



## OPEN Research on driving factors of consumer purchase intention of artificial intelligence creative products based on user behavior

Weiling Shi<sup>1</sup>, Li Li<sup>1</sup>✉, Zhixin Zhang<sup>1</sup>, Maoguo Li<sup>2</sup> & Junjie Li<sup>3</sup>

With the continuous advancement of artificial intelligence (AI) technology, AIGC (AI-generated content) has increasingly permeated various sectors, leading to a significant transformation in the design industry. This study aims to explore user purchase intention and the influencing factors of AI-generated cultural and creative products, thereby formulating strategies to enhance user satisfaction. Based on the stimulus-organism-response theory, the theory of planned behavior, the value adoption model, the innovation diffusion theory, and the unified theory of acceptance and use of technology<sup>2</sup>, a comprehensive model is constructed. The model also incorporates external variables such as perceived value (PV), perceived price (PP), social influence, hedonic motivation (HM), and cultural experience (CE). Additionally, self-innovation is considered as a key moderator to explore its role in moderating the relationships between PV, PP, and user perceived behavioral control. Using 526 valid samples, this study employs structural equation modeling to conduct exploratory factor analysis and confirmatory factor analysis, and further verifies the importance of variables through artificial neural networks. The findings indicate that behavioral attitude, HM, PP, PV, and generative quality are the primary factors influencing user purchase intention. In the decision-making process, users not only consider the price and quality of the products but also place significant importance on the pleasurable experience and cultural uniqueness they offer. This study extends the theoretical application of AIGC in the field of cultural and creative consumption, enriches the user behavior research model, and provides practical insights for companies to optimize AI-generated cultural products, enhance user experience, and improve market acceptance.

**Keywords** AIGC, Cultural and creative design, Artificial neural networks, Purchase intention, Structural equation modeling

In recent years, the scale of AIGC usage has been expanding rapidly, not only in the field of computer science but also across various industries, all of which are undergoing transformation and upgrading due to its influence<sup>1</sup>. According to data from QuestMobile, by June 2024, the monthly active user base of the AIGC app industry reached 61.7 million, reflecting a year-on-year growth of 653.3%<sup>2</sup>. Moreover, the rapid development of AIGC has brought about significant changes in the design industry, demonstrating immense potential in the creative and cultural sectors. In the trade of cultural and creative products, China has become a major producer and exporter<sup>3</sup>, and its cultural creative market holds vast commercial value.

With the widespread application of artificial intelligence, the interdisciplinary integration and diversified innovation capabilities of the design industry have also been continuously evolving, helping to overcome limitations encountered in traditional design processes<sup>4</sup>. AI has already been applied in multiple fields, including cultural creative design and product design. Currently, Chinese cultural and creative products face issues such as homogenization, excessive decoration, and superficial content, with similarities in shape, function, and color across various areas, lacking innovation and regional characteristics<sup>5</sup>. The involvement of AI in the design of cultural and creative products can improve design efficiency, reduce basic design tasks, empower the design process, and optimize workflows<sup>6</sup>, allowing designers to focus more on design innovation. Additionally, AI can break free from conventional thinking constraints by enabling cross-disciplinary, random combinations

<sup>1</sup>College of Art & Design, Lanzhou University of Technology, Lanzhou 730050, China. <sup>2</sup>College of Law and Humanities and Social Sciences, Wuhan University of Technology, Wuhan 430070, China. <sup>3</sup>College of Fashion and Art Design, Donghua University, Shanghai 201620, China. ✉email: w496895639@163.com

in design, providing designers with more creative inspiration. Furthermore, AI-generated cultural and creative designs can integrate multiple attributes, including product form, decorative elements, functional properties, and color combinations, making it an indispensable tool in the daily work of designers.

Previous research on AIGC has primarily focused on aspects such as platform usage experience, users' willingness to use, and the platform's usefulness and ease of use. For instance, some studies have combined wireless perception (WP) with AIGC to address the impact of AI model instability on user experience, thereby optimizing the service<sup>7</sup>. Previous research has indicated that conditions such as self-innovation (SINN) and effort expectancy positively influence the use of AIGC tools. Scholars have developed a foundational research model using Smart-PLS software and PLS-SEM technology to analyze the intrinsic factors and influences on designers' use of AIGC tools. The results show that perceived anxiety and risk negatively affect the use of AIGC tools, while promoting conditions such as social influence (SI) and effort expectancy have a positive impact<sup>8</sup>. Researchers built an experiential framework on user behavior patterns and psychological motivations based on 52 volunteers and 312 reports, analyzing communication strategies used by users when interacting with AI-generated art. They identified communication barriers and proposed strategies for overcoming them, aiming to enhance the user experience during human–computer interaction<sup>9</sup>. Previous studies have largely focused on user experience<sup>10</sup>, ethics and morality<sup>11</sup>, behavioral intentions<sup>8</sup>, and human–computer interaction<sup>9</sup>. However, research on user purchase intentions and related dimensions in the context of AIGC-assisted design generation remains an area of gap.

To address this gap, this study explores the factors influencing user purchase intention for AIGC-generated cultural and creative products by examining relevant research on AIGC platforms and conducting a systematic survey of the current mainstream AIGC platforms, while integrating relevant theories. This study proposes a comprehensive model, with the framework based on the stimulus-organism-response (SOR) theory. The internal influencing factors are primarily derived from the theory of planned behavior (TPB), innovation diffusion theory (IDT), unified theory of acceptance and use of technology (UTAUT2), and the value adoption model (VAM). Specifically, perceived value (PV) and perceived price (PP) are sourced from VAM<sup>10</sup>, while facilitating conditions (FC), social influence (SI), and hedonic motivation (HM) are derived from UTAUT2<sup>12,13</sup>. External variables, such as cultural experience (CE) and generation quality (GQ), are based on results from previous literature and practical research on AI platforms<sup>14</sup>. Furthermore, prior research suggests that innovation may influence user acceptance of new technologies<sup>15</sup>; therefore, this study incorporates self-innovation (SINN) as a potential moderating factor in the model design. This research combines IDT, UTAUT, and TPB with external variables to explore the factors influencing user purchase intention for AIGC-generated cultural and creative products under a multifaceted framework.

This study contributes to exploring consumers' purchase intention for AI-generated cultural and creative products and provides practical case references for the application of AIGC technology in the design field. The innovations of this study are as follows:

- (1) Integration of VAM and UTAUT2: This study combines the value adoption model (VAM) with the unified theory of acceptance and use of technology 2 (UTAUT2), representing a novel approach in AI research. It explores users' acceptance intentions, purchase intentions, and behavioral activities regarding AI-assisted design solutions, thereby enhancing the practicality and reliability of the study. This combination provides new insights and methodologies for research in this field.
- (2) Incorporation of TPB: This study introduces the theory of planned behavior (TPB), which is widely used in psychology and behavioral science. By applying the three core factors of TPB—behavioral attitude (AT), subjective norms (SN), and perceived behavioral control (PBC)—this research can specify the factors influencing users' purchase behavior. It helps precisely identify the key variables that affect user purchase decisions for AI-generated cultural and creative products.
- (3) Inclusion of SINN as a Moderator: Self-innovation (SINN) is an important factor influencing user behavior characteristics. One of the research questions of this study is whether SINN can moderate the relationship between perceived value (PV), perceived price (PP), and perceived behavioral control (PBC). By incorporating SINN into the model, this study offers a more comprehensive understanding of users' technology adoption behaviors.

The research process of this study is as follows: First, a systematic investigation of current mainstream AIGC platforms is conducted, including a competitive product analysis to clarify their technological implementations and content features. Second, based on a literature review and theoretical integration, the research model and hypotheses are proposed. Third, a questionnaire is designed, and sample data is collected, with empirical analysis performed using structural equation modeling (SEM) and artificial neural networks (ANN). Finally, the results of the analysis are discussed in depth, offering theoretical insights and managerial recommendations, which provide a reference for the further application and development of AIGC in the cultural and creative field.

## Research background and hypotheses

### AIGC research progress

#### *Theoretical research on AIGC*

AIGC refers to content such as text, images, music, and videos that are generated based on instructions using advanced generative artificial intelligence (GAI) algorithms<sup>16</sup>. AIGC technology typically relies on advanced machine learning models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Deep Neural Networks (DNNs). According to Adobe's "Creativity and Technology in the Age of Artificial Intelligence" report, three-quarters of artists in the United States, Europe, and Japan have embraced AIGC as a tool for assisting in design<sup>17</sup>. This indicates that AIGC holds vast market potential and has gained

Author	Product or service	Research contents	References
Ikpe Justice Akpan	Artificial intelligence (AI)	Scientific landscape	18
Emmanuelle Walkowiak	AI-Generated	Risks in creative industries	19
Junping Xu	AI Painting	User experience	20
Ahmad W. Sukkar	AI-Generated	Limitations of generation	21
Biao Gao	AI-Generated	Advertising industry	22
Hanaa Farouk Saleh	AI-Generated	Ethical challenges	23
Taewook Kim	AIcreative language arts	Values and attitudes	24
Nantheera Anantrasirchai	Artificial intelligence	Application status	25
Xiaoyue Ma	AI Painting	AI interaction	10
Yuntao Wang	AI-Generated	Ethical and social impact	26

Table 1. AI research progress.



Fig. 1. Competitive analysis of AIGC platforms.

widespread recognition, reflecting not only consumers’ open attitudes toward technological advancement but also highlighting the immense potential of AI in driving cultural creation and dissemination.

Currently, scholars have conducted a series of studies on AIGC from different fields, as shown in Table 1. Scholar Ikpe Justice Akpan investigated the prospects of artificial intelligence and assessed the advantages and challenges of interdisciplinary education and the operation of related industries<sup>18</sup>. Scholar Emmanuelle Walkowiak analyzed the risks involved in the cultural and creative industries related to generative AI, including eight risks such as privacy, cybersecurity, and intellectual property<sup>19</sup>. Junping Xu, through an extended model combining the extended technology acceptance model (ETAM) and AI-based painting systems (AIBPS), explored factors influencing user acceptance of AIBPS and validated the hypotheses using the SEM<sup>20</sup>.

Currently, AIGC has permeated various industries and plays an important role in the design sector. Previous scholars have explored the relationship between AIGC and user perception from different perspectives, combining various theories, thereby laying a theoretical and practical foundation for the development of AIGC.

AIGC platform competitor analysis

Through a competitive analysis of various AIGC platforms on the market, this study systematically discusses several aspects, including generation capabilities, user experience, technical strength, global rankings, and traffic volume (as shown in Fig. 1). Among the platforms, Midjourney and Stable Diffusion perform particularly well in terms of generation capabilities. Midjourney is renowned for its strong performance in artistic content generation, capable of producing highly creative and detailed visual content. Stable Diffusion, based on its stable diffusion model, exhibits high generation efficiency and offers various usage methods, including an online interface and API, making it particularly popular among developers and researchers<sup>21</sup>.

In terms of user experience, which includes platform ease of use and interface design, platforms like Playground and Lucidpic offer intuitive and interactive user interfaces that allow real-time viewing of generated content, greatly enhancing creative efficiency and user satisfaction<sup>27</sup>. “Wenxin Yige” provides more localized services, improving the experience for Chinese-speaking users.

Regarding technical strength, platforms such as Stable Diffusion, OpenAI, and Adobe Firefly possess robust technical backgrounds, with generative models that offer high scalability and flexibility. Surveys show that these

platforms excel in different fields, providing creators with rich tools and resources to meet the diverse needs of users in generating creative content, thereby promoting the application and development of AIGC technology.

### SOR model

The SOR model was proposed by environmental psychologists Mehrabian and Russell and is widely used in behavior prediction. S represents factors related to external stimulus dimensions, O represents factors related to the organism's cognitive and emotional states, and R represents factors related to the organism's behavioral responses. This model explains the influence of the three dimensions—stimulus, organism, and response—on behavior<sup>28</sup>.

Previous studies have demonstrated the strong explanatory power of the SOR model in purchase intention research. Nagano applied the SOR model to explore the impact of advertising voice stimuli on users' purchase intentions, finding that emotional states partially mediate the relationship between voice characteristics and purchase intention. The study confirmed the effectiveness of the SOR model in explaining the mechanism through which voice stimuli influence purchase intention<sup>29</sup>. Song, based on the SOR model, explored how stimulus characteristics such as visibility, interactivity, and authenticity in live streaming influence consumers' purchase intentions (response) through perceived value (PV) and perceived trust (organism)<sup>30</sup>. Hameed, also based on the SOR model, examined how external stimuli, such as relationship ties, influence consumers' purchase intentions in live retail by affecting trust and internal perceptual processes. The study, using PLS-SEM and ANN analysis, found that trust plays a key mediating role between stimulus and purchase intention<sup>31</sup>.

These studies strongly support the applicability of the SOR model in explaining the formation mechanism of purchase intention in the context of new technologies, and the model plays a significant role across various fields. The SOR model provides a complete chain of influence from external stimuli (S) to internal cognitive processing (O) and ultimately to behavioral responses (R). This aligns closely with the process of user purchase behavior for AI-generated cultural products on platforms. Users first receive external stimuli, such as product characteristics, which are then processed through internal cognitive evaluation, ultimately leading to the formation of purchase intention. Therefore, this study uses the SOR model as the foundational framework to explore users' purchase intentions for AI-generated cultural products on platforms.

### Value adoption model (VAM)

VAM was developed by Kim et al. to assess the acceptance of M-Internet and serves as a framework for understanding and predicting the adoption of new technologies<sup>12</sup>. It focuses on users' perceived value (PV) of the technology, which is influenced by various factors; the higher the PV, the greater the likelihood of adoption. VAM consists of four key components: perceived usefulness (PU), perceived ease of use (PEOU), PV, and behavioral intention (BI). In addition, PP is typically directly related to PV. Initially applied in the field of the internet, VAM has since been extended to various areas, including e-commerce<sup>32</sup>, smart homes<sup>33</sup>, enterprise services<sup>34</sup>, and e-learning<sup>35</sup>, to understand and predict the public acceptance of various technologies.

#### *Perceived value (PV)*

Perceived Value (PV) is one of the core concepts in the value adoption model (VAM), directly influencing users' overall evaluation of the value of a technology, product, or service. This evaluation is based on the balance between the perceived benefits and costs. As a core factor in VAM, PV is frequently used in studies exploring consumer behavior<sup>13</sup>.

In the research conducted by Milfelner-Borut, when investigating the interrelationships between PV, quality, image, and satisfaction, it was found that the relationship between quality and satisfaction is not direct. Instead, it is mediated by PV, and PV is positively correlated with both quality and satisfaction<sup>36</sup>. Moreover, studies using online purchase intention models have demonstrated that PV has a positive impact on consumers' purchasing intentions<sup>37</sup>. Purchase intention, in turn, enhances an individual's perceived behavioral control (PBC)<sup>38</sup>.

Extending PV to three dimensions—functional, emotional, and social—research using structural equation modeling (SEM) to test hypotheses on user behavior perception has shown that PV directly influences users' behavioral intentions and plays an important role in behavioral outcomes. When users recognize a particular result, the positive emotional connection strengthens their identification with the behavior, thus influencing their subjective norms (SN)<sup>39</sup>. Fiandari through a SEM model incorporating PV, SN, PBC, and Attitude (AT), conducted a survey of 365 individuals who consume fish annually. The study concluded that PV could influence both SN and PBC<sup>40</sup>.

Therefore, we propose the following hypothesis:

**H1** PV is positively correlated with PBC.

**H2** PV is positively correlated with SN.

#### *Perceived price (PP)*

PP refers to the user's subjective evaluation of the costs associated with a particular technology, product, or service. It is a critical factor influencing the user's PV and ultimately affects their intention to adopt or purchase the product or service. A higher perceived price may reduce the user's perceived value, thereby decreasing their intention to adopt the technology or make the purchase<sup>41</sup>. Wassouf's research on the impact of product price on consumer perception demonstrated that price significantly affects consumers' perceptions of products and their willingness to purchase<sup>42</sup>. Consumers' perceptions are often shaped by social and cultural factors. When a consumer's perception of a product aligns with the mainstream societal values or group norms, their intention to purchase tends to increase<sup>43</sup>. Therefore, price also influences an individual's SN.



In a study by Dorce, LC, the authors explored the factors affecting Brazilian consumers' decisions to purchase organic vegetables and developed a TPB model, incorporating PP as an independent variable. The results showed that price has a moderating relationship between intention and behavior. A higher price could prevent consumers from making a purchase<sup>44</sup>. When the perceived price is too high, an individual's sense of self-efficacy diminishes, thereby weakening their perceived behavioral control (PBC)<sup>45</sup>. Yen, YS employed hierarchical moderating factors and simple slopes to analyze a survey of 385 Taiwanese consumers, and found that PP is significantly correlated with the willingness to purchase domestic products<sup>46</sup>. Furthermore, when users have a strong intention to purchase, this tends to drive them toward actual purchasing behavior, which can be considered as an expression of their PBC<sup>47</sup>.

Therefore, we propose the following hypotheses:

**H3** PP is negatively correlated with PBC.

**H4** PP is negatively correlated with SN.

### Unified theory of acceptance and use of technology (UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed by Viswanath Venkatesh in 2003, focusing on the elimination of external motivations for users based on similarities in previous models<sup>48</sup>. With the advancement of technology and improvements in consumer levels, UTAUT was extended in 2012 to the UTAUT2 model, which emphasized intrinsic motivations by introducing new factors such as Hedonic Motivation (HM), Price Value, and Habit<sup>49</sup>. UTAUT2 provides a more comprehensive framework for explaining and predicting consumer behavior when using technology.

UTAUT2 is not limited to consumer users; it has been applied in various fields such as mobile banking<sup>50</sup>, social systems<sup>51</sup>, healthcare<sup>52</sup>, dining<sup>53</sup>, online shopping<sup>54</sup>, and education<sup>55</sup>. For example, a study on the impulsive online buying behavior of Generation Z extended the concept of convenience (FC) into four dimensions: relational convenience, possession convenience, post-possession convenience, and transaction convenience. The findings indicated that FC is a significant factor influencing consumers' impulsive buying behavior<sup>56</sup>.

In a study analyzing users' acceptance of autonomous vehicles using the UTAUT2 model, researchers surveyed 9118 drivers from eight countries. The results showed that HM and SI significantly affect consumers' intentions to purchase and use autonomous vehicles<sup>57</sup>.

Thus, UTAUT2 has become a well-established and widely used model for exploring users' perceptions and acceptance of emerging technologies. In this research, UTAUT2 will be used as an external variable to investigate its relationship with users' perceptions and their adoption of AI-generated cultural and creative products.

#### *Facilitating conditions (FC)*

Facilitating Conditions (FC) refer to the extent to which an individual perceives that the external environment supports the use of a particular technology. This includes the availability of necessary resources, the effectiveness of assistance, and the reliability of the surrounding environment. FC not only influences an individual's behavioral intention but also directly impacts the actual occurrence of the behavior. When consumers perceive higher convenience while performing a behavior, their intention to engage in that behavior increases<sup>58</sup>. However, research on the impact of FC on SN and PBC remains limited.

In a study on the factors influencing users' acceptance of a Mobile Medical Platform (MMP), the results showed that FC significantly affected patients' acceptance of the platform<sup>59</sup>. As consumers' acceptance of a product increases, their tendency to purchase that product grows, and their PBC also increases. Venkatesh's research proposed that improvements in FC during the technology usage process enhance users' confidence in using the technology, thereby boosting their PBC<sup>48</sup>. Based on this, we can infer that FC influences users' PBC. Furthermore, Venkatesh highlighted that the ease of use and accessibility of technology positively influence users' technology acceptance, which is affected by social norms<sup>48</sup>. SN reflects an individual's understanding of others' expectations and the social norms resulting from these expectations<sup>47</sup>. This suggests that FC has a positive indirect effect on SN<sup>60</sup>. Shirley Taylor, in exploring which UTAUT model better helps users understand technology use, collected data from 786 users at a computer resource center and conducted 3780 visits over 12 weeks. The study demonstrated that FC influences the adoption of new technologies, and this influence is moderated by SN<sup>47</sup>.

Based on this, we propose the following hypotheses:

**H5** FC is positively related to PBC.

**H6** FC is positively related to SN.

#### *Social influence (SI)*

Social Influence (SI) reflects the impact of the social environment on individual decision-making. Individuals are influenced by social pressures, perceiving certain behaviors or technologies as aligning with societal expectations. SI is typically facilitated by the behaviors of those around the individual, guiding them in a particular direction<sup>61</sup>. Previous scholars have used SI to study the public's intention to purchase solar technology, analyzing the roles of SI, social support, and environmental moderation. The results indicate that SI has a positive effect on purchase intention, and when consumers have the intention to purchase, they tend to demonstrate higher PBC<sup>62</sup>. Research by Terry shows that social norms and group influences can enhance an individual's PBC<sup>63</sup>. In Yang's study on consumer impulse buying behavior in mobile commerce, it was proposed that environmental stimuli significantly affect consumers' cognitive behaviors, which in turn influence their purchasing behaviors<sup>64</sup>.

This can be understood as an enhancement of consumers' PBC. Hsu C. L., in a study on public acceptance of blogging, surveyed 212 blog users and found that social factors significantly influenced participants' attitudes toward blogs, thereby affecting their intention to continue using blogs<sup>65</sup>. This demonstrates the impact of SI on PBC. In Cialdini R. B.'s 1998 study on SI and social norms, the research examined how social norms influence individual behavior. When individuals are subjected to societal expectations and pressures, their behaviors tend to align with these norms, indicating that SI affects an individual's PBC<sup>66</sup>. Fishbein M's research also supports this view, noting that individuals are often influenced by others' opinions in decision-making, and this SI directly affects their SN<sup>67</sup>.

Therefore, we propose the following hypotheses:

**H7** SI is positively correlated with PBC.

**H8** SI is positively correlated with PBC.

#### *Hedonic motivation (HM)*

HM refers to the pleasurable feelings individuals experience when using a particular technology or product, which significantly influences their acceptance and usage behavior. Scholar Susan A. Brown, in her study on the Household Technology Adoption Model (MATH), explored consumer behavior and proposed that HM plays a key role in consumers' decisions to use a product or technology. In a study involving 212 Taiwanese travelers, investigating factors influencing onboard duty-free shopping, the results showed that HM affected the intention to browse catalogs, which in turn increased purchase intention<sup>68</sup>. When consumer behavior is influenced by HM, it often boosts confidence in the behavior and enhances the intention to act, thus influencing PBC.

Zeinab Rezvani, in her research on consumer motivations for sustainable consumption, treated norms and hedonic motivation as variables. Based on a survey of Swedish car owners and using SEM, the results indicated that both norms and HM impacted consumer purchase intentions. Moreover, among consumers with higher social norms, HM had a more significant effect on behavioral intentions<sup>69</sup>. When HM is strong, consumers are more likely to focus on the expectations of others and society, seeking group identity through the hedonic experience, and are more influenced by SN<sup>70</sup>.

In a study by Aruna Polisetty on the relationship between environmental consumption and HM, a survey of 479 participants was conducted, and SEM was used to validate the results. The findings revealed that SN influences HM, ultimately leading to consumer purchase behavior. It was also noted that a sense of social responsibility and achievement motivates Generation Z to purchase green products, and HM has a significant effect on purchase intention<sup>71</sup>. This indicates that SN moderates the relationship between HM and purchase behavior. When the surrounding environment emphasizes a hedonic experience, consumers are influenced by these norms, thus increasing their purchase intention<sup>72</sup>.

Therefore, we propose the following hypotheses:

**H9** HM is positively correlated with PBC.

**H10** HM is positively correlated with SN.

#### **Theory of planned behavior (TPB)**

TPB was proposed by Icek Ajzen in 1985 as a psychological theory to predict and explain individual behavior<sup>73</sup>. TPB is based on theory of reasoned action (TRA) and adds PBC to better explain complex behaviors. The core concept of TPB is that an individual's behavioral intention is a direct precursor to behavior, and behavioral intention is determined by three key factors: AT, subjective norm (SN), and PBC<sup>74</sup>. TPB has been widely applied to explain consumer behavior in various contexts<sup>75</sup>, such as financial planning<sup>76</sup>, mobile payments<sup>77</sup>, self-service<sup>78</sup>, privacy protection<sup>79</sup>, and artificial intelligence<sup>80</sup>.

Among these, AT is determined by the outcomes of the behavior and the value of those outcomes, reflecting an individual's positive or negative evaluation of a behavior or product. The influence of AT on intention is stronger than that of SN and PBC. Djura L. Hoeksma used both TPB and VBN models to study factors affecting consumer purchase intention, surveying 329 consumers in the Netherlands. The results showed that AT, SN, and PBC were all positively correlated with purchase intention. It was also noted that AT and SN were more significant influencing factors<sup>81</sup>. Anssi Tarkiainen, in his research on Finnish consumers' purchasing behavior of organic food, used SEM to explore the relationship between SN and AT with purchase intentions. The results revealed a strong connection between consumers' intentions to purchase organic food and both SN and AT<sup>82</sup>, indicating that both AT and SN have a positive impact on purchase intention.

SN indirectly affects user behavior by influencing an individual's behavioral intention. When individuals perceive strong expectations from others regarding a certain behavior, they tend to align with those expectations. In a study by Chih-Chin Liang on airline satisfaction and repurchase, an investigation of 504 passengers found that user satisfaction is influenced by others' evaluations, and SN is a key factor in satisfaction. The study pointed out that SN has a positive influence on satisfaction and repurchase intention<sup>83</sup>. Chan S, based on TAM2 and social cognitive theory, used SEM to study user behavior in internet banking. A survey of 499 university students showed that SN has a significant impact on the intention to use internet banking<sup>84</sup>.

PBC refers to an individual's assessment of their ability to perform a behavior, considering factors such as time, skills, opportunities, and self-efficacy. Ajzen, I. highlighted that an individual's perception of AT is one of the key determinants of whether they will engage in a behavior. He also proposed that PBC improves an individual's sense of control over a behavior, which in turn enhances their AT, while SN influences AT by affecting an individual's perception of social approval. When individuals feel they can effectively control a behavior

and perceive societal approval of the behavior, their AT tends to become more positive<sup>73</sup>. In a study by Han, Joonhyoung on smartphone usage intentions, 330 users were surveyed through emails and interviews. The study found that PBC plays a positive role in product usage decisions and confirmed that PBC positively influences users' behavioral intentions<sup>85</sup>. Raman, Prashant conducted a survey with 529 online consumers to study women's purchase intentions in the e-commerce industry. The results indicated that PBC is the largest influencing factor on women's online shopping behavior<sup>86</sup>. Asif, Mirza Huzafa studied rural Chinese households' intentions to purchase solar energy, surveying 847 users. The findings revealed that both SN and PBC have a positive influence on solar energy purchase intentions<sup>87</sup>. Previous research by Icek Ajzen pointed out that the degree of PBC can moderate the effect of intention on behavior<sup>73</sup>, while also directly influencing intention<sup>88</sup>.

Therefore, we propose the following hypotheses:

- H11** PBC is positively correlated with AT.
- H12** PBC is positively correlated with user purchase intention.
- H13** SN is positively correlated with AT.
- H14** SN is positively correlated with user purchase intention.
- H15** AT is positively correlated with user purchase intention.

### External variables

#### *Cultural experience (CE) and generation quality (GQ)*

In addition to the aforementioned theoretical models and variables, this study also innovatively incorporates CE and GQ as external variables. Design is a culturally creative activity and a form of cultural expression. In fields such as landscape design<sup>89</sup>, urban design<sup>90</sup>, interior design<sup>91</sup>, and industrial design<sup>92</sup>, culture plays a crucial role. Luo LU, in his research on Eastern and Western cultures, analyzed how CE influences an individual's self-concept through social norms. When individuals gain deeper understanding of a culture, their identification with the social norms of that culture increases, thereby influencing their SN<sup>93</sup>. Previous studies have shown that CE and cultural memory can strengthen tourists' attachment to a destination<sup>94</sup>. This attachment enhances tourists' PBC at the destination, a process that can be understood as the positive influence of CE on PBC<sup>95</sup>. In a study on emotional attachment and revisit intention, SEM was used to analyze data from 504 tourists. The results showed that CE is positively correlated with revisit intention<sup>96</sup>. If tourists have a high revisit intention, it indicates that their PBC has increased<sup>74</sup>. In the cultural and creative industries, CE and cultural content are key attributes and hot topics for products<sup>97</sup>. In previous research on how traditional culture and cultural identity stimulate consumption, SEM was used to analyze data, and the results showed that traditional culture and cultural identity have a significant impact on consumers' emotional value, which in turn stimulates their purchase intention. Culture and consumers' purchase intention are positively correlated<sup>98</sup>. This process demonstrates that CE has a positive impact on an individual's PBC. All of the above studies indicate that CE has a positive impact on SN and PBC.

Therefore, we propose the following hypotheses:

- H16** CE is positively correlated with PBC.
- H17** CE is positively correlated with SN.

The development and prosperity of artificial intelligence tools in various industries have also been widely popular in the field of image generation. However, due to the diversity of AI source data, the complexity of models, and the randomness in the process, the generated images may exhibit instability<sup>99</sup>. There could be blurriness in the image details, and anatomical structures of generated characters may be unreasonable<sup>100</sup>. The quality of these system-generated images becomes increasingly important. Göring, S used AVT-AI-ImageDataset to assess the quality of AI-generated images<sup>15</sup>. Felderer, M explored the challenges AI faces in GQ, including the lack of standards, poor accuracy, and the need for data validation<sup>101</sup>. High GQ typically aligns more with social norms, leading to greater social acceptance and diffusion, and consumers are more likely to behave in ways that conform to group expectations<sup>102</sup>. Therefore, GQ has a positive impact on SN<sup>74</sup>. Muhammad Ashfaq explored the impact of GQ on AI system user satisfaction and acceptance, using the expectation confirmation model (ECM), information systems (ISS), and TAM model to survey 370 users. The results showed that high quality increases users' sense of control over the system, thus enhancing their PBC and boosting satisfaction with the AI system<sup>103</sup>. Labajová L explored users' views and acceptance of AI-generated content, using the TAM model to analyze the AI-generated experience of 100 participants. The results showed that GQ influences users' trust and acceptance of AI platforms<sup>104</sup>. This process shows that GQ impacts users' confidence in the platform, which in turn affects PBC. High-quality generated content reduces uncertainty and error rates, aligns better with users' expectations, and when generated content meets users' needs, their sense of control over the system increases. This confidence boosts users' PBC<sup>105</sup>. All of the above research demonstrates the influence of GQ on SN and PBC.

Therefore, we propose the following hypotheses:

- H18** GQ is positively correlated with PBC.

**H19** GQ is positively correlated with SN.

#### *IDT and self-innovation (SINN)*

IDT was proposed by Everett M. Rogers in his 1962 book *Diffusion of Innovations*, and it is an important theory in sociology, communication studies, and marketing, used to explain how innovations are adopted and disseminated within a social system. It emphasizes the behavioral and psychological processes individuals undergo when adopting innovations<sup>16</sup>. The theory consists of five stages: knowledge, persuasion, decision, implementation, and confirmation, with SINN being a key individual characteristic factor influencing the innovation diffusion process. SINN reflects an individual's openness and acceptance tendency toward new technologies and products.

Numerous studies have confirmed that SINN significantly influences users' technology acceptance behavior. In research on computer self-efficacy, scholars pointed out that the level of SINN directly affects an individual's self-efficacy judgment. Individuals with higher innovation awareness are more inclined to try new technologies and products<sup>106</sup>. This increase in self-efficacy effectively enhances the user's PBC<sup>107</sup>. Shirley Taylor's study further confirmed that SINN is a decisive factor in the behavioral control of information technology use, indicating a stable positive relationship between SINN and PBC<sup>47</sup>.

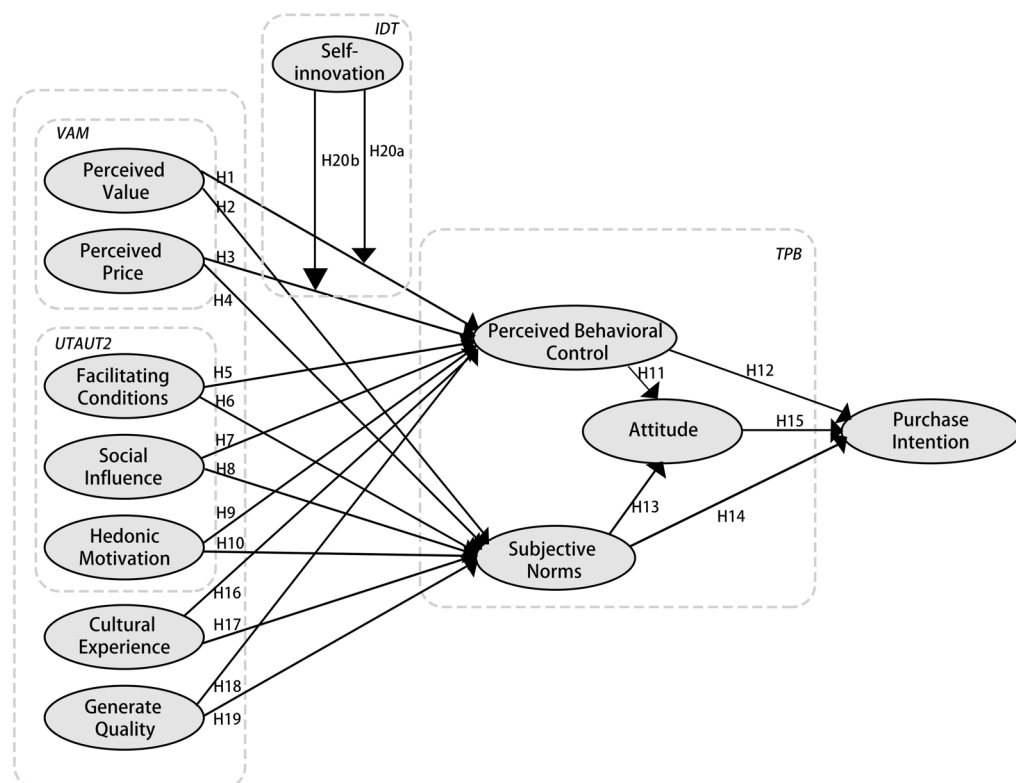
In terms of PV, Jeeyeon Jeong's research revealed that SINN indirectly enhances users' PV by increasing self-efficacy<sup>108</sup>. Innovative users are better able to recognize and appreciate the differentiated characteristics of new products, thus perceiving higher value<sup>109</sup>. Salem A's research more directly confirmed that SINN not only positively affects PV, but also plays a moderating role between PBC and PV<sup>110</sup>. Highly innovative users tend to focus more on the innovation and uniqueness of products rather than on price factors, exhibiting a different value evaluation pattern<sup>111</sup>.

Based on the above theoretical foundation, we infer that SINN may play a dual moderating role in the context of AI-generated cultural products: On one hand, highly innovative users may exhibit a stronger positive relationship when evaluating the impact of PV on PBC; on the other hand, they may show a weaker negative relationship when evaluating the impact of PP on PBC. Therefore, we propose more specific hypotheses:

**H20a** SINN positively moderates the relationship between PV and PBC, meaning that the positive impact of PV on PBC is stronger for users with high SINN.

**H20b** SINN negatively moderates the relationship between PP and PBC, meaning that the negative impact of PP on PBC is weaker for users with high SINN.

Based on the above hypotheses, a research model is constructed as shown in Fig. 2.



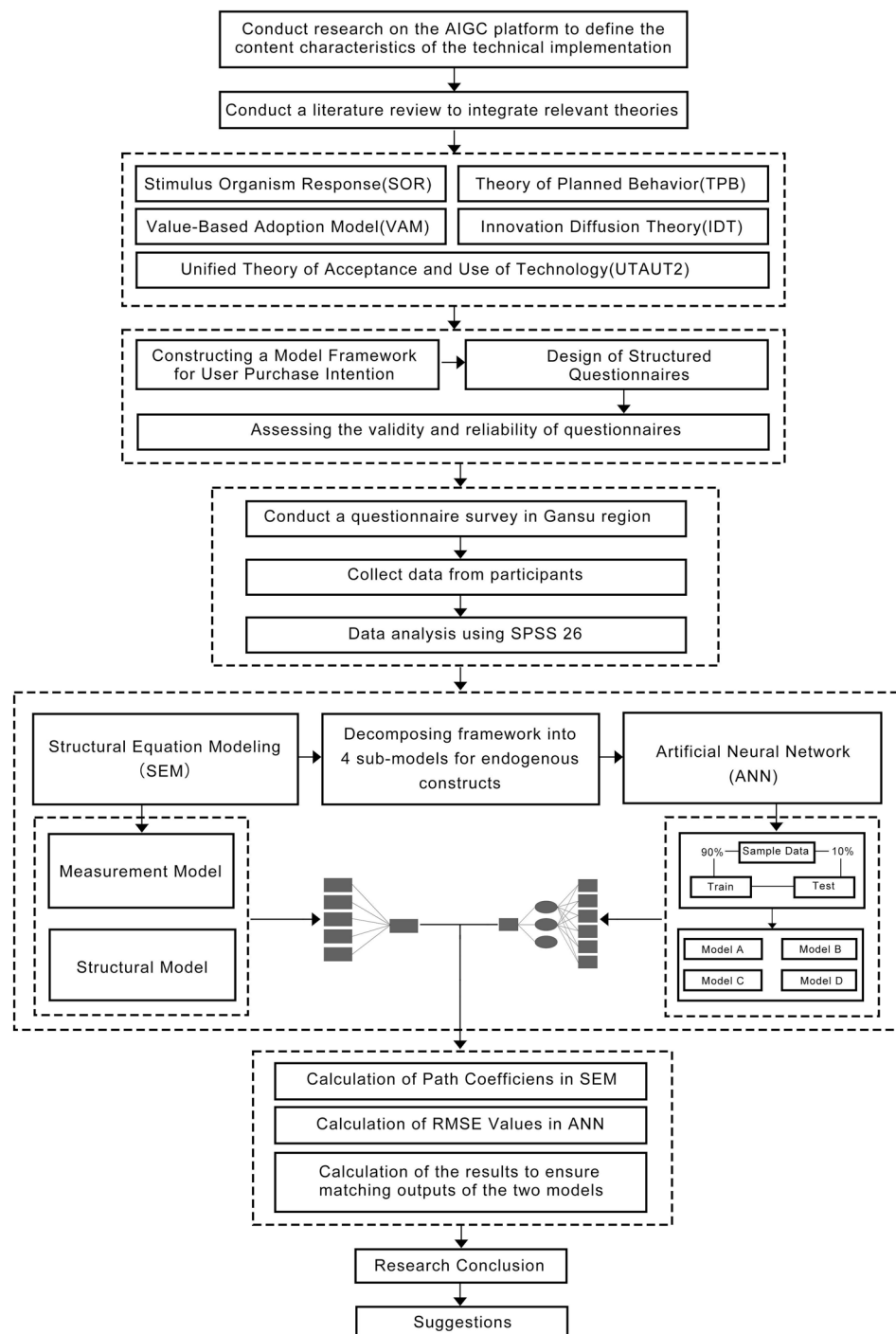
**Fig. 2.** The hypothesized model.



## Research methodology

### Introduction to the research methodology

This study employs a combination of SEM (structural equation modeling) and ANN (artificial neural networks) to construct the basic methodology of this research, with the specific process shown in Fig. 3. SEM is a method used to analyze complex variable relationships by combining multiple statistical techniques, allowing researchers to study various causal relationships. SEM integrates the advantages of factor analysis and path analysis and is commonly used to validate theoretical models, including the relationships between observed variables and latent variables<sup>112</sup>. ANN, on the other hand, is a computational model inspired by biological neural networks, and it is one of the key methods in machine learning. ANN constructs a network structure with learning capabilities by simulating the connection patterns of human brain neurons, which can handle complex nonlinear relationships and pattern recognition problems. ANN has stronger data fitting and predictive capabilities, especially suitable



**Fig. 3.** Research framework diagram.

for dealing with large datasets and complex nonlinear relationships<sup>113</sup>. Both SEM and ANN models are widely applied in various fields, including psychology<sup>114</sup>, marketing<sup>115</sup>, and heritage conservation<sup>116</sup>. Therefore, the combination of SEM and ANN integrates theoretical construction with data-driven predictive models, which not only reveals the causal paths between variables but also enhances the predictive power of the model, providing a more comprehensive and in-depth analytical perspective for this study.

### SEM

SEM (structural equation modeling) is a powerful multivariate statistical analysis method that combines the features of factor analysis and multiple regression analysis, enabling the simultaneous handling of complex relationships between multiple observed variables and latent variables. According to the guidance provided by Anderson, JC for researchers using SEM<sup>117</sup>, the process begins with preliminary data handling, integrating data from different sources and conducting initial analysis to ensure data completeness and consistency. Next, exploratory factor analysis (EFA) is conducted, which helps identify the underlying factors in the data and calculates the loading coefficients of each variable, revealing the structure behind the data to understand the relationships between variables and factors. Following this, confirmatory factor analysis (CFA) is performed using AMOS to verify the stability and accuracy of the factor structure from EFA, ensuring the reliability of the measurement model. Path analysis is then conducted to test the research hypotheses and explore the causal relationships among the variables in the model. In path analysis, the statistical significance of the model and fit indices (CFI, TLI, and RMSEA) are key to ensuring the model's applicability. Through these steps, strong statistical support is provided for theory construction and validation, ensuring the scientific and practical applicability of the results<sup>118</sup>.

### ANN

ANN is a computational model inspired by the neural networks of the human brain, capable of solving problems that traditional statistical methods struggle with by learning complex nonlinear relationships. According to Haykin's framework of neural network theory<sup>119</sup>, the implementation of an ANN begins with data preprocessing, including standardization, normalization, and handling missing values, to improve model training efficiency and prediction accuracy. Next, the network structure is determined, including the number of nodes in the input layer, hidden layers, and output layer, as well as the choice of activation functions, which directly impact the model's learning ability and generalization performance. Afterward, model training takes place, where the backpropagation algorithm is used to iteratively adjust network weights and minimize the error between predicted and actual values. Cross-validation is employed during the training process to prevent overfitting and ensure the model's good generalization ability. Finally, the model is evaluated and validated, using metrics such as Mean Squared Error (MSE) and the coefficient of determination ( $R^2$ ) to assess model performance, while the testing set is used to verify the model's prediction accuracy. This systematic approach enables the ANN to effectively capture complex patterns in the data, providing reliable support for decision-making<sup>120</sup>.

This study employs a tenfold cross-validation method to evaluate the model's performance. The specific implementation steps are as follows: First, the original dataset is evenly divided into ten mutually exclusive subsets. In each iteration, one subset is selected as the test set (10% of the total data), while the remaining nine subsets are combined to form the training set (90% of the data). This process is repeated ten times to ensure that each subset is used as the test set once. Finally, the model's validation performance is comprehensively assessed by aggregating the results of the ten tests<sup>121</sup>.

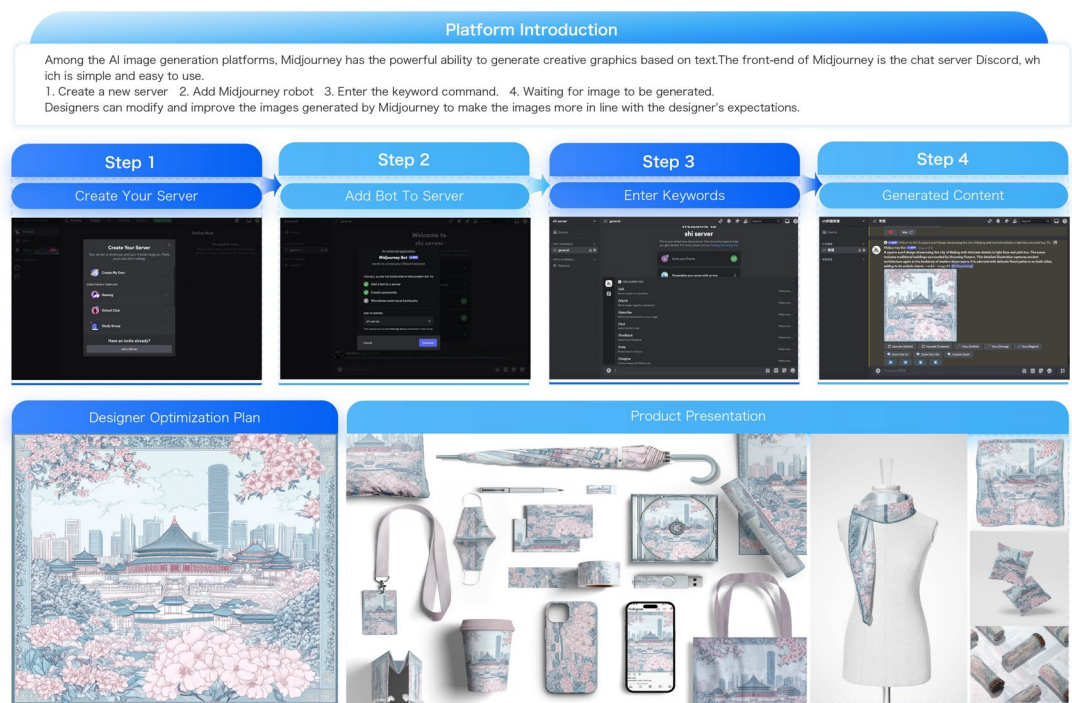
### AIGC operating logic

AIGC image generation platforms have been widely applied in the design field, with the basic process shown in Fig. 4. First, designers collect relevant materials related to the design object, such as regional cultural elements, distinctive architecture, and related craftsmanship. Next, users create a server, generate relevant instructions based on preliminary research results, add a robot, and input keywords. The platform then generates an image to complete the initial draft. Third, based on the generated content, designers use the platform's partial modification function to adjust the instructions, including changes to color, elements, composition, and other factors. Fourth, the generated image is imported into the design platform for detail optimization, refining the design plan. Finally, based on the generated design plan, the design of cultural and creative products is carried out.

Figure 1 has conducted a competitive analysis of AIGC-related platforms, discussing the strengths and weaknesses of current mainstream platforms. Among them, Midjourney, with its powerful data processing capabilities and optimization algorithms, can efficiently handle large volumes of data and boasts the largest user base. Its ease of use, fast generation speed, and the novelty and uniqueness of the generated images make it highly popular among users. Therefore, this study will use Midjourney as the image generation platform to explore user acceptance of its generated cultural and creative products.

### Questionnaire design and strategy

This study follows the questionnaire design procedure proposed by Sohn<sup>122</sup>. The TPB consists of 12 items, including 4 for SN, 4 for AT, and 4 for PBC. These items were adapted from the previous research of Dohnke<sup>123</sup>, Tarkiainen<sup>82</sup>, and Sohn<sup>122</sup>. The VAM consists of 8 items, divided into 4 for PV and 4 for PP. These items were adapted from the work of Sohn<sup>122</sup> and Baudier<sup>124</sup>. The UTAUT2 consists of 15 items, divided into 5 for FC, 5 for SI, 5 for HM, 5 for CE, and 5 for GQ. These items were adapted from the research of Baudier<sup>124</sup>, Sohn<sup>122</sup>, Li<sup>94</sup>, and Bounab<sup>125</sup>. SINN is measured using 4 items, which were derived from Baudier P's study<sup>124</sup>. Purchase intention is measured by 4 items, based on Sohn K's research<sup>122</sup>. The questionnaire uses a 7-point Likert scale to collect data on respondents' purchase intentions for AI-generated cultural and creative products, with participants rating their level of agreement from 1 (strongly disagree) to 7 (strongly agree). The questionnaire also includes five



**Fig. 4.** AIGC design flowchart.

demographic questions, covering age, gender, educational background, occupation, and income level, in order to more comprehensively analyze the respondents' background information.

After the preliminary design of the questionnaire, a pilot survey was conducted to ensure the validity of the questionnaire and the scientific nature of the questions. Based on the feedback from the pilot survey, the content of the questionnaire was optimized. The final questionnaire items are presented in Table 5.

### Ethical research statement

This study strictly followed the principles of ethical research to ensure that the rights and privacy of all participants were fully protected. This study was reviewed and approved by the Ethics Committee of Lanzhou University of Technology. The Ethics Committee confirmed that this study complied with the ethical standards and the relevant supporting materials were submitted. In addition, all participants obtained informed consent before participating in the study. Prior to the start of the study, participants were provided with detailed information about the purpose of the study, the process, the potential risks, and their rights (including the right to withdraw from the study at any time) to ensure that they participated voluntarily based on full understanding. Written consent was used for this study, with participants reading the informed consent form through an online questionnaire platform and confirming their consent by checking the "I agree to participate in this study" box. This option was designed to ensure that participants could only proceed with the questionnaire if they had given explicit consent, which was automatically saved through the online platform and stored as part of the study data. This study involved the participation of minors, whose verbal consent was obtained and whose written consent was obtained from their parents or guardians.

### Sample data collection

The formal questionnaire survey for this study was conducted in Gansu Province, China, from June 16 to July 6, 2024. The survey locations included high-traffic cultural and tourist sites such as the Gansu Provincial Museum, Gansu Geological Museum, Dunhuang Art Museum, Gansu Bamboo Slip Museum, Shui Ink Danxia Scenic Area, and A9 Art Gallery. These locations are both culturally significant and publicly accessible, making them highly representative and conducive to capturing a target group with potential interest in AI-generated cultural and creative products. To enhance the scientific rigor of the study and ensure the validity of the questionnaire data, the survey process was divided into the following steps:

- (1) *Product display and experience* The research team created physical prototypes based on the AI-assisted design of cultural and creative product proposals using the AIGC platform. These prototypes were then displayed to the participants on-site, ensuring they could visually experience the design style and usage scenarios of the products. This step aimed to enhance their understanding of the survey topic and increase participant engagement.
- (2) *Introduction to the technical process* Before the formal survey began, the researchers briefly introduced the basic process and core functions of the AIGC platform in generating cultural and creative products. This

Demographic variable	Categories	Frequency	Percentage (%)
Age	Under 20 age	63	11.98
	20–25 age	132	25.10
	26–30 age	144	27.38
	30–40 age	82	25.59
	Over 40 age	105	19.96
Gender	Male	283	53.80
	Female	243	46.20
Educational level	Secondary school	98	18.63
	Vocational degree	110	20.91
	Bachelor degree	181	34.41
	Graduate degree	137	26.05
Interest in AI	Interested	458	87.07
	Not interested	68	12.93
Income	Under 3000	170	32.32
	3000–7000	177	33.65
	7000–10,000	100	19.01
	Over 10,000	79	15.02

**Table 2.** Descriptive statistics of respondents’ characteristics.

KMO		0.916
Bartlett’s sphericity	Spherical test	18,378.713
	df-value	1326
	p-value	0

**Table 3.** KMO and Bartlett’s inspection.

- helped participants gain a comprehensive understanding of the application of artificial intelligence in cultural and creative design, ensuring that the survey was conducted based on informed consent.
- (3) *Explanation and guidance on the questionnaire* To ensure the reliability and validity of the data, the researchers provided detailed explanations of each measurement item in the questionnaire on-site. This helped participants accurately understand the meaning of the items, thereby improving the accuracy and consistency of their responses.
- (4) *Questionnaire completion and collection:*After completing the aforementioned preparations, the research team invited visitors to voluntarily participate in filling out the questionnaire and provided necessary guidance on-site. A total of 546 questionnaires were distributed, with 20 invalid responses being excluded due to logical inconsistencies or incomplete answers. Ultimately, 526 valid questionnaires were collected, yielding a response rate of 96.3%.

According to the sample size calculation standards proposed by Krejcie, this sample size meets the basic requirements for conducting Structural Equation Modeling SEM and ANN analysis, providing a reliable data foundation for the subsequent empirical analysis<sup>126</sup>.

**Data analysis and results**  
**Descriptive statistics**

Table 2 presents the demographic characteristics of the study sample. The results show that the majority of respondents are concentrated in the age groups of 26–30 years (27.38%) and 20–25 years (25.10%). In terms of gender, the distribution is relatively balanced, with a slight male predominance (53.80%) compared to female respondents (46.20%). Regarding educational level, most respondents hold a bachelor’s degree (34.41%), followed by those with a postgraduate degree (26.05%). The income distribution reveals that the largest group of respondents earn between 3000 and 7000 RMB (33.65%). The proportion of respondents earning between 7000 and 10,000 RMB and above 10,000 RMB is relatively lower, at 19.01% and 15.02%, respectively. The majority of respondents (87.07%) indicated a strong interest in AI platforms and AI-generated products, and are eager to explore content related to AIGC.

**SEM analysis results**

This study conducted reliability and validity analyses of the collected data using SPSS 26.0 software. As shown in Table 3, the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.916 (ranging from 0 to 1). A KMO value closer to 1 indicates higher validity of the questionnaire. Additionally, the Bartlett’s Test of Sphericity showed a significance level close to 0, further confirming the reliability of the questionnaire.

To assess the goodness-of-fit of the measurement model, this study applied the confirmatory factor analysis (CFA) method proposed by Eisinga<sup>127</sup>. As shown in Table 4, the overall fit of the model is good, with all indices meeting the recommended standards. Specifically, the Chi-square/df value is 1.606, which falls within the suggested range of 1.0–3.0; the RMSEA value is 0.034, which is below the recommended threshold of 0.10; and the NFI, IFI, and CFI values are 0.911, 0.964, and 0.964, respectively, all exceeding the suggested level of 0.85. These results indicate that the model in this study exhibits a good fit, with high adaptability and stability.

To assess the reliability and validity of the data, this study calculated the Cronbach's  $\alpha$  coefficient, composite reliability (CR), and average variance extracted (AVE). As shown in Table 5, the consistency range between variables is between 0.708 and 0.917, which meets the standard that the consistency coefficient should be greater than 0.70<sup>128</sup>. In this study, the CR values for all variables range from 0.819 to 0.933, meeting the acceptable standard that CR should be greater than or equal to 0.7, indicating good consistency between the variables<sup>127</sup>. Furthermore, the AVE values should be greater than 0.5<sup>128,129</sup>, and in this study, the AVE values range from 0.530 to 0.776, further indicating that the data collected in this study are highly robust. The Cronbach's  $\alpha$  coefficients, CR values, and AVE values for each variable all meet the recommended thresholds, suggesting that the data in this study possess good internal consistency and robustness.

Table 6 and Fig. 5 display the path coefficients of this study, with significance denoted as follows:  $P < 0.001$  is represented as \*\*\*;  $0.001 \leq P < 0.01$  as \*\*;  $0.01 \leq P < 0.05$  as \*; and other cases are considered non-significant<sup>125</sup>. The results of the study show that PV significantly influences PBC (H1:  $\beta = 0.252$ ,  $P < 0.001$ ) and SN (H2:  $\beta = 0.278$ ,  $P < 0.001$ ), confirming that hypotheses H1 and H2 are supported. Similarly, PV has a significant impact on PBC (H3:  $\beta = 0.21$ ,  $P < 0.001$ ) and SN (H4:  $\beta = 0.275$ ,  $P < 0.001$ ), confirming hypotheses H3 and H4. However, FC does not significantly influence PBC (H5:  $\beta = 0.06$ ,  $P = 0.183$ ) and SN (H6:  $\beta = -0.039$ ,  $P = 0.24$ ), indicating that hypotheses H5 and H6 are not supported. SI significantly affects PBC (H7:  $\beta = 0.232$ ,  $P < 0.001$ ) and SN (H8:  $\beta = 0.170$ ,  $P < 0.001$ ), supporting hypotheses H7 and H8. HM also has a significant effect on PBC (H9:  $\beta = 0.317$ ,  $P < 0.001$ ) and SN (H10:  $\beta = 0.171$ ,  $P < 0.001$ ), confirming hypotheses H9 and H10. CE significantly impacts PBC (H16:  $\beta = 0.181$ ,  $P < 0.001$ ) and SN (H17:  $\beta = 0.193$ ,  $P < 0.001$ ), supporting hypotheses H16 and H17. Furthermore, GQ significantly affects PBC (H18:  $\beta = 0.164$ ,  $P < 0.001$ ) and SN (H19:  $\beta = 0.268$ ,  $P < 0.001$ ), supporting hypotheses H18 and H19. In addition, PBC (H12:  $\beta = 0.147$ ,  $P = 0.007$ ) significantly affects purchase intention, supporting hypothesis H13. AT is influenced by PBC (H11:  $\beta = 0.399$ ,  $P < 0.001$ ) and SN (H13:  $\beta = 0.243$ ,  $P < 0.001$ ), confirming hypotheses H11 and H13. AT (H15:  $\beta = 0.254$ ,  $P < 0.001$ ) and SN (H14:  $\beta = 0.166$ ,  $P < 0.001$ ) significantly affect purchase intention, validating hypotheses H14 and H15.

This study includes SINN as a moderating variable, as shown in Fig. 6. Panel a illustrates the influence of SINN on PV when PBC ranges from low to high, while Panel b demonstrates the influence of SINN on PP when PBC ranges from low to high. The results indicate that both PV and PP positively promote PBC for both high and low SINN. However, the moderating effect of SINN on the relationship between PV/PP and PBC is more significant for low SINN than for high SINN. This finding is consistent with the results of Jeeyeon Jeong's study<sup>108</sup>, supporting hypothesis H20.

ANN analysis

Constructing the ANN model

To further enhance the predictive performance of the model, this study employs a hybrid approach combining SEM and ANN to construct a predictive model for users' purchase intention in AI-generated creative design. Based on the path analysis results from SEM and leveraging the nonlinear modeling capabilities of ANN, four interconnected neural network sub-models (Fig. 7) were designed, with the following specific structure:

- (1) Model A: The output is PBC, and the inputs are PV, PP, FC, SI, HM, CE, and GQ.
- (2) Model B: The output is SN, and the inputs are PV, PP, FC, SI, HM, CE, and GQ.
- (3) Model C: The output is AT, and the inputs are PBC and SN.
- (4) Model D: The output is PI, and the inputs are PBC, AT, and SN.

This design draws on the multi-stage neural network architecture proposed by Parhi et al., extracting latent variable relationships validated by SEM in stages. ANN is used to capture the complex nonlinear interactions between variables, enabling more precise prediction of purchase intention<sup>130</sup>.

Root mean square error (RMSE) verification

This study employs a ten-fold cross-validation method to systematically evaluate the predictive performance of Models A, B, C, and D. During the validation process, the original dataset is randomly divided into 10 equally sized subsets. Through iterative training and testing, each subset is used as a test set while the remaining nine subsets serve as the training set, ensuring that all data are involved in model validation. Based on this rigorous validation framework, we quantify the predictive accuracy of each model using the RMSE metric.

The empirical results (Table 7) show that the RMSE values of the four ANN models fall within the ideal range of 0.260–0.364, with Models A, B, and D exhibiting smaller prediction errors ( $RMSE < 0.30$ ), while the integrated

Fit indices	Chi-square/df	RMSEA	NFI	IFI	CFI	TLI
Actual	1.606	0.034	0.911	0.964	0.964	0.962
Recommended	<3	<0.06	>0.90	>0.90	>0.90	>0.90

Table 4. The values of fit indices.



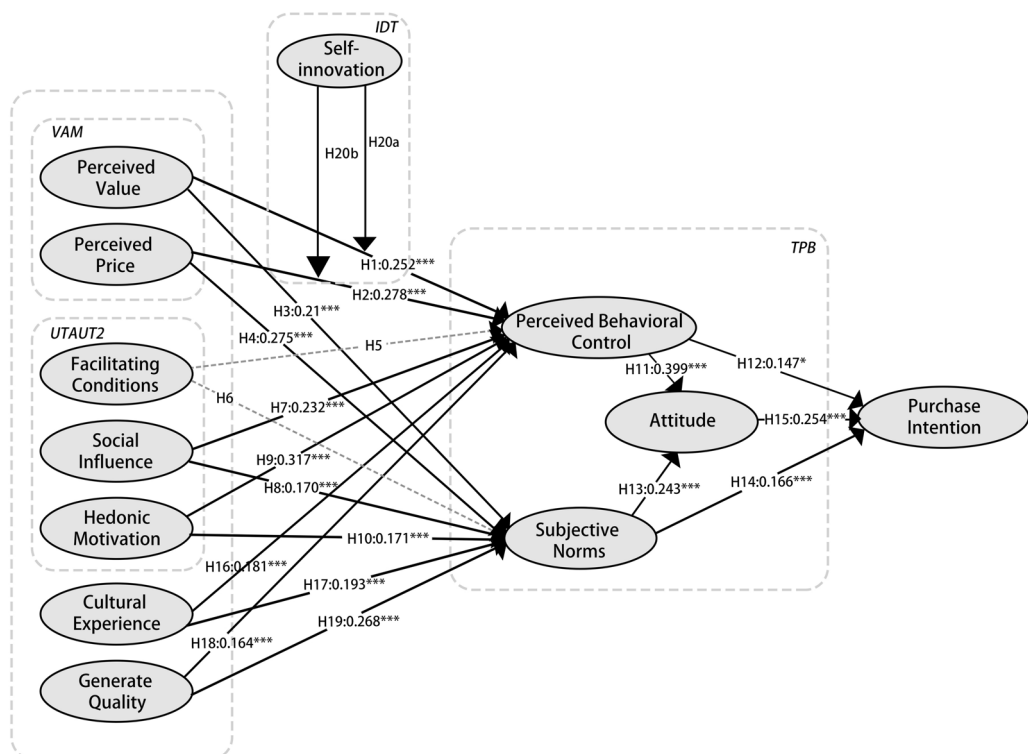
Construct	Item	Factor loading	$\alpha$	AVE	CR
Perceived value	PV1: Compared to the costs I need to pay, purchasing AI-generated cultural and creative products offers good value for money	0.804	0.895	0.681	0.895
	PV2: Overall, purchasing AI-generated cultural and creative products offers great value	0.824			
	PV3: I think that purchasing AI-generated cultural and creative products is worthwhile	0.825			
	PV4: AI-generated cultural and creative products embody significant cultural value and depth	0.847			
Perceived price	PP1: I think that the cost of purchasing AI-generated cultural and creative products is reasonable	0.9	0.922	0.749	0.923
	PP2: I think the prices of AI-generated cultural and creative products are clear and transparent	0.846			
	PP3: I think the cost of AI-generated cultural and creative products is more competitive than traditional cultural and creative products	0.852			
	PP4: At current prices, AI-generated cultural and creative products offer good value	0.862			
Facilitating conditions	FC1: I have channels to purchase AI-generated cultural and creative products	0.739	0.818	0.530	0.819
	FC2: It is convenient to purchase AI-generated cultural and creative products services	0.744			
	FC3: I think the transaction process is smooth when purchasing AI-generated cultural and creative products	0.708			
	FC4: The payment process is simple when purchasing AI-generated cultural and creative products	0.721			
Social influence	SI1: People who influence my behavior will think that I should buy AI-generated cultural and creative products.	0.917	0.932	0.776	0.933
	SI2: People who are important to me think I should buy AI-generated cultural and creative products	0.884			
	SI3: People around me will have a positive attitude toward my purchase of AI-generated cultural and creative products	0.842			
	SI4: If people around me buy AI-generated cultural and creative products, then I will buy them too	0.879			
Hedonic motivation	HM1: AI-generated cultural and creative products are interesting	0.844	0.890	0.670	0.890
	HM2: Purchasing AI-generated cultural and creative products is a pleasure	0.79			
	HM3: Enjoy buying AI-generated cultural and creative products	0.813			
	HM4: Have fun buying cultural and creative products generated by AI	0.826			
Cultural experience	CE1: I want to buy cultural and creative products with cultural heritage	0.767	0.854	0.594	0.854
	CE2: I am passionate about understanding the culture behind cultural and creative products	0.747			
	CE3: The more I feel about this culture, the more I want to buy it	0.759			
	CE4: I want to see the world through culture in cultural and creative products	0.809			
Generate quality	GQ1: The higher the quality of the cultural and creative products generated by AI, the more willing I am to buy them	0.834	0.877	0.640	0.877
	GQ2: I am more willing to buy creative and unique AI cultural and creative products	0.792			
	GQ3: The cultural and creative products generated by AI are highly detailed and I am more willing to buy them	0.8			
	GQ4: AI-generated cultural and creative products have high aesthetic value and I am more willing to buy them	0.774			
Perceived behavioral control	PBC1: Purchasing AI-generated cultural and creative products is completely within my control	0.804	0.897	0.617	0.865
	PBC2: I have the ability to understand and choose cultural and creative products generated by AI	0.797			
	PBC3: I have enough information to make a choice to purchase AI-generated cultural and creative products	0.748			
	PBC4: I have enough financial resources to purchase AI-generated cultural and creative products	0.791			
Attitude	AT1: It is advisable to purchase AI-generated cultural and creative products in daily life	0.865	0.921	0.639	0.876
	AT2: It's fun to buy AI-generated cultural and creative products in daily life	0.755			
	AT3: It is helpful to buy AI-generated cultural and creative products in daily life	0.782			
	AT4: It is a good thing to buy AI-generated cultural and creative products in daily life	0.792			
Subjective norms	SN1: People who are important to me will buy AI-generated cultural and creative products	0.876	0.906	0.717	0.910
	SN2: People who are important to me will want me to buy AI-generated cultural and creative products	0.818			
	SN3: People important to me think I will buy AI-generated cultural and creative products	0.838			
	SN4: I buy AI-generated cultural and creative products and have a positive attitude towards the people who matter to me	0.855			
Purchase intention	PI1: I plan to purchase AI-generated cultural and creative products in the future	0.809	0.893	0.660	0.886
	PI2: When I buy cultural and creative products, I will first consider AI-generated products	0.824			
	PI3: I plan to recommend AI-generated cultural and creative products to people around me	0.791			
	PI4: I plan to purchase AI-generated cultural and creative products soon	0.826			

**Table 5.** Results of confirmatory factor analysis.

Model C demonstrates good predictive stability ( $RMSE < 0.37$ ). These empirical data not only confirm that the models possess high predictive accuracy (all  $RMSE$  values are significantly below the empirical threshold of 0.5) but also validate the unique advantage of artificial neural networks in capturing the nonlinear features of user behavior from a methodological perspective. This provides a reliable theoretical foundation and technical support for subsequent decision-making analysis. The results further indicate that the combination of SEM and ANN methods presents significant scientific value and practical implications.

Hypothesis				Estimate	S.E	C.R	P	$\beta$
H1	Perceived behavioral control	<---	Perceived value	0.227	0.04	5.669	***	0.252
H2	Subjective norms	<---	Perceived value	0.278	0.043	6.406	***	0.278
H3	Perceived behavioral control	<---	Perceived price	0.182	0.037	4.925	***	0.21
H4	Subjective norms	<---	Perceived price	0.26	0.04	6.481	***	0.275
H5	Perceived behavioral control	<---	Facilitating conditions	-0.059	0.044	-1.331	0.183	0.06
H6	Subjective norms	<---	Facilitating conditions	0.056	0.048	1.174	0.24	-0.039
H7	Perceived behavioral control	<---	Social influence	0.18	0.033	5.497	***	0.232
H8	Subjective norms	<---	Social influence	0.142	0.035	4.068	***	0.170
H9	Perceived behavioral control	<---	Hedonic motivation	0.279	0.039	7.117	***	0.317
H10	Subjective norms	<---	Hedonic motivation	0.162	0.041	3.963	***	0.171
H11	Attitude	<---	Perceived behavioral control	0.494	0.06	8.29	***	0.399
H12	Purchase intention	<---	Perceived behavioral control	0.17	0.063	2.72	0.007	0.147
H13	Attitude	<---	Subjective norms	0.275	0.052	5.303	***	0.243
H14	Purchase intention	<---	Subjective norms	0.176	0.053	3.319	***	0.166
H15	Purchase intention	<---	Attitude	0.236	0.051	4.623	***	0.254
H16	Perceived behavioral control	<---	Cultural experience	0.184	0.045	4.068	***	0.181
H17	Subjective norms	<---	Cultural experience	0.213	0.049	4.365	***	0.193
H18	Perceived behavioral control	<---	Generate quality	0.14	0.037	3.741	***	0.164
H19	Subjective norms	<---	Generate quality	0.253	0.041	6.153	***	0.268

**Table 6.** Standardised regression weights for testing hypotheses.



**Fig. 5.** Path analysis results.

#### Sensitivity analysis

The sensitivity analysis results reveal the relative importance of covariates to the dependent variables in each of the ANN models (Table 8). In Model A, the predictor variables are ranked in the following order of importance: HM (100%), PV (89.6%), SI (89.5%), GQ (79.0%), CE (70.5%), PP (59.1%), and FC (24.7%). In Model B, the ranking of predictor variables is as follows: PV (100%), PP (100%), SI (97.9%), GQ (84.2%), HM (72.3%), CE (68.1%), and FC (37.1%). In Model C, the predictor variables are ranked as follows: PBC (100%) and SN (67.6%). In Model D, the ranking of predictor variables is: PBC (100%), SN (73.2%), and AT (70.8%).

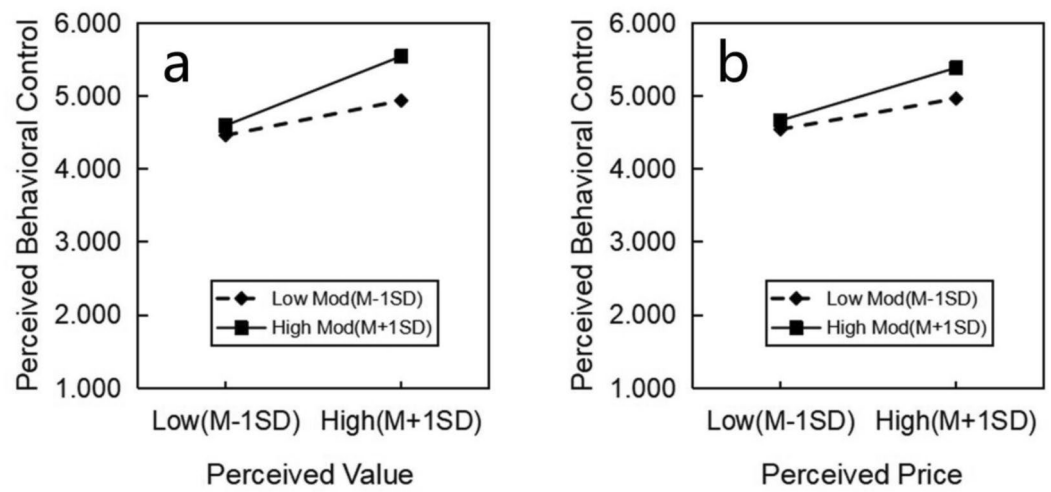


Fig. 6. Moderated effects plots.

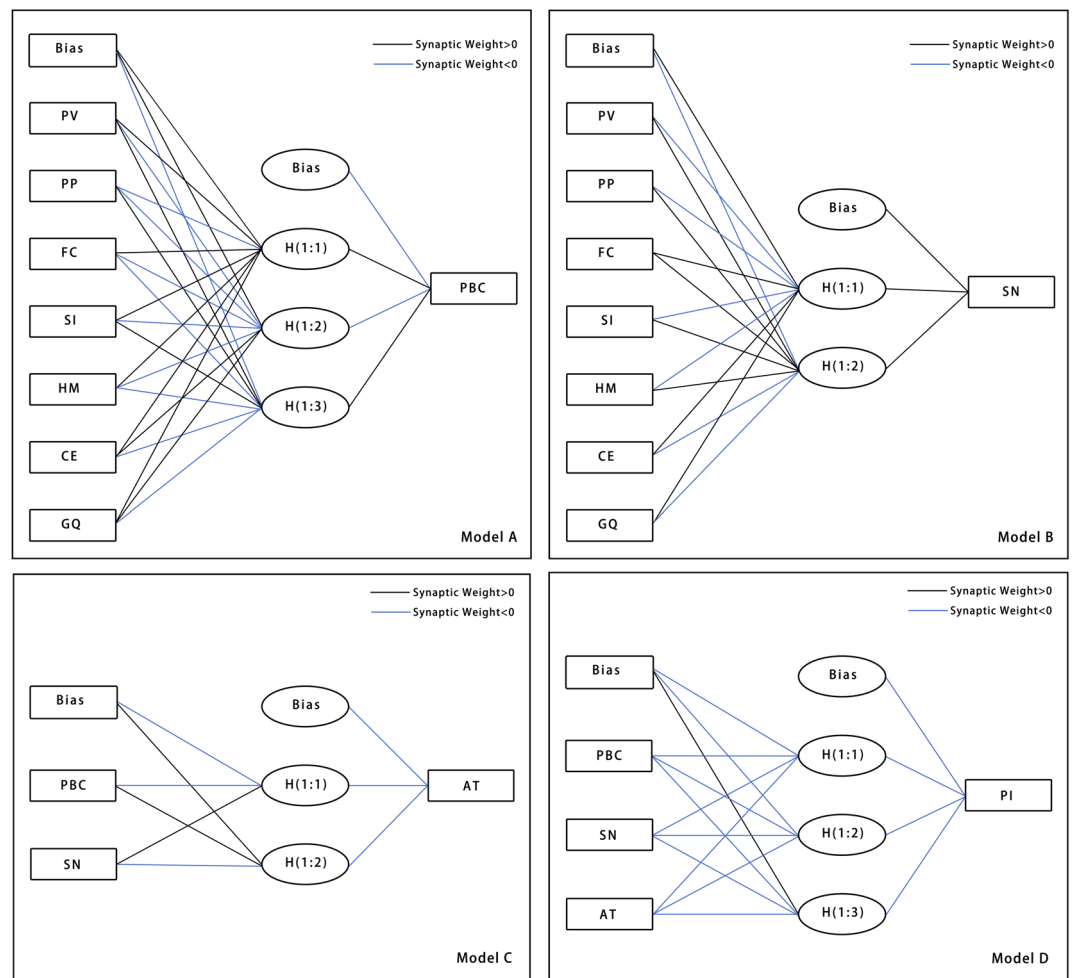


Fig. 7. ANN model construct.

Neural network	Moder A		Moder B		Moder C		Moder D	
	Input: PV,PP,FC,SI,HM,CE,GQ		Input: PV,PP,FC,SI,HM,CE,GQ		Input: PBC,SN		Input: PBC,AT,SN	
	Output: PBC		Output: SN		Output: AT		Output: PI	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN1	0.293	0.349	0.292	0.283	0.373	0.326	0.288	0.258
ANN2	0.275	0.380	0.323	0.320	0.345	0.420	0.258	0.225
ANN3	0.311	0.258	0.342	0.374	0.343	0.466	0.220	0.148
ANN4	0.298	0.288	0.309	0.183	0.367	0.269	0.276	0.397
ANN5	0.290	0.230	0.282	0.167	0.366	0.237	0.314	0.277
ANN6	0.289	0.296	0.290	0.262	0.351	0.460	0.258	0.314
ANN7	0.277	0.309	0.276	0.289	0.363	0.397	0.321	0.222
ANN8	0.327	0.243	0.296	0.189	0.388	0.219	0.316	0.301
ANN9	0.330	0.280	0.289	0.269	0.366	0.212	0.330	0.249
ANN10	0.286	0.236	0.276	0.265	0.377	0.528	0.289	0.426
Mean	0.298	0.287	0.298	0.260	0.364	0.353	0.287	0.282
SD	0.135	0.216	0.142	0.248	0.116	0.331	0.182	0.280

Table 7. RMSE test for artificial neural network models.

Path		ANN1	ANN2	ANN3	ANN4	ANN5	ANN6	ANN7	ANN8	ANN9	ANN10	Average relative importance	Normalized relative importance (%)
Moder A (Output: PBC)	PV	0.166	0.155	0.020	0.157	0.177	0.179	0.168	0.288	0.257	0.182	0.175	0.896
	PP	0.104	0.127	0.203	0.133	0.110	0.109	0.109	0.088	0.041	0.129	0.115	0.591
	FC	0.039	0.031	0.070	0.076	0.038	0.040	0.039	0.046	0.061	0.041	0.048	0.247
	SI	0.169	0.196	0.152	0.183	0.182	0.201	0.170	0.140	0.153	0.201	0.175	0.895
	HM	0.222	0.225	0.211	0.184	0.219	0.211	0.233	0.162	0.081	0.203	0.195	100.000
	CE	0.164	0.141	0.138	0.154	0.141	0.133	0.134	0.051	0.196	0.123	0.138	0.705
	GQ	0.135	0.126	0.206	0.114	0.132	0.127	0.146	0.225	0.211	0.120	0.154	0.790
Moder B (Output: SN)	PV	0.128	0.283	0.094	0.172	0.166	0.166	0.145	0.236	0.225	0.177	0.179	100.000
	PP	0.157	0.237	0.246	0.077	0.220	0.175	0.177	0.159	0.162	0.176	0.179	100.000
	FC	0.055	0.076	0.080	0.037	0.042	0.107	0.074	0.056	0.079	0.056	0.066	0.371
	SI	0.164	0.148	0.183	0.257	0.177	0.184	0.141	0.137	0.176	0.182	0.175	0.979
	HM	0.163	0.128	0.101	0.101	0.129	0.159	0.168	0.091	0.139	0.112	0.129	0.723
	CE	0.153	0.064	0.093	0.129	0.100	0.098	0.156	0.163	0.129	0.131	0.122	0.681
	GQ	0.179	0.064	0.202	0.227	0.166	0.111	0.139	0.158	0.091	0.166	0.150	0.842
Moder C (Output: AT)	PBC	0.458	0.788	0.653	0.623	0.559	0.667	0.582	0.459	0.644	0.534	0.597	100.000
	SN	0.542	0.212	0.347	0.377	0.441	0.333	0.418	0.541	0.356	0.466	0.403	0.676
Moder D (Output: PI)	PBC	0.321	0.389	0.439	0.419	0.338	0.492	0.516	0.402	0.403	0.379	0.410	100.000
	AT	0.311	0.322	0.304	0.258	0.351	0.269	0.204	0.284	0.324	0.275	0.290	0.708
	SN	0.368	0.289	0.257	0.324	0.311	0.239	0.280	0.315	0.272	0.346	0.300	0.732

Table 8. ANN model normalized significance analysis.

These differentiated variable importance patterns not only reflect the specificity of each model’s structure but also reveal the distinct mechanisms by which latent variables influence the outcome variables. This provides essential insights into the predictive logic of the models and the complex interactions between variables, contributing to a deeper understanding of the results.

Conclusions and findings

This study explores the factors influencing users’ purchase intentions for AI-generated cultural and creative products using both SEM and ANN methods. By integrating the SOR, VAM, UTAUT2, and TPB theories, the study analyzes the impact pathways of PP, PV, FC, SI, HM, CE, and GQ on users’ purchasing decisions. The findings enrich the theoretical contributions in the field of AI-generated content and emphasize the significance of cultural experience and emotional factors in the digital consumption environment. This study innovatively introduces CE and GQ as key variables and examines the moderating role of SINN, providing new perspectives for understanding the user acceptance of AI-generated cultural and creative products.

This study proposed 20 hypotheses, and the results indicate that all hypotheses were validated except for H5 and H6. A comparative analysis of the SEM and ANN models reveals a high degree of consistency. In Model A, both research methods identified HM and PV as the most significant determinants, with FC being the least influential factor. Similarly, in Model B, both methods highlighted PV and PP as the most important factors, while the impact of FC was found to be minimal. In Model C, the results from both methods were fully aligned, with the importance ranking being: PBC and SN. In Model D, SN was consistently identified as the second most significant determinant.

### The influence of PV and PP under the VAM framework

This study employs a dual approach using SEM and ANN to validate that, within the VAM framework, both PV and PP have a significant impact on PBC and SN, with the influence on SN being particularly prominent. The results from the ANN model further confirm this finding, showing that PV and PP are core factors across all models, which is highly consistent with the SEM analysis results. When users perceive AI-generated cultural products as innovative and unique, they form a positive AT, which enhances the shopping experience and increases satisfaction. Price, as a critical factor in users' evaluation of product rationality<sup>42</sup>, directly influences their judgment of the value of AI-generated products. The ANN analysis indicates that, among all variables predicting users' purchase intentions, PV and PP hold the highest relative importance. This suggests that users prioritize the perceived value-for-money when making purchasing decisions. PV meets users' demand for personalized customization, allowing them to experience the product's unique cultural connotations, while a reasonable PP ensures high cost-effectiveness in terms of value. The ANN model reveals the nonlinear impact patterns of these two variables, indicating complex interaction effects rather than a simple linear relationship between them.

### The role of SI and HM in the UTAUT2 model

Both ANN and SEM analyses consistently demonstrate that SI and HM have a significant impact on PBC and SN, which is in line with the findings of Yang<sup>64</sup> and Rezvani<sup>69</sup>. The ANN model further reveals the relative importance ranking of SI and HM across various models. SN is directly related to how individuals perceive others' expectations of their behavior and the social expression of those expectations. SI drives SN through group identity and societal expectations, while HM influences individuals' perception of societal expectations by providing emotional fulfillment. The ANN analysis shows that the effects of these two variables follow a nonlinear pattern, which may lead to synergistic effects under specific conditions. As technological advancements and cultural innovation continue to merge, an increasing number of people are purchasing AI-generated cultural products. Users perceive this behavior as aligning with mainstream social expectations, making them more willing to purchase such products. Additionally, users may derive satisfaction from purchasing AI-generated custom artwork or be attracted to its unique design, fulfilling their desire for novelty.

However, FC does not have a significant impact on users' PBC and SN, which contradicts previous studies<sup>47</sup>. The ANN model confirms this finding, showing that FC holds the lowest relative importance across all models. This may be because existing e-commerce platforms have matured, and the convenience of purchasing products has become a basic expectation for users, no longer a key decision-making factor. In contrast, the uniqueness and novelty of AI-generated cultural products are more important.

### The importance of CE and GQ

This study innovatively introduces CE and GQ as key variables. Both SEM and ANN analyses validate their significant influence on users' PBC and SN, which aligns with prior research<sup>98,104</sup>. The ANN model further reveals that among the factors influencing SN, GQ and CE rank just below PV and PP, indicating that they play an important role in shaping users' social identity.

High-quality generated products and a profound CE can enhance social acceptance and strengthen users' cultural identity. Products with rich cultural connotations often represent cultural symbols, and when users perceive these products as aligned with their cultural background or values, their subjective norms are influenced by this cultural identification, making them more inclined to choose products that align with their cultural identity.

The ANN analysis identifies complex nonlinear interactions between CE, GQ, and other variables, relationships that are difficult to fully capture in traditional SEM analysis. The deeper users' perception of cultural elements in AI-generated cultural products, and the higher the GQ, the more they recognize the uniqueness and innovation of these products, thereby increasing their purchase intention. High-quality GQ and rich CE enhance the product's value, stimulate user recognition of the product, and drive the purchasing decision.

### Impact pathways of TPB theory variables

Under the framework of TPB, both SEM and ANN analyses confirm that PBC and SN have a positive influence on users' AT, consistent with the findings of Han, Joonhyoung's study<sup>85</sup>. The ANN model further reveals that in Model C, the importance ranking of PBC and SN's influence on AT is identical, while in Model D, SN is confirmed as the second most important determinant, with PBC having a more significant impact.

When users perceive that they have the ability to successfully complete the purchase behavior, they tend to form a more positive attitude. This reflects their confidence and expectations toward AI-generated cultural products. In contrast, SN influences attitude by shaping users' sense of social approval for the behavior. However, this effect is typically less direct and intense than PBC, as it relies on users' perception of others' opinions and societal expectations.

The research results validate hypotheses H11–H15, indicating that PBC and SN not only have a positive impact on AT but also directly enhance users' purchase intention. The more users feel they have control over



their purchasing decisions, the more likely they are to engage in purchase behavior. Similarly, if users perceive their purchasing decisions as consistent with social norms, their purchase intention is strengthened.

The ANN analysis reveals that AT is a key determinant influencing users' purchase intention, with the highest relative importance in Model D. According to Ajzen's research<sup>73</sup>, users' attitude toward a behavior directly determines whether they will take action. Users with a positive attitude toward AI-generated cultural products exhibit a significantly higher purchase intention, while those with a negative attitude are less likely to make a purchase.

### The moderating effect of SINN

This study further verifies the moderating role of SINN in the relationship between PV, PP, and users' PBC, consistent with the findings of Jeeyeon Jeong<sup>108</sup>. The ANN model effectively captures this nonlinear moderating effect, revealing the varying impact of PV and PP on PBC at different SINN levels. Users with high SINN typically evaluate PV and PP based on their interest in novelty and the need for new experiences, which, in turn, influences their PBC. The ANN analysis indicates that these users place a higher value on product innovation and unique value, exhibiting relatively lower price sensitivity. In contrast, users with low SINN show a weaker response to these factors, with their perceptions of PP and PV being more influenced by inherent personal preferences and traditional views. This finding suggests that for users with lower innovativeness, the balance between price and value may be a more critical factor in determining their purchase decisions, while highly innovative users are more likely to pay a premium for novel experiences.

This study, through robust data analysis, demonstrates the impact of variables related to VAM, UTAUT2, TPB, CE, and GQ on users' purchase decisions regarding AI-generated creative products. It provides valuable insights for the AI-generated creative product sector. Additionally, the findings of this study assist enterprises in formulating more efficient design strategies and help platforms understand the key factors influencing AI-generated creative products, thereby enhancing the user experience.

### Suggestions

With the continuous application of AI technology in the cultural and creative industries, AI-generated creative products are gradually becoming a new market trend. However, to truly enhance users' purchase intentions and satisfaction, technological advancements alone are far from sufficient. Based on the results of the SEM and ANN analyses in this study, the following recommendations are proposed to improve user satisfaction and purchase intention for AI-generated creative products.

- (1) *Enhancing purchase intention* To increase users' purchase intention for AI-generated creative products, designers should focus on the product's PV, HM, and CE. Designers should prioritize the product's entertainment value and visual experience to evoke emotional responses from users, thereby enhancing HM and prompting purchase behavior. Additionally, from the perspective of CE, the design should integrate deep cultural connotations. By incorporating culturally symbolic elements and historical stories, designers can imbue the product with unique emotional value, allowing users to experience cultural resonance and recognition during both the purchase and use process. Furthermore, designers can innovate by reinterpreting traditional culture and presenting classical elements with modern methods, thereby creating products that balance artistry and practicality, fulfilling users' deeper CE needs. This approach will enhance product recognition and increase purchase desire.
- (2) *Optimizing platform algorithms and technological advancements* Platforms should focus on optimizing algorithms and enhancing technological capabilities. Continuous updates and upgrades to AI technology are necessary to ensure that the generated products meet user requirements in terms of design details, artistry, and quality. Additionally, platforms can incorporate more user feedback and data analysis to continually improve the generation model, enhancing the product's personalization and accuracy. By improving GQ, users will develop stronger trust in the products, while the enjoyment and unique CE provided by the products will further stimulate purchase motivation.
- (3) *Improving purchase intention through multiple approaches* Finally, enterprises should take a multifaceted approach to enhance users' purchase intention for AI-generated creative products.

First, ensuring reasonable product pricing is essential. The PP should align with the product's actual value to improve cost-effectiveness and meet users' price sensitivity. Second, enterprises should focus on enhancing CE by integrating rich cultural elements into the product design, thereby increasing the product's cultural depth. This will allow users to experience the unique charm of culture when making a purchase. Third, enterprises should strengthen SI by leveraging social media, celebrity endorsements, and user reviews to boost the product's social acceptance. This can help users perceive the product as trendy and socially recognized, thereby increasing their purchase intention. Fourth, cultivating a positive AT is crucial to ensure that the product meets users' design and functional expectations. Positive emotional evaluations of the product can further promote purchase behavior. Enterprises can enhance product recognition by showcasing positive user feedback and real-life product usage scenarios, influencing users' purchase decisions. Finally, PBC is another important factor. Enterprises should optimize the purchasing process and user experience to ensure that users feel the process is smooth and controllable. This sense of control can further enhance their purchase intention.

By implementing these strategies, enterprises can effectively increase users' purchase intention for AI-generated creative products.

## Limitations

This study extensively explored the factors influencing users' purchase intention for AI-generated creative products, analyzing the impacts of factors such as CE, GQ, PP, and HM on users. However, there are certain limitations to this study.

First, this research has not accounted for all possible factors that may influence users' intention to purchase AI-generated creative products. Future studies should explore additional variables, such as individual differences among users, market trends, socio-cultural backgrounds, situational factors, and technological ethics, and investigate their effects on users' purchase behavior.

Second, this study focused solely on the perceptions of domestic consumers regarding AI-generated creative products. Consumers from different countries and cultural backgrounds may have varying expectations toward these products. Future research should incorporate international consumer perspectives to compare the cognitive differences between domestic and international consumers regarding AI-generated creative products, thus providing empirical evidence for optimizing these products. Additionally, identifying culturally attractive elements with cross-cultural appeal could provide guidance for the development of global AI creative products.

Finally, this study developed its model based on the current stage of generative AI technology. It has not fully considered the future evolution of AI in areas such as generation quality optimization, ethical standards, and user trust, all of which could impact user behavior. Subsequent research should dynamically adjust the model in line with technological advancements to enhance its foresight and adaptability.

## Data availability

The datasets generated and/or analyzed in the current study are available from the corresponding author upon reasonable request.

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## References

- Yin, H., Zhang, Z. & Liu, Y. The exploration of integrating the midjourney artificial intelligence generated content tool into design systems to direct designers towards future-oriented innovation. *Systems* **11**(12), 566 (2023).
- QuestMobile, China Mobile Internet Half-Yearly Report. <https://www.questmobile.com.cn/research/report/1818126420037177346.2024.7.30>. (2024).
- Li, L. & Sun, Q. Research on the factors of China's cultural and creative products export trade: An empirical analysis based on constant market share model. In *Proceedings of the 2019 5th International Conference on E-Business and Applications (ICEBA 2019)*. Association for Computing Machinery, New York, NY, USA, 110–113 (2019).
- Verganti, R., Vendraminelli, L. & Iansiti, M. Innovation and design in the age of artificial intelligence. *J. Prod. Innov. Manag.* **37**(3), 212–227 (2020).
- Yan, D. Research on the innovative design of museum cultural and creative products in Liaoning. In *IOP Conference Series: Materials Science and Engineering*, vol. 573, 012010. (IOP Publishing, 2019).
- Wu, F., Hsiao, S. W. & Lu, P. An AIGC-empowered methodology to product color matching design. *Displays* **81**, 102623 (2024).
- Zhang, L. & Hu, F. Analysis of the design of cultural and creative products from the perspective of regional culture. In *IOP Conference Series: Materials Science and Engineering*, vol. 573, 012071 (IOP Publishing, 2019).
- Wang, Y. et al. A survey on ChatGPT: AI-generated contents, challenges, and solutions. *IEEE Open J. Comput. Soc.* **4**, 280 (2023).
- Li, W. A study on factors influencing designers' behavioral intention in using AI-generated content for assisted design: Perceived anxiety, perceived risk, and UTAUT. *Int. J. Hum. Comput. Interact.* **41**, 1–14 (2024).
- Ma, X. & Huo, Y. Drawing a satisfying picture: An exploratory study of human-AI interaction in AI painting through breakdown-repair communication strategies. *Inf. Process. Manag.* **61**(4), 103755 (2024).
- Wang, J. et al. Guiding AI-generated digital content with wireless perception. *IEEE Wirel. Commun.* <https://doi.org/10.1109/MWC.008.2300162> (2024).
- Kim, H. W., Chan, H. C. & Gupta, S. Value-based adoption of mobile internet: An empirical investigation. *Decis. Support Syst.* **43**(1), 111–126 (2007).
- Zeithaml, V. A. Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *J. Mark.* **52**(3), 2–22 (1988).
- Tamilmani, K. et al. The extended unified theory of acceptance and use of technology (UTAUT2): A systematic literature review and theory evaluation. *Int. J. Inf. Manag.* **57**, 102269 (2021).
- Göring, S. et al. Appeal and quality assessment for AI-generated images. In *2023 15th International Conference on Quality of Multimedia Experience (QoMEX)*, 115–118 (IEEE, 2023).
- Rogers, E. M., Singhal, A. & Quinlan, M. M. Diffusion of innovations. In *An integrated approach to communication theory and research* 432–448 (Routledge, 2014).
- Cao, Y. et al. A comprehensive survey of AI-generated content (AIGC): A history of generative AI from GAN to ChatGPT. Preprint at arxiv:2303.04226 (2023).
- Akpan, I. J. et al. Conversational and generative artificial intelligence and human-chatbot interaction in education and research. *Int. Trans. Oper. Res.* **32**, 1251 (2024).
- Walkowiak, E. & Potts, J. Generative AI, work and risks in cultural and creative industries. Available at SSRN 4830265, (2024).
- Xu, J. et al. Is everyone an artist? A study on user experience of AI-based painting system. *Appl. Sci.* **13**(11), 6496 (2023).
- Sukkar, A. W. et al. Analytical evaluation of midjourney architectural virtual lab: Defining major current limits in AI-generated representations of islamic architectural heritage. *Buildings* **14**(3), 786 (2024).
- Gao, B. et al. Artificial intelligence in advertising: Advancements, challenges, and ethical considerations in targeting, personalization, content creation, and ad optimization. *SAGE Open* **13**(4), 21582440231210760 (2023).
- Saleh, H. F. AI in media and journalism: Ethical challenges. Prof. Hanaa Farouk Saleh.
- Kim, T. et al. Authors' values and attitudes towards AI-bridged scalable personalization of creative language arts. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–16 (2024).
- Anantrasirichai, N. & Bull, D. Artificial intelligence in the creative industries: A review. *Artif. Intell. Rev.* **55**(1), 589–656 (2022).
- Wang, Y., Pan, Y., Yan, M., Su, Z. & Luan, T. H. A survey on ChatGPT: AI-generated contents, challenges, and solutions. *IEEE Open J. Comput. Soc.* **4**, 280–302. <https://doi.org/10.1109/OJCS.2023.3300321> (2023).
- Tan, L. & Luhrs, M. Using Generative AI midjourney to enhance divergent and convergent thinking in an architect's creative design process. *Des. J.* **27**, 1–23 (2024).

28. Zhang, Y. & Liu, C. Unlocking the potential of artificial intelligence in fashion design and e-commerce applications: The case of midjourney. *J. Theor. Appl. Electron. Commer. Res.* **19**(1), 654–670 (2024).
29. Nagano, M., Ijima, Y. & Hiroya, S. Perceived emotional states mediate willingness to buy from advertising speech. *Front. Psychol.* **13**, 1014921 (2023).
30. Song, Z., Liu, C. & Shi, R. How do fresh live broadcast impact consumers' purchase intention? Based on the SOR theory. *Sustainability* **14**(21), 14382 (2022).
31. Hameed, I. et al. Decoding willingness to buy in live-streaming retail: The application of stimulus organism response model using PLS-SEM and SEM-ANN. *J. Retail. Consum. Serv.* **84**, 104236 (2025).
32. Srivastava, A. et al. Impact of perceived value on the online purchase intention of base of the pyramid consumers. *Int. J. Consum. Stud.* **47**(4), 1291–1314 (2023).
33. Kim, Y., Park, Y. & Choi, J. A study on the adoption of IoT smart home service: Using value-based adoption model. *Total Qual. Manag. Bus. Excell.* **28**(9–10), 1149–1165 (2017).
34. Yu, H., Seo, I. & Choi, J. A study of critical factors affecting adoption of self-customisation service—focused on value-based adoption model. *Total Qual. Manag. Bus. Excell.* **30**(sup1), S98–S113 (2019).
35. Liao, Y. K. et al. The integration of the technology acceptance model and value-based adoption model to study the adoption of e-learning: The moderating role of e-WOM. *Sustainability* **14**(2), 815 (2022).
36. Milfelnor, B., Snoj, B. & Korda, A. P. Measurement of perceived quality, perceived value, image, and satisfaction interrelations of hotel services: Comparison of tourists from Slovenia and Italy. *Drustvena Istrazivanja* **20**(3), 605 (2011).
37. Diao, X. & He, L. An empirical research on the influence of perceived value on buyers' purchase intention—Based on the regulation of freight. In *Proceedings of the 33rd Chinese Control Conference*, 3445–3449 (IEEE, 2014).
38. Bandura, A. *Self-efficacy: The exercise of control*. (Macmillan, 1997).
39. Oliver, R. L. Whence consumer loyalty?. *J. Market.* **63**(4\_suppl1), 33–44 (1999).
40. Fiandari, Y. R. et al. Perceived value dimension in repetitive fish consumption in Indonesia by using an extended theory of planned behavior. *Br. Food J.* **121**(6), 1220–1235 (2019).
41. Chiang, C. C. The effects of the antecedents of service purchase intention in the context of monetary sales promotion. *Acta Oecon.* **64**(Supplement-2), 177–197 (2014).
42. Wassouf, F. The influence of product price and advertisement on customer's perception of product. In *Proceedings of the 5th International Conference on Conference on Innovation U Management, I & II*, 1061–1065 (2008).
43. Bearden, W. O. & Etzel, M. J. Reference group influence on product and brand purchase decisions. *J. Consum. Res.* **9**(2), 183–194 (1982).
44. Dorce, L. C. et al. Extending the theory of planned behavior to understand consumer purchase behavior for organic vegetables in Brazil: The role of perceived health benefits, perceived sustainability benefits and perceived price. *Food Qual. Prefer.* **91**, 104191 (2021).
45. Lichtenstein, D. R. & Bearden, W. O. Contextual influences on perceptions of merchant-supplied reference prices. *J. Consum. Res.* **16**(1), 55–66 (1989).
46. Yen, Y. S. Extending consumer ethnocentrism theory: The moderating effect test. *Asia Pac. J. Mark. Logist.* **30**(4), 907–926 (2018).
47. Taylor, S. & Todd, P. A. Understanding information technology usage: A test of competing models. *Inf. Syst. Res.* **6**(2), 144–176 (1995).
48. Venkatesh, V. et al. User acceptance of information technology: Toward a unified view. *MIS Q.* **27**, 425–478 (2003).
49. Venkatesh, V., Thong, J. Y. L. & Xu, X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q.* **36**(1), 157–178 (2012).
50. Hilal, A. & Varela-Neira, C. Understanding consumer adoption of mobile banking: Extending the UTAUT2 model with proactive personality. *Sustainability* **14**(22), 14708 (2022).
51. Oechslein, O., Fleischmann, M. & Hess, T. An application of UTAUT2 on social recommender systems: Incorporating social information for performance expectancy. In *2014 47th Hawaii international conference on system sciences*, 3297–3306 (IEEE, 2014).
52. Alazzam, M. B. et al. Physicians' acceptance of electronic health records exchange: An extension of the with UTAUT2 model institutional trust. *Adv. Sci. Lett.* **21**(10), 3248–3252 (2015).
53. Seo, K. H. A study on the application of kiosk service as the workplace flexibility: The determinants of expanded technology adoption and trust of quick service restaurant customers. *Sustainability* **12**(21), 8790 (2020).
54. An, L., Han, Y. & Tong, L. Study on the factors of online shop\*\* intention for fresh agricultural products based on UTAUT2. In *The 2nd Information technology and mechatronics engineering conference (ITOEC 2016)*, 303–306 (Atlantis Press, 2016).
55. Kittinger, L. I. & Law, V. A Systematic Review of the UTAUT and UTAUT2 Among K-12 Educators. *J. Inf. Technol. Educ. Res.* **23**, 017 (2024).
56. Lina, Y., Hou, D. & Ali, S. Impact of online convenience on generation Z online impulsive buying behavior: The moderating role of social media celebrity. *Front. Psychol.* **13**, 951249 (2022).
57. Nordhoff, S. et al. Using the UTAUT2 model to explain public acceptance of conditionally automated (L3) cars: A questionnaire study among 9,118 car drivers from eight European countries. *Transport. Res. F: Traffic Psychol. Behav.* **74**, 280–297 (2020).
58. Bandura, A. Self-efficacy: Toward a unifying theory of behavioral change. *Psychol. Rev.* **84**(2), 191 (1977).
59. Wang, H. et al. The determinants of user acceptance of mobile medical platforms: An investigation integrating the TPB, TAM, and patient-centered factors. *Int. J. Environ. Res. Public Health* **19**(17), 10758 (2022).
60. Venkatesh, V. & Davis, F. D. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Manag. Sci.* **46**(2), 186–204 (2000).
61. O'keefe, D. J. Persuasion. In *The handbook of communication skills* 333–352 (Routledge, 2006).
62. Armitage, C. J. & Conner, M. Efficacy of the theory of planned behaviour: A meta-analytic review. *Br. J. Soc. Psychol.* **40**(4), 471–499 (2001).
63. Terry, D. J. & O'Leary, J. E. The theory of planned behaviour: The effects of perceived behavioural control and self-efficacy. *Br. J. Soc. Psychol.* **34**(2), 199–220 (1995).
64. Yang, F. et al. Consumer perceived value and impulse buying behavior on mobile commerce: The moderating effect of social influence. *J. Retail. Consum. Serv.* **63**, 102683 (2021).
65. Hsu, C. L. & Lin, J. C. C. Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Inf. Manag.* **45**(1), 65–74 (2008).
66. Cialdini, R. B. & Trost, M. R. Social influence: Social norms, conformity and compliance (1998).
67. Fishbein, M. & Ajzen, I. Belief, attitude, intention, and behavior: An introduction to theory and research (1977).
68. Brown, S. A. & Venkatesh, V. A model of adoption of technology in the household: A baseline model test and extension incorporating household life cycle. *Manag. Inf. Syst. Q.* **29**(3), 11 (2005).
69. Rezvani, Z., Jansson, J. & Bengtsson, M. Consumer motivations for sustainable consumption: The interaction of gain, normative and hedonic motivations on electric vehicle adoption. *Bus. Strateg. Environ.* **27**(8), 1272–1283 (2018).
70. Fournier, S. & Mick, D. G. Rediscovering satisfaction. *J. Mark.* **63**(4), 5–23 (1999).
71. Polisetty, A. et al. Examining the relationship between pro-environmental consumption behaviour and hedonic and eudaimonic motivation. *J. Environ. Manag.* **359**, 121095 (2024).

72. Sahu, A. K., Padhy, R. K. & Dhir, A. Envisioning the future of behavioral decision-making: A systematic literature review of behavioral reasoning theory. *Australas. Mark. J.* **28**(4), 145–159 (2020).
73. Ajzen, I. & Madden, T. J. Prediction of goal-directed behavior: Attitudes, intentions, and perceived behavioral control. *J. Exp. Soc. Psychol.* **22**(5), 453–474 (1986).
74. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **50**(2), 179–211 (1991).
75. Yang, M. et al. Modeling the intention to consume and willingness to pay premium price for 3D-printed food in an emerging economy. *Human. Soc. Sci. Commun.* **11**(1), 1–14 (2024).
76. Yeo, K. H. K., Lim, W. M., Yii, K. J. Financial planning behaviour: A systematic literature review and new theory development. *J. Financ. Serv. Market.* 1–23 (2023).
77. Flavián, C., Guinaliú, M. & Lu, Y. Mobile payments adoption—introducing mindfulness to better understand consumer behavior. *Int. J. Bank Market.* **38**(7), 1575–1599 (2020).
78. Lien, C. H., Hsu, M. K., Shang, J. Z. & Wang, S. W. Self-service technology adoption by air passengers: A case study of fast air travel services in Taiwan. *Serv. Ind. J.* **41**(9–10), 671–695 (2019).
79. Saeri, A. K. et al. Predicting Facebook users' online privacy protection: Risk, trust, norm focus theory, and the theory of planned behavior. *J. Soc. Psychol.* **154**(4), 352–369 (2014).
80. Belanche, D., Casaló, L. V. & Flavián, C. Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. *Ind. Manag. Data Syst.* **119**(7), 1411–1430 (2019).
81. Hoeksma, D. L. et al. An extended theory of planned behavior to predict consumers' willingness to buy mobile slaughter unit meat. *Meat Sci.* **128**, 15–23 (2017).
82. Tarkiainen, A. & Sundqvist, S. Subjective norms, attitudes and intentions of Finnish consumers in buying organic food. *Br. Food J.* **107**(11), 808–822 (2005).
83. Liang, C. C. & Shiao, W. L. Moderating effect of privacy concerns and subjective norms between satisfaction and repurchase of airline e-ticket through airline-ticket vendors. *Asia Pac. J. Tour. Res.* **23**(12), 1142–1159. <https://doi.org/10.1080/10941665.2018.1528290> (2018).
84. Chan, S. Understanding internet banking adoption and use behavior: A Hong Kong perspective. *J. Glob. Inf. Manag. (JGIM)* **12**(3), 21–43 (2004).
85. Han, J., Kang, S. & Moon, T. An empirical study on perceived value and continuous intention to use of smart phone, and the moderating effect of personal innovativeness. *Asia Pac. J. Inf. Syst.* **23**(4), 53–84 (2013).
86. Raman, P. Online shopping characteristics and their influence on female buying behavior: An extension of the theory of planned behavior. *J. Electron. Commer. Organ. (JECO)* **18**(4), 1–29 (2020).
87. Asif, M. H. et al. Influencing factors of consumers' buying intention of solar energy: A structural equation modeling approach. *Environ. Sci. Pollut. Res.* **30**(11), 30017–30032 (2023).
88. Ajzen, I. & Schmidt, P. Changing behavior using the theory of planned behavior. In *The handbook of behavior change* 17–31 (2020).
89. Wang, H. & Wang, H. Research on landscape design from the perspective of regional culture. In *2014 2nd International Conference on Education Technology and Information System (ICETIS 2014)*. (Atlantis Press, 2014).
90. Wansborough, M. & Mageean, A. The role of urban design in cultural regeneration. *J. Urban Des.* **5**(2), 181–197 (2000).
91. Zhu, X. Discussion on the inheritance and development of traditional culture in interior design. In *International Conference on Education, Management and Computing Technology (ICEMCT-16)*, 1090–1098 (Atlantis Press, 2016).
92. Sun, X. F. Inheriting of traditional culture in design. *Adv. Mater. Res.* **189**, 724–728 (2011).
93. Lu, L. Culture, self, and subjective well-being: Cultural psychological and social change perspectives. *Psychologia* **51**(4), 290–303 (2008).
94. Li, Y. Q. & Liu, C. H. Impact of cultural contact on satisfaction and attachment: Mediating roles of creative experiences and cultural memories. *J. Hosp. Market. Manag.* **29**(2), 221–245 (2020).
95. Lee, C. K. et al. Role of cultural worldview in predicting heritage tourists' behavioural intention. *Leis. Stud.* **40**(5), 645–657 (2021).
96. Zhou, Q. & Pu, Y. Impact of cultural heritage rejuvenation experience quality on perceived value, destination affective attachment, and revisiting intention: Evidence from China. *Asia Pac. J. Tour. Res.* **27**(2), 192–205 (2022).
97. Nie, H. & Zhu, D. Research on the design of cultural creative products based on \*\*gchu regional culture. In *3rd International Conference on Art Studies: Science, Experience, Education (ICASSEE 2019)*. 193–196. (Atlantis Press, 2019).
98. Zong, Z., Liu, X. & Gao, H. Exploring the mechanism of consumer purchase intention in a traditional culture based on the theory of planned behavior. *Front. Psychol.* **14**, 1110191 (2023).
99. Arjovsky, M. & Bottou, L. Towards principled methods for training generative adversarial networks. Preprint at [arXiv:1701.04862](https://arxiv.org/abs/1701.04862).
100. Creswell, A. et al. Generative adversarial networks: An overview. *IEEE Signal Process. Mag.* **35**(1), 53–65 (2018).
101. Felderer, M. & Ramler, R. Quality assurance for AI-based systems: Overview and challenges (introduction to interactive session). In *Software Quality: Future Perspectives on Software Engineering Quality: 13th International Conference, SWQD 2021, Vienna, Austria, January 19–21, 2021, Proceedings* 13, 33–42. (Springer International Publishing, 2021).
102. Gotlieb, J. B., Grewal, D. & Brown, S. W. Consumer satisfaction and perceived quality: Complementary or divergent constructs?. *J. Appl. Psychol.* **79**(6), 875 (1994).
103. Ashfaq, M. et al. I. Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telemat. Inform.* **54**, 101473 (2020).
104. Labajová, L. The state of AI: Exploring the perceptions, credibility, and trustworthiness of the users towards AI-generated content. (2023).
105. Elie-Dit-Cosaque, C., Pallud, J. & Kalika, M. The influence of individual, contextual, and social factors on perceived behavioral control of information technology: A field theory approach. *J. Manag. Inf. Syst.* **28**(3), 201–234 (2011).
106. Agarwal, R., Sambamurthy, V. & Stair, R. M. The evolving relationship between general and specific computer self-efficacy—An empirical assessment. *Inf. Syst. Res.* **11**(4), 418–430 (2000).
107. Bandura, A. *Self-efficacy: The exercise of control* Vol. 2, 143–154 (Freeman, 1997).
108. Jeong, J., Kim, Y. & Roh, T. Do consumers care about aesthetics and compatibility? The intention to use wearable devices in health care. *SAGE Open* **11**(3), 21582440211040070 (2021).
109. Lin, C. Y. Conceptualizing and measuring consumer perceptions of retailer innovativeness in Taiwan. *J. Retail. Consum. Serv.* **24**, 33–41 (2015).
110. Al-Jundi, S. A., Shuhaiber, A., Augustine, R. & Wright, L. T. Effect of consumer innovativeness on new product purchase intentions through learning process and perceived value. *Cogent Bus. Manag.* **6**(1), 1698849 (2019).
111. Park, S. & Chung, K. The effect of consumer innovativeness, perceived risk and price sensitivity on new product adoption: The moderating effect of gender: The moderating effect of gender. *Internet e-Commer. Res.* **16**(5), 99–114 (2016).
112. Kline, R. B. *Principles and practice of structural equation modeling* (Guilford Publications, 2023).
113. Agatonovic-Kustrin, S. & Beresford, R. Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *J. Pharm. Biomed. Anal.* **22**(5), 717–727 (2000).
114. Byrne, B. M. *Structural equation modeling with Mplus: Basic concepts, applications, and programming* (Routledge, 2013).
115. Bagozzi, R. P. & Yi, Y. On the evaluation of structural equation models. *J. Acad. Mark. Sci.* **16**, 74–94 (1988).
116. He, T.-L. & Qin, F. Exploring how the metaverse of cultural heritage (MCH) influences users' intentions to experience offline: A two-stage SEM-ANN analysis. *Heritage Sci.* **12**(1), 193 (2024).



117. Anderson, J. C. & Gerbing, D. W. Structural equation modeling in practice: A review and recommended two-step approach. *Psychol. Bull.* **103**(3), 411 (1988).
118. Fan, Yi. et al. Applications of structural equation modeling (SEM) in ecological studies: An updated review. *Ecol. Process.* **5**, 1–12 (2016).
119. Haykin, S. Neural networks expand SP's horizons. *IEEE Signal Process. Mag.* **13**(2), 24–49 (2002).
120. Braspenning, P. J., Thuijsman, F. & Weijters, A. *Artificial neural networks: An introduction to ANN theory and practice* (Springer Verlag, 1995).
121. Wu, W., Dandy, G. C. & Maier, H. R. Protocol for developing ANN models and its application to the assessment of the quality of the ANN model development process in drinking water quality modelling. *Environ. Model. Softw.* **54**, 108–127 (2014).
122. Sohn, K. & Kwon, O. Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. *Telemat. Inform.* **47**, 101324 (2020).
123. Dohnke, B., Weiss-Gerlach, E. & Spies, C. D. Social influences on the motivation to quit smoking: Main and moderating effects of social norms. *Addict. Behav.* **36**(4), 286–293 (2011).
124. Baudier, P., Ammi, C. & Deboeuf-Rouchon, M. Smart home: Highly-educated students' acceptance. *Technol. Forecast. Soc. Change* **153**, 119355 (2020).
125. Bounab, Y., Oussalah, M. & Beddier, D. R. Impact of quality of images on users behavior on social media. In *2020 Tenth International Conference on Image Processing Theory, Tools and Applications (IPTA)*, Paris, France, 1–6. <https://doi.org/10.1109/IPTA50016.2020.9286466> (2020).
126. Krejcie, R. V. Determining sample size for research activities. *Educ. Psychol. Meas.* **30**, 307 (1970).
127. Eisinga, R., Grotenhuis, M. & Pelzer, B. The reliability of a two-item scale: Pearson, Cronbach, or Spearman-Brown?. *Int. J. Public Health* **58**, 637–642 (2013).
128. Muilenburg, L. Y. & Berge, Z. L. Student barriers to online learning: A factor analytic study. *Distance Educ.* **26**(1), 29–48 (2005).
129. Fornell, C. *Structural equation models with unobservable variables and measurement error: Algebra and statistics*. (Publications Sage, 1981).
130. Parhi, S. et al. Factors affecting Industry 4.0 adoption—A hybrid SEM-ANN approach. *Comput. Ind. Eng.* **168**, 108062 (2022).

## Author contributions

Weiling Shi wrote the main manuscript text. All authors reviewed the manuscript.

## Declarations

## Competing interests

The authors declare no competing interests.

## Additional information

**Correspondence** and requests for materials should be addressed to L.L.

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