Research on the Evaluation and Decision-making of Artistic Creation Generation: Taking the Augmented Reality Means of AIGC Platform in the Internet Era as an Example

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Abstract

In the 21st century, with the internet deeply integrated into daily life and rapid advancements in Internet technology, artificial intelligence (AI) is increasingly used in creative industries, significantly improving content generation efficiency and usability. As a result, numerous AI art generation platforms have emerged. Artists often rely on their knowledge and experience to select the most suitable images or videos generated from text inputs, making this decision-making process a key intersection of human cognition and technological innovation. This paper explores how Augmented Reality (AR) can serve as an innovative human-computer interaction method to help artists evaluate and choose among multiple outputs from AIGC platforms. The unique lightweight nature, accessibility, and cross-platform interaction mechanisms of Web AR further provide technical support for this concept. This study evaluates the effectiveness of AR-assisted decision-making on AIGC platforms by integrating user feedback and decision fatigue indicators, based on Cognitive Load Theory and the Technology Acceptance Model (TAM). Key evaluation factors include perceived usability, perceived interactivity and overall user satisfaction. The findings highlight both the potential opportunities of using Web AR as a decision-support tool in artistic creation. Furthermore, the paper outlines feasible strategies for integrating AR features within existing network technologies and architectures. Ultimately, these insights aim to support user-centered art creation and design strategies in the Internet era, enhance the depth of interaction between the AIGC website interface and users, thereby improving the user experience of art practitioners on the AIGC platform and injecting diversity and sustainable development momentum into the art industry.

Keywords: Augmented reality, AIGC platforms, Decision making process, Web AR, User satisfaction

1 Introduction

With the continuous breakthroughs in machine learning (ML) and internet technology, the European Commission's recently released Web 4.0 strategy heralds the accelerated arrival of a highly interactive and intelligent digital ecosystem [1]. Against this backdrop, Artificial Intelligence (AI) is emerging as a key enabling tool, gradually reshaping the production models and workflows of artistic creation and the creative industries [2]. The widespread application of AI in the design field is driven by the continuous upgrading of underlying network infrastructure, particularly the development of models such as Generative Adversarial Networks (GANs), which have significantly enhanced image generation efficiency and interaction convenience. This technological evolution has given rise to Artificial Intelligence Generated Content (AIGC) platforms such as Midjourney and DALL·E 3, which combine natural language processing (NLP) with advanced generative models to enable computers to understand, interpret, and produce images and videos that align with human linguistic intent [3]. For example, in an experiment on AI-assisted fashion design, Midjourney generated 12 images meeting the requirements in less than 60 seconds [4].

However, AIGC has significantly improved content production efficiency, creators still need to invest a significant amount of cognitive resources in prompt design, result filtering, and multi-round adjustments. This continuous judgment process can easily lead to cognitive load and decision fatigue [5]. Compared to human-driven decision-making, AI decision-making still has shortcomings in fairness and understanding perception [6]. The "human-machine-prompt" collaborative mechanism emphasizes the critical role of users in the generation process [7], but high-frequency selection tasks may weaken users' initiative and creative motivation, potentially leading to abandonment of use [8]. Therefore, focusing solely on model performance and algorithm optimization is insufficient to optimize the user experience; it is also essential to consider users' decision-making processes in the "post-generation" phase.

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As a result, this research focus on building supportive decision-making systems. In recent years, immersive technologies have brought new opportunities for human-machine interaction. While VR offers immersion, it is detached from real-world contexts and may increase cognitive load [9]; MR, though highly interactive, is constrained by cost and technical barriers [10]. In contrast, AR overlays digital content onto real-world scenes, combining intuitiveness with realism. It has demonstrated potential to enhance user engagement and decision-making efficiency in areas such as virtual try-on and product visualization [11]. Further, compared to App AR, Web AR based on Web3.0 technology offers greater immediacy and accessibility, making it suitable for rapid decision-making scenarios [12]. Based on this, this paper proposes the following two research questions:

RQ1: How do Web technologies and their development promote the application of augmented reality technology and improve users' perception of virtual content?

RQ2: How can augmented reality technology assist artistic creators in making creative decisions on AIGC platforms and enhance their overall satisfaction with the platform?

2 Literature Review

To address the above research questions, this study reveals the potential and challenges of AIGC platforms from the perspectives of Web AR technological evolution, AIGC generation characteristics, and user decision-making process.

2.1 The Evolution of Web AR Technology and its Integration with User Perception

In recent years, internet technology has evolved from a static information dissemination system to an intelligent platform supporting multimodal interaction, real-time computing, and semantic understanding. The evolution of the Web from 1.0 to 3.0 has driven a fundamental shift in technical architecture toward data-driven systems, personalized services, and the integration of virtual and real-world experiences. Web 3.0 leverages distributed technologies to address data ownership issues and reconfigures the internet's structure, thereby significantly enhancing platform utility [13]. This evolutionary process is driven by key technologies such as cloud computing, edge computing, AI, and blockchain [14]. Web 4.0, as proposed by the European Commission, establishes a semantic communication framework to alleviate bandwidth pressure, further addressing VR/XR's demands for data rates and connectivity [1].

In this background, the user-experience evaluation paradigm has been redefined. From the "browsing - accepting" mode centered on content loading speed to the "selection - control - immersion" continuous experience that emphasizes more responsiveness, interface logic, visualization and personalized feedback [15]. Usability, interactivity, immersion [16] and cognitive load [17] have gradually replaced a single performance metric and become the key dimensions for measuring the system experience. However, in scenarios with complex information or improper design, users are easy to cognitive overload and decision fatigue [18]. Consequently, how to reconstruct the interaction mechanism between the system and users to enable it to have the capabilities of immediate response, user control and context awareness has become the core of the new generation of Internet experience design.

AR technology emerged in this trend, reshaping the user's perception structure and interaction methods through spatial mapping, dynamic feedback and multi-channel perception input [19]. However, traditional AR often relies on dedicated hardware or local App, which has a threshold of use. The rise of Web AR promotes AR from a closed ecosystem to an open network environment. Based on HTML, JavaScript, WebGL and other technologies, combined with the AR.js, Three.js development framework, Web AR enables users to load virtual content through the browser without downloading Apps, greatly improving accessibility [20].

In order to achieve immersive experience, Web AR must provide accurate recognition, real rendering and low latency feedback capability [21], and depends on modern Web standards such as WebGL, WebRTC, Web Assembly (WASM) and WebXR API. WebGL implements 3D rendering and animation control with GPU acceleration. WebRTC supports camera and microphone access to enable image recognition and virtual-real fusion functions. WASM compiles languages such as C/C++ or Rust into high-performance modules such as 3D physics calculations and embed them into web pages with low latency, which can overcome the bottlenecks of traditional JavaScript in high-load calculations, improving image recognition and spatial calculation efficiency [22]. The new platform further integrates spatial computing frameworks such as SLAM, VSLAM, and GMM to realize spatial tracking and occlusion processing of virtual objects, enhancing immersion and interaction stability in the browser [23] (Figure 1).

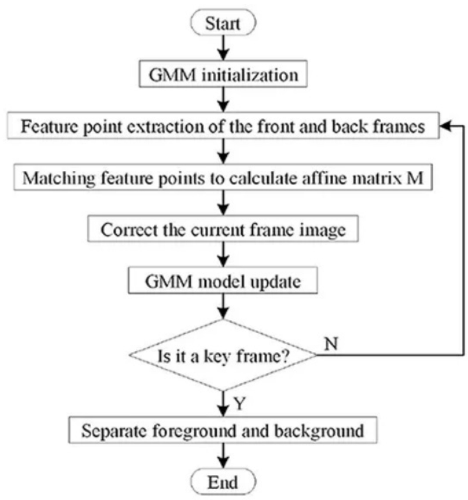

Figure 1. Flowchart of dynamic target detection combining GMM and affine matrix [23]

2.2 AIGC Generation Characteristics

Image generation technology has undergone multiple innovations from generative adversarial networks (GANs) to diffusion models (DMs) and Transformer architectures, which have gradually driven breakthroughs of AIGC systems in image quality, generation efficiency, and controllability. GANs are composed of a generator and a discriminator, which improve the authenticity and discrimination ability of images through adversarial training [24]. For example, DCGAN integrates convolutional neural networks (CNN) to enhance image detail representation, and has been widely applied in image generation scenarios such as facial recognition [25]. In the fields of creative design, GAN-based models demonstrate strong capabilities in generating high-quality and diverse visual content, while improving visual quality, enhancing creative flexibility, and supporting efficient AI-assisted design processes through automated image synthesis and generation techniques [26].

Currently, diffusion models have become the mainstream architecture for image generation. Their core mechanisms include a “forward process” that gradually adds Gaussian noise to the data and a “reverse process” that gradually removes noise through learning, offering improved stability and greater image diversity. In addition, Stable Diffusion adds a latent diffusion model (LDM) to diffusion in a low-dimensional latent space, reducing computational resource consumption, and combines it with text encoders such as CLIP to achieve high-quality text-to-image generation [27]. Moreover, this architecture has been extended to 3D modeling tasks, enabling the generation of 3D objects from textual input [28].

In terms of model structure, the appearance of Transformer represents a significant advancement in image generation toward sequence modeling. Traditional autoregressive models such as PixelRNN and PixelCNN offer high fidelity, but their computational complexity increases with higher image resolution ratio. Transformer has increasingly dominated image generation due to its global modeling capabilities and multi-head attention mechanism [29]. Additionally, ViT-VQGAN combines Transformer and VQ-VAE to optimize computational efficiency and improve image quality [30]. The Transformer-CNN parallel architecture (TCPCNet) combines the advantages of both and achieves significant results in image completion and detail reconstruction [31].

As technology advances, AIGC is moving toward multimodal and controllable generation. OpenAI’s CLIP model provides robust support for text-driven image generation by aligning images and text features through contrastive learning. On this basis, some researchers focus on platforms like Unity3D, enhancing information integration and contextual understanding capabilities across multiple sources [32]. Multi-agent systems based on large language models (LLMs) are being designed to integrate human cognition with chain-of-cognition reasoning, thus advancing AIGC toward explainable and controllable collaborative generation [33]. Meanwhile, in real-time systems such as AR and Metaverse, the integration of AIGC with text-generated 3D scenes has enabled visual reconstruction in WebAR/Edge-AR environments, facilitating instant visualization and immersive interactive within these ecosystems [24]. This further demonstrates the advantages of AIGC services in wireless edge networks.

2.3 User Decision-making Process

In the use of AIGC platforms (Figure 2), users typically generate content by inputting prompts, then select from multiple results or further modify the prompts for iteration [34]. Because AI lacks the deep understanding of context and creative intent, the generated content often requires human intervention for judgment and optimization [35]. Yu [36] further emphasized that while AI as a co-creation tool can expand creative boundaries, it may also weaken creators’ agency autonomy and intrinsic motivation. Retaining final decision-making authority not only helps improve output quality but also prevents over-reliance on algorithms, avoiding creators losing a sense of control and engagement [37]. In the field of design education, scholars also have proposed the concept of a “design arbitrator,” suggesting that creators should assume responsibility for judgment and decision-making in order to retain dominance [38]. This implies that creators play dual roles as both guides and evaluators in this process: they must control the direction of generation while deciding the results with humanistic meaning, thereby achieving the integration of technology and creativity and keeping initiative and value orientation.

Although AIGC technology has significant advantages in improving the efficiency of creative generation, its output commonly suffers from issues such as high homogeneity, lack of details control, and strong unpredictability, which brings cognitive challenges for artistic creators. AI-generated images often exhibit high similarity in contours, textures, and styles, lacking originality [35]. Research on the application of generative AI in story creation also supports this phenomenon: AI-generated stories are more similar to each other [39]. In addition to the issue of high similarity, AI-generated images also exhibit randomness. Combs et al. [40] pointed out that AIGC involves cross-domain concepts through lateral thinking, breaking inertia, but it also leads to unstable output quality and increases the difficulty of evaluation. In this technological context, creators need to repeatedly assess the accuracy of images, style, and alignment of outputs with intended objectives. This continuous process of judgment, guidance, and optimization will unconsciously cause a load on the user’s cognitive system [36]. A similar phenomenon has been observed in the retail e-commerce sector, where consumers have to expend considerable effort to screen and compare products in a high information density environment, leading to choice overload and decision fatigue [41].

Research related to AIGC continues to increase, but most studies still focus on the generation technology itself, such as the cultural adaptability of content [42], the ability to express emotions in images [43], or the approach to embed the design process [2]. There is still insufficient research on the human decision-making process after generation, including screening mechanisms, judgment biases, cognitive load, and the changes of satisfaction. Based on this theoretical and practical gap, this study focuses on the decision-making process in the post-generation stage.

Overall, with the advent of Web 3.0 and 4.0, the development of Web AR technology makes users achieve immersive interactive experiences within browsers, providing the technological foundation for the application of AR in user decision. Then, the evolution of AIGC image generation technology has provided a wealth of image output methods for creators and changed the interactive relationship between users and content. Nevertheless, the complexity, uncertainty, and repetitiveness of AI-generated content may cause cognitive load during the image selection process, leading to decision fatigue and impacting user experience and satisfaction.

This study will explore how emerging technologies such as Web AR can relieve decision fatigue caused by cognitive load, thereby enhancing the overall creative experience of users on AIGC platforms.

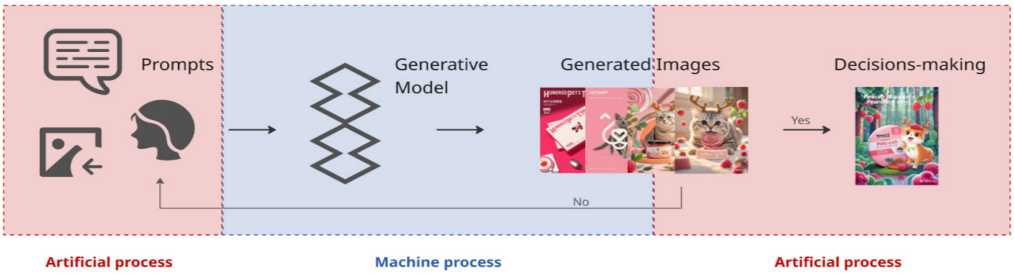

Figure 2. The process used by AIGC

3 Theoretical Framework

To gain a deep understanding of the cognitive and judgment challenges users face in the decision-making stage of AIGC platforms, this paper adopts cognitive load theory and the Technology Acceptance Model (TAM) to explain why WebAR can reduce users' cognitive load and thereby decreasing decision fatigue.

3.1 Theory Background

According to the classical definition, cognitive load refers to the occupation of an individual's psychological resources by a task, primarily divided into three types: (i) internal load, arising from the inherent complexity of the task; (ii) external load, originating from inappropriate information presentation methods; (iii) germane load, related to long-time memory. When cognitive load becomes excessive, the judgment ability and decision-making efficiency of users will decline, resulting in decision fatigue [5]. As the key medium between users with the system, the web interface may significantly increase the external cognitive load if the interface hierarchy is chaotic, the information arrangement is not clear or the device adaptation is limited [18]. Currently, mainstream AIGC platforms (such as Midjourney and DALL·E) adopt two-dimensional flat image displays. While this format meets basic visual requirements, it disrupts the integration of visual information and spatial cognition. Users are forced to alternate frequently between abstract interfaces and concrete understanding, which increasing cognitive load [44].

Decision fatigue theory further points out that when faced with continuous multiple-choice, high-uncertainty tasks, an individual's self-regulation ability will decline as cognitive resources are depleted, causing irrational behaviors such as avoidance of choice, preference for default options, or complete abandonment of the task [45].

The environmental integration mechanism of Web AR provides a new approach to relieve the above issues. AR embeds virtual information into real space, which is more in line with human visual and spatial perception patterns, reducing cognitive load [44]. For example, in AR-based shopping scenarios, the cognitive processing required by consumers decreased, thereby assisting consumers make decisions [46]. In particular, Web AR has cross-platform compatibility, low barriers to entry, and high interactivity, which overcome the limitations of traditional app-based AR [21].

This study combines the TAM model with cognitive load theory to propose a path mechanism whereby in which the Web AR environment integration mechanism reduces user decision fatigue by improving perceived usability and perceived interactivity, thereby enhancing overall satisfaction.

The TAM model is commonly used to explain users' acceptance of new technologies, primarily influenced by factors such as perceived usability and perceived ease of use and has incorporated perceived interactivity to promote its explanatory power for complex systems [47]. It is worth noting that traditional "perceived ease of use" more focuses on the difficulty of users' initial learning and use of the system, rather than their overall evaluation of the system's support and efficiency [48]. However, the targeted users in this study have a certain level of technical literacy, and they have already surpassed the initial adaptation phase. As such, the dimension of perceived ease of use was not relevant to this study.

Therefore, this research identifies perceived usability and perceived interactivity as key mediating pathways of Web AR interventions, aiming to explore the influence on decision making and user satisfaction. In this paper, Web AR intervention refers to the environmental integration mechanism of Web AR, which emphasizes that AIGC-generated content can be embedded in the real environment in the form of spatial superposition and dynamic interaction through Web technology. Its advantages of cross-platform and high flexibility are especially suitable for visual decision-making scenarios [12].

3.2 The Development of Hypothesis

AR technology provides users with an immersive and interactive operating experience by superimposing virtual information onto real space, growing creators' sense of control and involvement of system [49]. Satisfaction is a subjective evaluation of the user experience with a product [50]. Hence, the following hypothesis is offered:

H1: Web AR intervention positively affects user satisfaction

3.2.1 Perceived Usability

Perceived usability has been conceived as the degree to which users perceive a system as easy to use and efficient to operate [51]. As one of the core variables in the TAM, it has a key impact on user experience. Web AR platforms are usually available on common laptops or desktop computers, and the support of such universal devices significantly improves the portability and usability of AR [52]. Empirical studies on stage design scenarios also showed that [53], WebAR can effectively reduce the cognitive load when users understand technical drawings and project processes, thus improving the overall usability, and received positive evaluations from participants. In addition, AR systems have been shown to support consumers' judgment and efficiency in decision-making [46]. Similarly, user satisfaction, as an important indicator to measure the effect of digital systems, has been proved to be closely related to system availability [54].

This results in the set of hypotheses:

H2: Web AR intervention indirectly improves user satisfaction by improving perceptual usability and reducing decision fatigue.

H2a: Web AR intervention positively affects perceived usability.

H2b: Perceived usability has a negative effect on decision fatigue.

H2c: Perceived usability positively affects user satisfaction.

3.2.2 Perceived Interactivity

AR demonstrates potential to enhance interactivity and user engagement across various scenarios, particularly in complex task or decision-making environments [11]. By overlaying computer-generated 3D models onto real-world environments in real time, AR significantly improves visual interactivity and imaginative, offering a more intuitive and immersive way to understand and experience [55]. Further, perceived interactivity can enhance users' sense of control, engagement, and emotional connection with the system, which also has a positive impact on satisfaction [12]. In this context, the research extends the hypotheses:

H3: Web AR intervention indirectly improves user satisfaction by improving perceived interactivity and reducing decision fatigue.

H3a: Web AR intervention positively affects perceived interactivity.

H3b: Perceived interactivity has a negative effect on decision fatigue.

H3c: Perceived interactivity positively affects user satisfaction.

3.2.3 Decision Fatigue

In e-commerce environments, AR technology effectively reduces the cognitive load of users in the process of browsing information by fusing the virtual 3D information of commodities on the real environment, so that they form a more positive attitude [56]. While previous studies have indicated that cognitive load is an important precursor to decision fatigue [45]. Long-term decision fatigue not only affects the quality of judgment, but also may lead to the decline of user trust and the willingness to reuse the platform [57]. Extrapolating from the above, this research see that this information visualization and contextualized interaction mode optimizes the allocation of cognitive resources, enables users to process and filter options more efficiently, and is beneficial to alleviate decision fatigue and increase the user satisfaction.

H4: Web AR intervention indirectly improves user satisfaction by reducing decision fatigue.

H4a: Web AR intervention negatively affects decision fatigue.

H4b: Perceived interactivity negatively affects user satisfaction.

Based on all hypotheses, this study proposes the following conceptual framework (Figure 3):

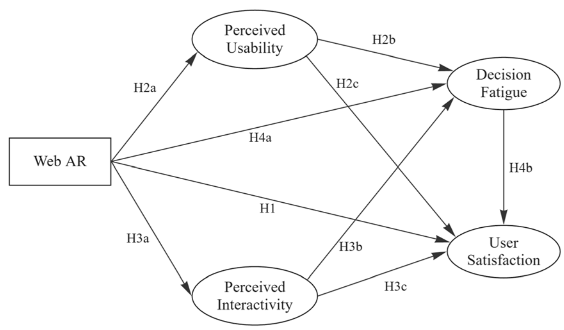

Figure 3. Hypotheses conceptual framework

4 Methodology

This method combines experiments with questionnaires survey. The experimental design between the two factor groups (AR function: yes/no) was designed to verify the influence of Web AR environment integration mechanism on decision fatigue and user satisfaction.

4.1 Participants

Participants for the study (310) were recruited from two Universities in Jiangsu and Anhui provinces of China (Southeast University and Wuhu Vocational Technical

University). From the 310 participants, 3 did not complete the survey, resulting in a sample size of 307. They are all from the second to fourth year of the School of Art and Design, which ensures that the respondents have design ability and experience, and meet the sample type of this study. The sample data were collected in May 2025, with 64% males and 36% females aged between 18 and 25.

4.2 Questionnaire Design

In the questionnaire section, this study adopted widely used and verified scales. The whole scale is divided into four dimensions: perceived interactivity (PI), perceived usability (PU), decision fatigue (DF) and user satisfaction (US). Perceived interactivity often included responsiveness, sense of control and participation, and user feedback [58]. Meanwhile, referencing established assessment scales for the interactivity of AI in education [59], a questionnaire was developed for the perceived interactivity section.

In terms of evaluating perceived usability and user satisfaction, this study adopted the part of the Positively-worded System Usability Scale (SUS) proposed by Lewis [60]. The dimension of decision fatigue used the single-factor scale developed by Pignatiello et al. [61] to assess the psychological load and fatigue of individuals in decision scenarios. The final questionnaire is shown in Table 1. Additionally, the Web AR group has three additional pre-screening questions (Table 2).

Table 1. Questionnaire

Variable	Number	Item	Source
Perceived Interactivity (PI)	PI1	Q1:When using the system, I can freely choose the content I want.	[58-59]
	PI2	Q2: I can flexibly adjust the display of information.	
	PI3	Q3: I feel that I can actively participate in the website.	
	PI4	Q4: I can obtain the information I want from the system in real time.	
	PI5	Q5: The system provides clear decision-making assistance information.	
	PI6	Q6: The system's feedback helps me determine the direction of my creation.	
	PI7	Q7: I can communicate directly with AI to learn more about issues.	
Perceived Usability (PU)	PU1	Q8: I find this website simple.	[60, 51]
	PU2	Q10: I believe I can use this website without technical support.	
	PU3	Q11: I feel I can easily master how to use this system.	
	PU4	Q12: I can quickly find the image generation features I need.	
	PU5	Q13: I can personalize the content and display according to my preferences.	
	PU6	Q14: I find the website's interface and functional layout very intuitive.	
	PU7	Q15: I think the system is flexible and convenient for me to complete tasks.	
	PU8	Q16: I can use this website without learning any new content.	
Decision Fatigue (DF)	DF1	Q18: I cannot concentrate, so it is difficult to make a decision.	[61]
	DF2	Q19: I find it hard to obtain information and use it to make decisions.	
	DF3	Q20: I lack the confidence to make the right decision.	
	DF4	Q21: Making decisions is too exhausting.	
	DF5	Q22: Someone else should make decisions for me.	
	DF6	Q23: I can't decide which option is best.	
	DF7	Q24: I don't think carefully before making decisions.	
	DF8	Q25: My emotions make it hard for me to make decisions.	
User Satisfaction (US)	US1	Q26: Overall, I am very satisfied with this website.	[60]
	US2	Q27: I think I would be willing to use this website frequently.	
	US3	Q28: I would be willing to recommend it to my peers.	

Table 2. Pre-screening questions

Variable	Number	Item
PI	Q1	AR overlay information helps me understand options faster
PU	Q2.	Spatial visualization reduces my decision-making stress.
US	Q3.	If I use the system again, I plan to use the AR environment integration function.

4.3 Task Design and Treatments

The study design randomly assigned participants into two groups (Web AR group and control group). Respondents were asked to imagine themselves as designers creating summer promotional posters for a virtual pet store, using the well-known AIGC platform Mid-Journey to generate their own creative ideas. The specific tasks are as follows: the control group task consisted of browsing browse a video of 12 posters generated by Midjourney website (the prompt words are generated by Deepseek including three styles) and select the one they think is most appropriate (as shown in Figure 4). The Web AR group is also about watching videos and making choices, but the difference is that it simulates the Midjourney website interface with an additional AR button. After clicking the button, a virtual pet store scene will appear, and 12 candidate posters will be projected in real time onto this preset 3D store scene (Figure 5).

The experiment was conducted entirely online, so respondents could complete the study using any computer with an Internet connection, which can facilitate the data collection process. Following the completion of the task, respondents completed an online survey (using a 5-point Likert scale) about their experiences.

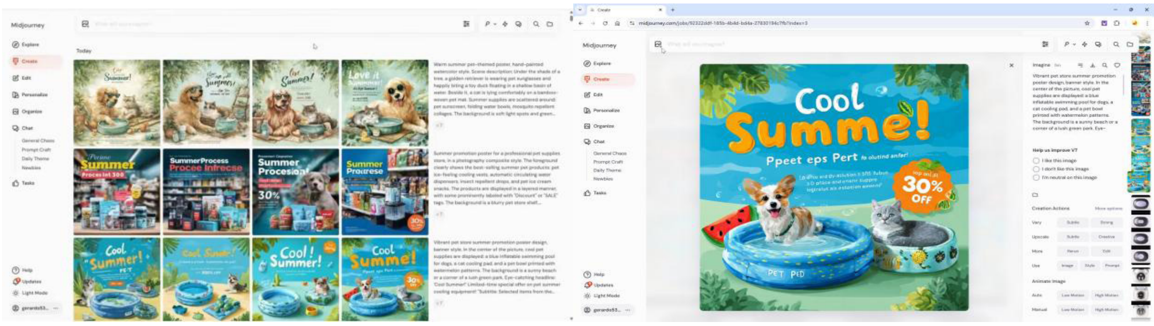

Figure 4. Screenshot of the control group video

Figure 5. Screenshot of the Web AR group video

4.4 Measurement Validation

In order to ensure the effectiveness of structural model test, this study conducted a systematic analysis of questionnaire data.

Since all constructs were collected through the same self-report questionnaire scale, there was a potential risk of common method bias (CMB). Therefore, Harman's One-Factor Test was used for analysis. The results showed that the initial factor explained 35.346% of the variance, which was below the required threshold of 40% [62]. Every construct demonstrated high independence. Then, the reliability was evaluated. As shown in Table 3, the Cronbach's α values for every construct is all above 0.7, indicating that the scale demonstrated good reliability.

A CB approach to confirmatory factor analysis (CFA) was used to assess the model and the multiitem scales. Table 4 summarizes the results of the model fitting indicators: χ^2/df=2.358, which is less than 5; TLI=0.933 and CFI=0.940, both exceeding 0.9, meeting the acceptable standard; RMSEA=0.067 and SRMR=0.048, both below 0.08 and within the ideal range. All fitting indicators comply with the evaluation criteria. Convergent validity was assessed for the similarity in results when different measurement methods are used to test the same characteristic, by constructing composite reliability (CR) and average variance extraction (AVE). The standard reference value of CR is usually greater than 0.7, and AVE is greater than 0.5 [63]. As evident from Table 5, this criteria is satisfied. In the discriminant validity test (Table 6), the AVE square root of all latent variables is larger than its correlation coefficient with other variables (PU 0.811, PI 0.859, DF 0.822, US 0.806), proving that each construct has good theoretical discrimination [17].

In conclusion, the indicators of the measurement model are good, which lays a solid foundation for the subsequent path analysis.

Table 3. Reliability test

Construct	Item	Cronbach's α
Perceived Interactivity	7	0.951
Perceived Usability	8	0.938
Decision Fatigue	8	0.943
User Satisfaction	3	0.847

Table 4. Model fit indices of the measurement model

Fit index	$\chi 2/df$	TLI	CFI	RMSEA	SRMR
Value	2.358	0.933	0.940	0.067	0.048
Recommended threshold	<5	>0.9	>0.9	<0.08	<0.08
Interpretation	fit	fit	fit	fit	fit

Table 5. Convergent validity of reflective constructs

Construct	Item	β	b	Se	C.R.	P	CR	AVE
Perceived Usability	PU1	0.786	1				0.939	0.658
	PU2	0.834	1.101	0.067	16.377	***		
	PU3	0.843	1.092	0.066	16.632	***		
	PU4	0.853	1.102	0.065	16.883	***		
	PU5	0.813	1.049	0.066	15.853	***		
	PU6	0.806	1.028	0.066	15.678	***		
	PU7	0.696	0.88	0.068	13.025	***		
	PU8	0.845	1.155	0.069	16.686	***		
Decision Fatigue	DF1	0.918	1				0.943	0.675
	DF2	0.767	0.685	0.038	17.97	***		
	DF3	0.842	0.821	0.038	21.781	***		
	DF4	0.861	0.853	0.037	22.944	***		
	DF5	0.807	0.751	0.038	19.835	***		
	DF6	0.865	0.795	0.034	23.175	***		
	DF7	0.735	0.553	0.033	16.641	***		
	DF8	0.763	0.702	0.04	17.765	***		
Perceived Interactivity	PI1	0.873	1				0.952	0.738
	PI2	0.904	1.06	0.046	23.056	***		
	PI3	0.836	0.86	0.044	19.703	***		
	PI4	0.883	1.006	0.046	21.936	***		
	PI5	0.852	0.895	0.044	20.417	***		
	PI6	0.841	0.834	0.042	19.885	***		
	PI7	0.82	0.959	0.051	18.983	***		
User Satisfaction	US1	0.801	1				0.847	0.649
	US2	0.827	0.956	0.067	14.177	***		
	US3	0.789	0.888	0.065	13.728	***		

***, $P < 0.001$

Table 6. Discriminant validity of reflective constructs

	US	PU	PI	DF
US	**0.806**			
PU	0.455	**0.811**		
PI	0.249	0.185	**0.859**	
DF	-0.416	-0.423	-0.176	**0.822**

5 Results

5.1 Descriptive Statistics

Table 7 presents the descriptive statistics and Pearson correlation analysis results for each construct. The mean values ranged from 2.976 to 3.560, with standard deviations between 0.861 and 1.193, indicating moderate overall levels. A positive correlation is indicated by a significant the Pearson correlation coefficient(r) greater than 0.1, while a negative correlation is demonstrated by an r-value below 0.1. Therefore, there are strong structural links between the constructs in this study, which support the theoretical hypotheses of subsequent structural equation modeling.

Table 7. Descriptive statistics

	Web AR	Perceived Interactivity	Perceived Usability	Decision Fatigue	User Satisfaction
Web AR	1				
Perceived Interactivity	.168**	1			
Perceived Usability	.285**	.171**	1		
Decision Fatigue	-.350**	-.172**	-.402**	1	
User Satisfaction	.353**	.226**	.398**	-.362**	1
M	0.460	3.029	3.259	3.560	2.976
SD	0.499	0.861	0.914	1.054	1.193

**, $P < 0.01$

5.2 Covariance-Based Structural Equation Modeling

A covariance-based structural equation modeling (SEM) approach was adopted in data analysis, as it is suitable for theory verification oriented research, which possess many advantages over traditional methods [63]. The fitting degree of the model meets the expected standard (Table 8).

This study adopted SPSS®AMOS26.0 software for SEM path analysis to derive SEM path coefficients and Critical Ratio (C.R.). Path coefficients reflect the relationships of effect between constructs, while C.R. serves as a criterion for determining regression coefficient significance. Generally, C.R.≥1.96 indicates statistically significant differences at the 0.05 level.

The results of the CB analysis of the research model shown in Figure 3, are presented in Figure 6. Web AR intervention showed significant positive effects on both Perceived Usability (PU) and Perceived Interactivity (PI), with H2a and H3a being validated. Additionally, it exhibited a significant negative impact on decision fatigue. H4a was established. Further, PU significantly negatively affected Decision Fatigue (DF), and H2b was verified. However, the effect of PI was insignificant, and H3b was not established. In the User Satisfaction (US) pathway, Web AR, PU, and PI all demonstrated significant positive impacts, supporting H1, H2c, and H3c. Conversely, DF exhibited a significant negative effect, validating H4b (Table 9).

Table 8. Model fitting results

Fit index	$\chi2$/df	TLI	CFI	RMSEA	SRMR
Value	2.315	0.931	0.938	0.066	0.059
Recommended threshold	<5	>0.9	>0.9	<0.08	<0.08
Interpretation	fit	fit	fit	fit	fit

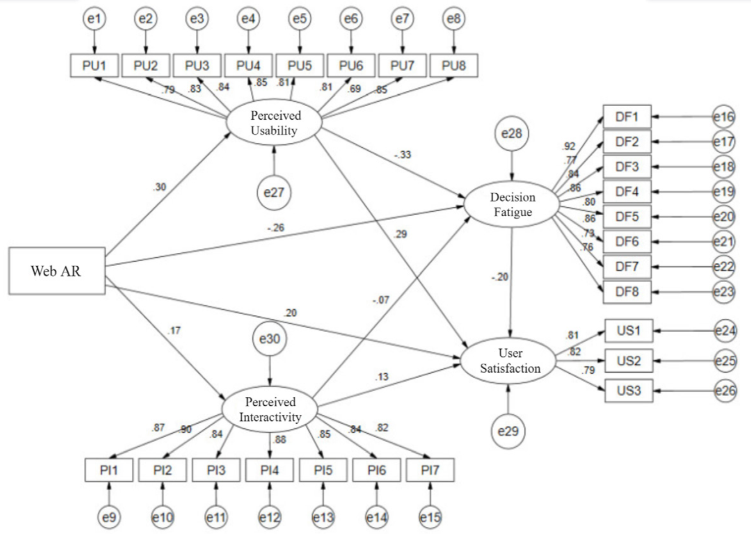

Figure 6. Results of SEM diagram (n =307)

Table 9. Path coefficient

Regression path			β	b	S.E.	C.R.	P
Perceived Usability	←	Web AR	0.298	0.503	0.098	5.153	***
Perceived Interactivity	←	Web AR	0.168	0.299	0.103	2.892	0.004
Decision Fatigue	←	Web AR	-0.257	-0.683	0.147	-4.650	***
Decision Fatigue	←	Perceived Usability	-0.334	-0.526	0.092	-5.731	***
Decision Fatigue	←	Perceived Interactivity	-0.074	-0.11	0.08	-1.374	0.169
User Satisfaction	←	Web AR	0.203	0.472	0.139	3.390	***
User Satisfaction	←	Decision Fatigue	-0.197	-0.173	0.057	-3.053	0.002
User Satisfaction	←	Perceived Usability	0.289	0.398	0.089	4.467	***
User Satisfaction	←	PI	0.132	0.172	0.074	2.343	0.019

β: Standardized path coefficient; b: Unstandardized path coefficient, ***, $P < 0.001$

5.3 Mediation Test

In order to explore how the intervention of Web AR affects User Satisfaction through the mediation path, this study further tested the mediating effect in the SEM by using the Bootstrapping method. If the indirect effect of Bias-Corrected 95% CI does not include zero (0), it can be considered that the mediating path is established and significantly affects the dependent variable.

Table 10 shows that all the paths of Web AR indirectly affecting US through PU are significant. H2 was supported. Additionally, the path "Web AR→ PI → Decision fatigue → User Satisfaction" was insignificant (β = .006 ; p >.05). H3 was not established. Overall, the total indirect effect of Web AR intervention accounted for 47.09%, and the direct effect accounted for 52.81%. Based on the analysis of comprehensive path and mediation test, most of the research hypotheses were widely supported. The Web AR environment integration mechanism can not only directly enhance satisfaction, but also has indirect influence through mediating variables such as the growth of perceived usability and the decrease of decision fatigue. Among these, perceived usability plays a particularly prominent role in reducing cognitive load and improving satisfaction.

In contrast, Perceived Interactivity has a positive effect on satisfaction, but is less effective in alleviating decision fatigue. It may be due to the cost of the additional operation and the load of task switching caused by frequent interaction [64]. Especially on the AIGC platform, interactive behaviors tend to focus on multiple rounds of parameter adjustment and image comparison. If the feedback is delayed or the interface is complex, it may increase the decision load.

6 Conclusion, Limitations and Future Work

In contrast to previous studies that have primarily focused on AI generation performance and content quality, this research emphasizes the decision-making and evaluation processes in the post-generation stage. With the ongoing development of Internet technology from Web 1.0 to Web 4.0, WebAR, as an important medium for human-machine connection, has shown high flexibility and broad applicability. Based on open protocols, WebAR enables real-time interaction and visual overlays through an environment integration mechanism, without the need for additional applications and hardware equipment. In the creative context of AIGC platforms, it can provide users with instant and contextual decision support to alleviate cognitive load and improve satisfaction.

Table 10. Mediation test

Mediation path	Indirect effect (β)	SE	Bias-corrected 95%CI			Proportion
			Lower	Upper	*p*	
Web AR→ Perceived Usability → User Satisfaction	0.201	0.063	0.098	0.349	0.000	22.48%
Web AR→ Perceived Interactivity → User Satisfaction	0.051	0.031	0.007	0.136	0.018	5.70%
Web AR→Decision Fatigue → User Satisfaction	0.118	0.053	0.027	0.236	0.010	13.20%
Web AR→ Perceived Usability → Decision Fatigue → User Satisfaction	0.046	0.021	0.013	0.097	0.007	5.15%
Web AR→ Perceived Interactivity → Decision Fatigue → User Satisfaction	0.006	0.005	0.000	0.025	0.071	0.67%
Total Indirect Effect	0.421	0.083	0.274	0.604	0.000	47.09%
Direct Effect	0.472	0.145	0.198	0.773	0.001	52.81%
Total Effect	0.894	0.144	0.616	1.180	0.000	

The findings support that Web AR can assist creators on AIGC platforms intuitively evaluate generated results in real-world contexts, and making creative decisions, especially, particularly through its perceived usability. However, the indirect effect of perceived interactivity on decision fatigue was not significant, likely due to cognitive load from frequent interactions that diminished its positive impact. This study also has several limitations. First, the participant sample is composed of students, so future research should involve a broader range of creative user groups. Second, the experiment uses simulated interface instead of real system. Thus, a high-fidelity prototype will be built to incorporate task complexity and other contextual variables, improving the external validity.

In general, WebAR offers a novel cognitive support mechanism for enhancing user experience on AIGC platforms and is expected to establish a user-centered, human-machine-environment integrated creative ecosystem. This advancement facilitates the broader application of generative AI in education, design, and other fields.

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