 461-468.

Gao, B., Xie, H., Yu, S., Wang, Y., Zuo, W., & Zeng, W. (2023, August). Exploring user acceptance of Al image generator: unveiling influential factors in embracing an artistic AIGC software. In International Conference on AI-generated Content (pp. 205-215). Singapore: Springer Nature Singapore.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS quarterly*, 213-236.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

Volume 10 Issue 41 (December 2025) PP. 269-292
DOI: 10.35631/JISTM.1041018
Gera, P. (2024). *Integrating Mindfulness: Enhancing Art and Design Student Well-being through AI Voice Assistants and Wearable Technology* (Doctoral dissertation, OCAD University).
Hu, L., Chen, M., & Ding, N. (2025). Factors influencing digital media designers' subscription to premium versions of AI drawing tools through a mixed methods study. *Scientific Reports*. *15*(1), 15994.
Huang, T. (2021). Research on the use intention of potential designers of unmanned cars based on the Technology Acceptance Model: PLoS one, 16(8), e0256570.
Karpova, E., Marcketti, S., & Kamm, C. (2013). Fashion industry professionals' viewpoints on creative traits and strategies for creativity development. *Thinking Skills and Creativity*. *10*, 159-167.
Kurniawan, P. A., Chau, M., & Gui, A. (2024). Unveiling Generative Adversarial Network Adoption in Design Processes. In 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA), (pp. 666-671). IEEE.
Lai, S., Wu, Z., Zhou, J., & Chen, Y. (2025). Factors Influencing Designers' Adoption of AI-Generated Content Tools: Task Characteristics, Technology Characteristics. In Proceedings of the 2025 4th International Conference on Big Data, Information, and Computer Network (pp. 478-486).
Latané, B. (1981). The psychology of social impact. *American psychologist*, *36*(4), 343.
Lazarus, R. S. (1991). Progress on a cognitive-motivational-relational theory of emotion. *American psychologist*. *46*(8), 819.
Lee, S.Y., Law, M., & Hoffman, G. (2025). When and how to use AI in the design process? Implications for human-AI design collaboration. *International Journal of Human-Computer Interaction*. *41*(2), 1569-1584.
Li, X., Shen, L., & Ren, X. (2024). Explore the fashion industry's behavioral intention to use artificial intelligence generated content tools based on the UTAUT model. *International Journal of Human-Computer Interaction*, 41(16), 10285-10300.
Li, W. (2025). A study on factors influencing designers' behavioral intention in using AI-generated content for assisted design: Perceived anxiety, perceived risk, and UTAUT. International Journal of Human–Computer Interaction, 41(2), 1064-1077.
Liang, Y., Lee, S.-H., & Workman, J. E. (2020). Implementation of artificial intelligence in fashion: Are consumers ready? *Clothing and Textiles Research Journal*, *38*(1), 3-18.
Liu, J., Zou, J., Zhang, J., & Teng, J. (2025). Investigating users' acceptance of AI-based creativity support tools: an empirical study from China's creative industries. *Current Psychology*, *44*(16), 13933-13950.
Ma, D., Akram, H., & Chen, I.H. (2024). Artificial intelligence in higher education: A cross-cultural examination of students' behavioral intentions and attitudes. *International Review of Research in Open and Distributed Learning*. *25*(3), 134-157.
Mårtensson, F., & Norma, S. (2025). The Rise of Generative AI in Creative Agencies: An Examination of Opportunities, Challenges & Threats.
Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021a). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, *372*
Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021b). PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *bmj*, *372*

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Volume 10 Issue 41 (December 2025) PP. 269-292
DOI: 10.35631/JISTM.1041018
Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*. *241*, 108250.
Sharma, A. K., & Sharma, R. (2024). Assessing the influence of artificial intelligence on sustainable consumption behavior and lifestyle choices. *Young Consumers*.
Shen, B., Tan, W., Guo, J., Zhao, L., & Qin, P. (2021). How to promote user purchase in metaverse? A systematic literature review on consumer behavior research and virtual commerce application design. *Applied Sciences*, *11*(23), 11087.
Shen, X., Mo, X., & Xia, T. (2025). Exploring the attitude and use of GenAI-image among art and design college students based on TAM and SDT. *Interactive Learning Environments*, *33*(2), 1198-1215.
Stroud, R., & Du, J. (2025). Student acceptance of ChatGPT in higher education: a mixed-method study of attitudes, intentions, and concerns. *Journal of Applied Learning and Teaching, 8*(2).
Tao, W., Gao, S., & Yuan, Y. (2023). Boundary crossing: an experimental study of individual perceptions toward AIGC. *Frontiers in psychology*, *14*, 1185880.
Toh, S. Y., Ng, S. A., & Phoon, S. T. (2023). Accentuating technology acceptance among academicians: A conservation of resource perspective in the Malaysian context. *Education and Information Technologies*, *28*(3), 2529-2545.
Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. M*anagement science*, *46*(2), 186-204.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.
Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 1, 36, 157–178. https://doi.org/10.2307/41410412
Verano-Tacoronte, D., Bolívar-Cruz, A., & Sosa-Cabrera, S. (2025). Are university teachers ready for generative artificial intelligence? Unpacking faculty anxiety in the ChatGPT era. *Education and Information Technologies*, 1-28.
Wang, S. F., & Chen, C. C. (2024). Explore the driving factors of designers' AIGC usage behavior based on SOR framework. *Frontiers in Computer Science, 6*, 1417016.
Zhou, E., & Lee, D. (2024). Generative artificial intelligence, human creativity, and art. *PNAS nexus*, *3* (3), 52.
Zhu, Z., Yu, T., Wang, Y., & Xu, J. (2025). Revolutionizing Design Content with AIGC: User-Centered Challenges, Opportunities, and Workflow Evolution. *iEEE Access*.