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Research on Cultural IP Digital Design Generation and User Acceptance Based on CNN and AIGC

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Abstract: This study aims to investigate the impact of digital design generation for cultural IPs based on Convolutional Neural Networks (CNN) and AI-generated content (AIGC) on user acceptance, whilst analyzing the moderating role of design management capabilities within this process. Dunhuang patterns were selected as cultural IP material, with design proposals generated through CNN feature extraction combined with the Stable Diffusion model. Hypothesis testing employed Structural Equation Modelling (SEM). Findings indicate that design management capabilities play a pivotal integrative role in the process of enabling cultural IP design generation through CNN and AIGC technologies. Establishing a human-machine co-creation design management pathway-guided by strategic positioning, underpinned by resource integration, and safeguarded by innovation management-constitutes the core approach to achieving the unification of technological and cultural value.

Keywords: CNN; AIGC; cultural IP; design management; user acceptance

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1. Introduction

The rapid advancement of artificial intelligence (AI) is profoundly reshaping every facet of economic, social and cultural life, with particularly marked effects within the cultural sphere [1]. As the nation increasingly prioritises the high-quality development of cultural industries, the creative transformation and innovative development of cultural intellectual property (IP) - a vital vehicle for national values - has become a central imperative of our era. Traditional cultural IP, through digital means, has been imbued with dynamic, interactive, and immersive vitality. In recent years, AI technologies, exemplified by deep learning, have catalysed a wave of AI-generated content (AIGC), presenting revolutionary challenges to cultural IP design [2]. Concurrently, computer vision (CV) technologies, particularly convolutional neural networks (CNNs), demonstrate formidable potential in the automatic recognition, feature extraction, and classification of cultural elements, providing a robust technical foundation for the digital analysis of cultural IP.

However, the inherent sophistication of these technologies does not automatically translate into commercial or cultural success. Against the backdrop of widespread application of CNN and AIGC technologies in cultural IP digital design, a crucial yet under-explored question remains: what is the ultimate 'user acceptance' of these AI-generated design solutions? Existing research predominantly focuses on technological innovation or commercial monetisation, with insufficient exploration of the 'disconnect' between technology and humanities, or between machine creation and user sentiment [3]. Classic theories such as the Technology Acceptance Model (TAM) provide explanatory frameworks for understanding user adoption of new technologies. However, when applied to the specific domain of cultural products, these models may require expanded variable dimensions. Therefore, systematically investigating the mechanisms influencing user acceptance of digital design generated for cultural IP using CNN and AIGC, and identifying key drivers, constitutes the core problem this study urgently addresses.

More crucially, at the organisational level, how should enterprises or design agencies manage this innovation process to maximise technological benefits while controlling associated risks? Merely possessing advanced technological tools is insufficient to guarantee success. Effectively integrating these technologies into design workflows to produce high-quality solutions meeting both market and cultural standards tests an organisation's 'Design Management Capability' [4]. Design management is regarded as a dynamic capability, concerning an organisation's capacity to integrate internal and external resources, perceive market shifts, and reconfigure design strategies to navigate uncertain environments [5]. An organisation possessing robust design management capability demonstrates keener insight into user needs, more effectively guides AI tools towards creative outputs, and conducts culturally nuanced and market-forward screening, optimisation, and interpretation of generated results. Consequently, design management capability is no longer treated as a passive background variable in this study but rather as a core active factor potentially exerting a crucial 'moderating effect'. It may amplify or attenuate the strength of the association between technology and user acceptance. Based on the foregoing analysis, this study aims to investigate the mechanisms through which CNN- and AIGC-based digital design generation for cultural IP influences user acceptance, while dissecting the moderating role of design management capabilities within this process. This endeavour seeks to provide theoretical insights for the deep integration of technology, culture, and commerce.

2. Literature Review

2.1. Definition of Core Concepts

2.1.1. CNN and AIGC-Driven Paradigms for Cultural IP Design Generation

The technological core of this research lies in the integrated application of convolutional neural networks (CNNs) and artificially generated content (AIGC). As a deep learning model specialized in processing grid-structured data, CNNs form an efficient 'feature extraction and pattern recognition engine' through the stacking of their convolutional and pooling layers. In the digitalization of cultural IP, CNNs undertake the deep analysis of visual elements, stylistic patterns, and compositional structures within cultural resources, providing a high-quality, structured data foundation for subsequent creative generation [6].

AIGC, meanwhile, represents an entirely new paradigm for creative production. Leveraging advanced technologies such as generative adversarial networks, diffusion models, and large language models, it learns the intrinsic logic within vast datasets to automatically generate novel multimodal content including text and images. Within cultural IP design, AIGC processes features extracted by CNN as input. Leveraging its capacity for infinite combinations, it generates vast design proposals within minimal timeframes. This fundamentally disrupts traditional, inspiration-dependent workflows, significantly expanding the boundaries of creative exploration.

Thus, the integration of CNN and AIGC forms a closed-loop system spanning 'understanding' to "creation": CNN handles precise 'cultural decoding', furnishing AIGC with richly meaningful 'creative raw materials'; AIGC then performs efficient 'intelligent encoding', transforming cultural elements into novel visual expressions. Together, they constitute the foundational technological capability driving the digital design and generation of cultural IP.

2.1.2. User Acceptance: The Ultimate Test of Technological Value Realization

Regardless of technological sophistication, the ultimate realization of commercial and cultural value remains highly contingent upon user adoption. User Acceptance-defined as the degree to which target users are willing to adopt new products, technologies, or services-serves as the pivotal benchmark for assessing the success or failure of digital cultural IP. Within this study, the concept carries dual connotations: it encompasses both end consumers' acceptance of the final digital cultural IP product and creators' adoption of next-generation design tools and workflows integrating CNN and AIGC technologies. Consequently, understanding and enhancing user acceptance constitutes the core challenge in ensuring the successful implementation of technology-enabled solutions [7].

2.1.3. Design Management Capability: The Dynamic Capacity to Harness Technological Integration

In the face of disruptive technologies such as CNN and AIGC, mere technological adoption falls far short of guaranteeing success. Organizational levels must possess an integrating force to harness the synergy between technology and creativity - namely, design management capability. This capability encompasses multiple dimensions including strategic planning, resource coordination, quality assurance, and innovation guidance. Its core lies in the dual practice of 'managing design' and 'managing through design'.

Within the specific context of this study, design management capability plays a pivotal 'steering' role. It ensures alignment between technological application and the core value of intellectual property, optimizes the allocation of data, talent, and algorithmic resources, controls the pace of innovation to mitigate cultural misinterpretation and copyright risks, and fosters cross-disciplinary collaboration. This study posits that design management capability is not merely a functional competency but a dynamic capacity. It serves as a pivotal variable for organizations to maintain competitive advantage amid technological transformation, translating technological potential into market value. Furthermore, it may play a significant moderating role in the process of converting technological capability into user acceptance.

2.2. Construction of an Integrated Research Framework

The Technology Acceptance Model (TAM) provides a classic theoretical lens for understanding individual users' adoption behavior [8]. TAM posits that users' willingness to adopt is primarily determined by two core psychological variables: perceived usefulness (PU) and perceived ease of use (PEOU). A system perceived as both 'useful' and 'easy to use' is more likely to be accepted. TAM provides foundational analytical tools at the micro-level for this study, enabling the measurement and prediction of users' willingness to adopt design tools or products integrating CNN and AIGC technologies (as shown in **错误!未找到引用源。**).

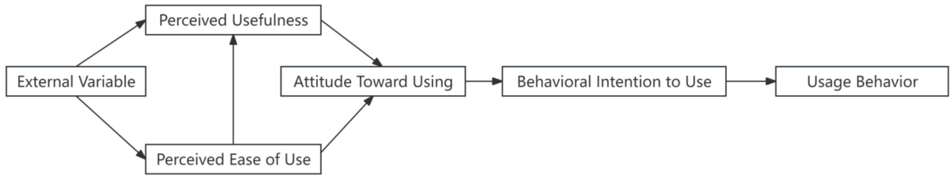

Figure 1. Model of technology acceptance.

However, user acceptance constitutes only part of a technology's diffusion process within social systems. Innovation Diffusion Theory (IDT) offers a broader perspective, revealing key factors influencing the speed and scope of a new technology's diffusion within specific communities [9]. These factors include the innovation's relative advantage, compatibility, complexity, trial ability, and observability. IDT complements the limitations of TAM by broadening the research scope from individual psychology to organizational diffusion dynamics. It suggests that even if individual users perceive a technology as useful and easy to use, widespread adoption remains challenging if it lacks compatibility within teams or if demonstrating its outcomes proves difficult. The intervention of design management capabilities-such as establishing pilot projects, providing training, and optimizing workflow integration-systematically addresses these diffusion challenges identified by IDT.

Finally, at the highest level of organizational strategy, Dynamic Capabilities Theory (DCT) explains why enterprises sustain competitive advantage in rapidly changing environments [10]. DCT posits that competitive advantage stems from an organization's capacity to integrate, construct, and reconfigure internal and external resources to adapt to environmental shifts. The 'design management capability' examined in this study aligns precisely with DCT's essence. Confronted by the technological wave of CNN and AIGC, enterprises possessing robust design management capabilities can more effectively 'perceive' technological opportunities, "seize" and integrate these technologies, and ultimately 'reconfigure' their design processes and business models through organizational transformation. Consequently, DCT elevates design management capability from a managerial function to the strategic level of an organizational dynamic capability, providing the most fundamental theoretical underpinning for this study's core hypothesis: that design management capability serves as the pivotal link connecting technology and users, and mediating their relationship.

3. Research Model and Hypothesis

3.1. Theoretical Model Construction

This study's theoretical model integrates core concepts from the Technology Acceptance Model (TAM), Dynamic Capability Theory (DCT), and Innovation Diffusion Theory (IDT). The model uses user acceptance as the dependent variable, with the innovativeness, cultural fit, and aesthetic quality of AIGC -generated content serving as key independent variables. Design management capability is introduced as a core moderating variable to explore its influence on the relationship between **错误!未找到引用源。**independent and dependent variables. Additionally, the model employs perceived usefulness and perceived ease of use from the TAM as mediating variables to reveal the underlying psychological pathways through which AIGC content characteristics affect user acceptance. The primary measurement indicators are detailed in the following table (as shown in Table 1).

Table 1. Operational definitions and measurement indicators of main variables.

variable classes	Variable name	definition	Measurement dimensions/indicators (reference source)
argument	AIGC - generated content features	Users' objective perception of the design scheme generated by AIGC.	1. Innovation: The degree of uniqueness and novelty in form, concept, or interaction compared to traditional designs. 2. Cultural Congruence: The design demonstrates alignment with the original Dunhuang culture in both visual symbols and spiritual essence. 3. Aesthetic Quality: The design demonstrates professional excellence in

			visual composition, color application, and aesthetic form.
dependent variable	User Acceptance	Users' willingness and attitude towards adopting and using AIGC to generate cultural products.	1. Perceived Usefulness: The extent to which using this product enhances cultural experience, learning efficiency, or aesthetic satisfaction. 2. Perceived Ease of Use (PEU): The perceived effort required to learn and operate the product. 3. Attitude & Intention: This refers to users' positive or negative perceptions of the product, along with their future usage intentions.
regulated variable	Design Management Capability	The dynamic capability of organizations to harness AI technology and integrate resources to realize the value of cultural IP.	This variable will be measured as individual-level ability perception, i.e., the strength of the participant's design management ability in the organization. Based on dynamic competence theory and design management literature, a three-dimensional scale is constructed: 1. Strategic positioning capability: The ability to integrate design into corporate strategy and define IP market objectives. 2. Resource integration capability: The ability to coordinate resources such as technology, talent, and data to support AI design processes. 3. Innovative management skills: The ability to manage creative exploration, risk assessment, and iterative optimization in AI-assisted design processes.
metavariable	Core Perceptual Variables	The core psychological variables based on TAM theory.	1. Perceived usefulness (PU) 2. Perceived Ease of Use (PEOU) These measurement indicators are identical to those of PU and PEOU in the dependent variable, but are tested as mediating pathways in the model.

3.2. Research Hypotheses

According to the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use are key determinants of user acceptance. The innovation, cultural relevance, and aesthetic quality of AIGC-generated content directly shape users' initial perceptions and subsequently influence acceptance. Innovation refers to AIGC technology creating designs that transcend traditional formats, capturing user attention and enhancing perceived product usefulness, thereby positively impacting acceptance (H1a). For cultural IP products, acceptance depends not only on novelty but more importantly on cultural roots. Cultural relevance means design solutions that capture the essence of the IP, evoke emotional resonance, and improve perceived usefulness, thus boosting acceptance (H1b). High-quality aesthetic design provides sensory enjoyment, reduces cognitive load, and subconsciously enhances perceived ease of use. Aesthetic quality directly shapes first impressions, elevates perceived usability, and consequently strengthens acceptance (H1c).

Dynamic Capability Theory (DCT) states that organizational capability is the key factor determining whether an enterprise can transform new technologies into competitive advantages. Design management capability actively guides, screens, and optimizes technological outcomes, thereby influencing the value perception of end-users.

Strong strategic positioning capability enables organizations to clearly define the objectives and target markets for cultural IP digital transformation. When design management capabilities are robust, the innovativeness of AIGC content becomes more closely aligned with market demands, making it more clearly perceived as "useful" by users. Therefore, the strategic positioning capability within design management positively moderates the relationship between AIGC content innovativeness and user acceptance (H2a). On this basis, the digital transformation of cultural IP, particularly when involving high-fidelity AIGC content generation, requires substantial investments in high-quality data, computing resources, and professional talent. When resource integration capabilities are strong, organizations can provide more precise cultural feature data (literature) for AIGC models. This leads to the conclusion that resource integration capability within design management positively moderates the relationship between AIGC content cultural fit and user acceptance (H2b).

The AIGC generation process involves extensive exploratory outcomes. Organizations with strong innovation management capabilities can establish effective evaluation and screening mechanisms to identify the most aesthetically superior design solutions within the realm of 'infinite possibilities,' while effectively managing potential cultural misinterpretations or copyright risks. Thus, innovation management capability within design management positively moderates the relationship between the aesthetic quality of AIGC content and user acceptance (H2c).

The perceived usefulness and perceived ease of use are the mediating variables to explain the influence of the independent variables on the user acceptance. The perceived usefulness mediates the relationship between the innovation, cultural fit and user acceptance (H3a, H3b), and the perceived ease of use mediates the relationship between the aesthetic quality and user acceptance (H3c) (as shown in **错误!未找到引用源。**).

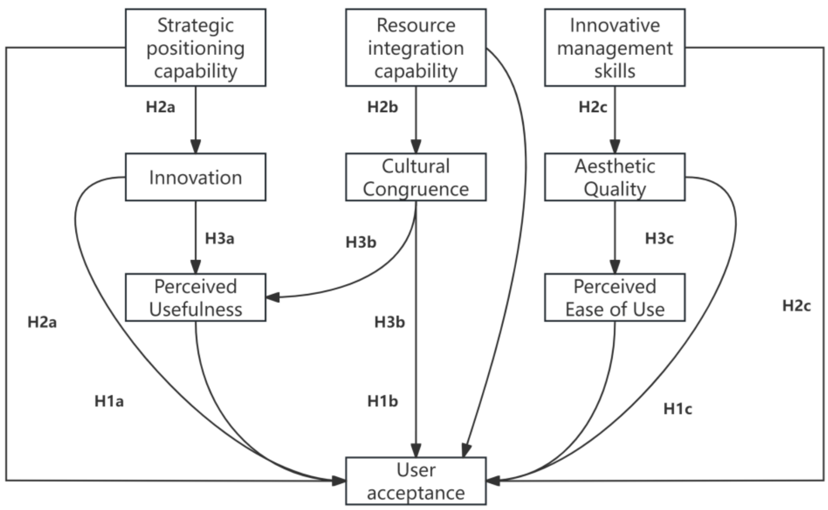

Figure 2. Overall theoretical model.

4. Research Process

4.1. Research Design

The study will utilize the highly representative cultural IP "Dunhuang patterns" as the design material repository. In the initial phase, a pre-trained deep convolutional neural network (CNN) model extracts features from the Dunhuang pattern image dataset. The resulting cultural feature vector is then fed into the advanced Stable Diffusion XL (SD) model. Through prompt engineering, the model generates multiple design proposals. These are subsequently screened by professional reviewers based on creativity, cultural relevance, and aesthetic quality to produce the final experimental materials [11].

The study will recruit two groups of participants: end consumers and cultural product professionals. Using an online questionnaire platform, participants will view digital design proposals generated through the aforementioned technical approach. A validated scale will be employed to measure user acceptance and related perceived variables. The questionnaire data will be used for hypothesis testing in structural equation modeling (SEM) [12]. Additionally, to explore the complex motivations underlying user psychology, the study will conduct semi-structured in-depth interviews with selected participants and cultural IP experts to gather qualitative insights, thereby enriching the research findings (as shown in 错误!未找到引用源。).

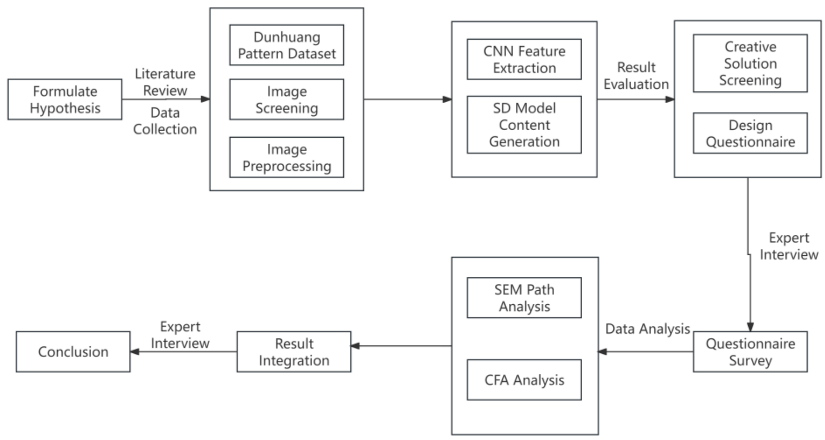

Figure 3. Research Logic Road map.

4.2. Experimental Process

This study utilized Dunhuang mural imagery as its source material to construct a dataset comprising 20 high-resolution images. A pre-trained Convolutional Neural Network (CNN) model (VGG-19) was employed to extract depth feature vectors from the images, which were then fed into the Stable Diffusion model as conditional inputs to steer the generation process through prompt words. The model produced 50 images in total, from which the research team selected 6-8 distinct design proposals as experimental stimuli based on three criteria: originality, cultural relevance, and aesthetic quality [13].

All scales were adapted from established literature while being tailored to the study's context, with reliability and validity validated through pilot testing. The questionnaire was distributed via platforms like Wenjuanxing, with participants being fully informed of the study's purpose and data usage to ensure informed consent. Before administering the questionnaire or conducting interviews, participants received detailed explanations of the research objectives, procedures, potential risks and benefits, and were clearly informed of their right to withdraw at any time. All data was anonymized. The questionnaire began with basic participant information, followed by the random presentation of a stimulus, after which participants completed the scale based on their perceived design.

The study collected data through the Wenjuanxing platform, with 392 valid questionnaires recovered. Among the respondents, 240 were cultural product consumers (61.2%) and 152 were professionals in the field (38.8%), with an age distribution of 18-45 years. All scales underwent reliability and validity testing, yielding Cronbach's α coefficients ranging from 0.73 to 0.81, composite reliability between 0.73 and 0.81, and average variance extraction values of 0.50-0.63, indicating strong reliability and convergent validity of the measurement tools. The Harman single-factor analysis revealed that the first factor accounted for 31.7% of the variance, with no significant common method bias.

The correlation analysis showed that the independent variable and dependent variable were significantly positive correlated ($p < 0.01$), which was consistent with the hypothesis H1a, H1b and H1c.

This study employed structural equation modeling (SEM) to holistically validate the theoretical framework and research hypotheses [14]. Smart PLS was selected as the analytical tool due to its robust performance with small samples and non-normal data, and its suitability for exploratory theoretical model testing (as shown in Table 2).

Table 2. Structural Equation Model Fit Index.

fitting index	fitted value	judge
χ^2/df	4.14	qualified
RMSEA	0.094	qualified
CFI	0.918	good
TLI (NNFI)	0.905	good
SRMR	0.078	good

This study employed structural equation modeling to test theoretical hypotheses. The results demonstrated that the innovativeness of AIGC -generated content and cultural fit significantly enhanced perceived usefulness, confirming Hypotheses H1a and H1b. Aesthetic quality also positively influenced perceived ease of use, validating Hypothesis H1c. Both perceived usefulness and perceived ease of use significantly affected user acceptance, with perceived usefulness demonstrating stronger explanatory power. This indicates that users prioritize the product's ability to deliver tangible value.

Bootstrap mediation analysis reveals that innovation and cultural fit exert significant indirect effects on user acceptance through perceived usefulness, while aesthetic quality exerts a significant indirect effect through perceived ease of use. The total effect analysis indicates that innovation and cultural fit simultaneously demonstrate both direct and indirect effects, whereas the direct effect of aesthetic quality is not statistically significant, suggesting its primary mechanism involves enhancing perceived ease of use (as shown in Table 3).

Table 3. Results of Main Effect and Mediation Effect Tests.

hypothesis	way	Standardized path coefficient (β)	p price	effect type	gross effect	direct effect	indigo effect
H1a	Innovation → User Acceptance	0.35	<0.001	intermediary	0.35	0.35	-
H1b	Cultural fit → user acceptance	0.38	<0.001	intermediary	0.38	0.38	-
H1c	Aesthetic Quality → User Acceptance	0.30	<0.001	intermediary	0.30	0.30	-

H3a	Innovation → Perceived usefulness	0.18	0.023	intermediary	0.22	0.18	0.04***
H3b	Cultural Fit → Perceived Usefulness	0.20	0.015	intermediary	0.25	0.20	0.05***
H3c	Aesthetic Quality → Perceived Usability	0.13	0.081	n.s.	0.17	0.13	0.04***
H4	Perceived usefulness → user acceptance	0.52	<0.001	intermediary	0.52	0.52	-
H5	Perceived ease of use → User acceptance	0.21	0.005	intermediary	0.21	0.21	-

Note: n.s. indicates not significant (p> 0.05). *** indicates p <0.001 (Bootstrap 95% CI).

The moderation analysis further reveals that the three dimensions of design management capability significantly moderate the relationship between technical features and user acceptance. Strategic positioning capability enhances the impact of innovation on user acceptance, demonstrating that organizations can more effectively translate innovation value through clear market objectives. Resource integration capability strengthens the correlation between cultural fit and user acceptance, as evidenced by the efficient coordination of cultural data and expert resources, which improves content accuracy. Innovation management capability optimizes the effect of aesthetic quality on user acceptance, indicating that establishing evaluation and screening mechanisms can enhance the artistic quality of generated content (as shown in Table 4).

Table 4. Results of the Moderating Effect Test for Design Management Capability.

hypothesis	adjustment path	Standardized path coefficient (β)	p price
H2a	Innovation × Strategic Positioning Ability → User Acceptance	0.09	0.047
H2b	Cultural Fit × Resource Integration Ability → User Acceptance	0.13	0.032
H2c	Aesthetic Quality × Innovative Management Ability → User Acceptance	0.08	0.041

4.3. Result Analysis

Based on the above analysis, this study posits that the key to successfully harnessing CNN and AIGC technologies for the creative transformation and innovative development of cultural IPs lies not in the technologies themselves, but in establishing a systematic and efficient human-machine co-creation design management framework. This framework positions design management capabilities as the core integrative force, spanning the entire life cycle management from strategy and resources to processes. Its objective is to maximize technological potential while controlling risks, ultimately achieving the unification of technological, cultural, and commercial values.

Phase One: Strategic Positioning Capability. A robust strategic positioning capability serves as the "ballast" ensuring human-machine collaboration stays on course. At this stage, design managers must act as "pilots," with their core mission being to translate the long-term value of cultural IP and brand vision into clear constraints and guidance for AI-generated design activities. This requires organizations to address fundamental questions: What new zeitgeist do we aim to infuse into this cultural IP through AI technology? Which target user groups do we hope to reach and serve? How do we strike a balance between preserving traditional essence and embracing modern aesthetics? For instance, in this study, strategic positioning determined whether the generated content would prioritize academic rigor or mass-market entertainment and interactivity. A management team with strong strategic positioning capabilities will guide AIGC to produce solutions highly aligned with organizational strategic goals within the vast creative space by creating detailed design briefs, establishing multi-dimensional evaluation matrices, and integrating brand core values into AI prompt engineering. This top-down value alignment effectively prevents risks of technical abuse or content misalignment with brand tone, ensuring every human-machine interaction advances toward predefined value objectives. As revealed by Hypothesis H2a in this study, the stronger the strategic positioning capability, the more effectively AIGC content innovation can be transformed into user-perceived value, thereby enhancing acceptance.

Phase Two: Resource Integration Capability. A clear strategic positioning must be built upon a solid resource foundation, and resource integration capability serves as the crucial bridge to transform strategic blueprints into reality. In the context of human-machine co-creation, the concept of resource integration extends far beyond traditional human, financial, and material dimensions, emphasizing the integration of high-quality, multimodal cultural data. The training effectiveness of CNN models and the cultural depth of AIGC -generated content directly depend on the quantity and quality of input data. Therefore, one of the core tasks for design managers is to establish and maintain a high-quality digital repository of cultural IP assets. This requires a collaborative "cultural gene decoding" process involving cultural scholars, historians, digital technology experts, and designers. Our research reveals that resource integration capability positively moderates the relationship between cultural fit and user acceptance (H2b). This precisely demonstrates that only when organizations possess strong resource integration capabilities-providing rich, precise cultural feature data for AI models-can AIGC generate designs that truly "understand" culture and align with the core spirit of original IPs, rather than remaining at the level of superficial style imitation. Additionally, resource integration includes the integration of professional talent, i.e., forming interdisciplinary teams with both technical expertise and humanistic literacy who can understand cultural needs and translate them into tasks executable by AI.

Phase Three: Innovation Management Capability. The transition from AIGC' s "unlimited generation" to producing "finite yet high-quality" final solutions requires an efficient and agile innovation management process. This constitutes the core domain where innovation management capability plays its pivotal role, serving as the critical link that transforms human-machine co-creation from "possibility" to "reality." At this stage, design managers must establish a comprehensive dynamic cycle process. First, designers should be encouraged to boldly utilize AIGC for divergent exploration, generating massive design variations that break through conventional thinking patterns. Second, a multi-dimensional evaluation system should be established-not solely determined by designers, but integrating feedback from cultural experts, marketing personnel, and even target users. In this study, the impact of aesthetic quality on user acceptance highlights the importance of this phase. Robust innovation management capability can systematically evaluate and identify designs that combine aesthetic appeal, innovation, and cultural depth from vast proposals, advancing them to subsequent optimization rounds. This process forms a continuous feedback loop of iterative improvement, creating a spiraling upward progression.

Finally, innovative management capabilities are also demonstrated through risk control. This involves employing technical tools to detect potential cultural misinterpretations or copyright infringements in generated content, while establishing clear ethical guidelines to ensure digital products meet both aesthetic and legal requirements. The study confirms the positive mediating effect of innovative management capabilities on the relationship between aesthetic quality and user acceptance (H2c), demonstrating that a structured and efficient innovation management process is essential for amplifying the aesthetic value of AIGC and securing market recognition.

Phase IV: Value Co-creation. The dynamic and collaborative interaction between "human" and "machine" that permeates the three preceding phases must be emphasized.

It is crucial to clarify that AIGC is not intended to replace designers but rather to serve as a "super tool" that enhances their creativity. A core responsibility of design managers lies in establishing effective human-machine collaboration mechanisms and defining clear role divisions. AI's strength lies in processing massive information, exploring unconventional combinations, and tirelessly iterating; while human value resides in providing cultural insights, making value judgments, infusing designs with emotion and warmth, and conducting refined "secondary creation" based on AI-generated content. An excellent design management process should clearly define when and to what extent AI assistance is introduced. During the conceptualization phase, AI can act as an "inspiration generator"; in the design execution phase, it functions as an "efficient renderer"; while in the final review phase, humans remain the ultimate "value adjudicators." This human-machine collaboration model requires designers to continuously update their knowledge, transitioning from traditional "executors" to "guides." The goal of design management is to establish this new type of human-machine collaboration through process reengineering, tool training, and cultural cultivation, ultimately achieving value co-creation between human wisdom and machine intelligence to produce outstanding designs that combine technical depth with cultural warmth (as shown in 错误!未找到引用源。).

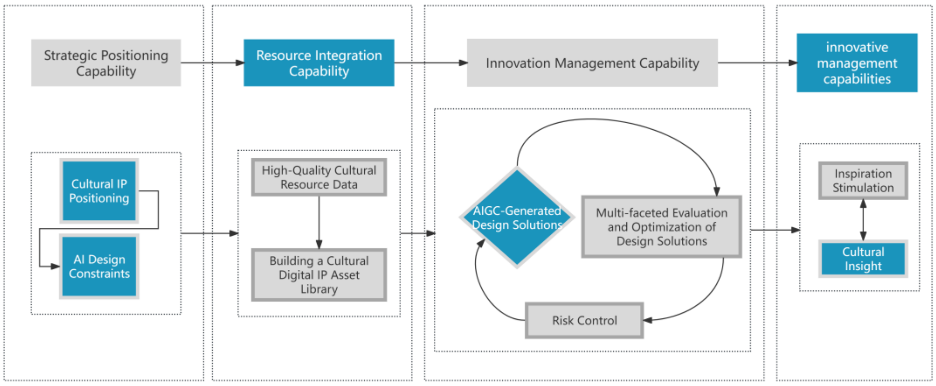

Figure 4. The Human-Machine Co-creation Design Management Path Generated by Cultural IP Digital Design.

5. Conclusion

This study systematically explores the impact mechanisms of cultural IP digital design generation based on CNN and AIGC on user acceptance. The research conclusions emphasize that the cultural fit, innovation, and aesthetic quality of AIGC content are core technical characteristics influencing user acceptance, while the ultimate realization of its value heavily depends on organizational design management capabilities. The human-machine co-creation design management path established in this study-guided by strategic positioning capabilities, grounded in resource integration capabilities, supported by innovation management capabilities as process safeguards, and consistently integrated with the value co-creation concept of human-machine collaboration-provides an operational theoretical framework and practical guide for how the cultural technology industry can effectively harness emerging technologies to achieve high-quality development of cultural IPs. Ultimately, whether the value of technology can be fully unleashed does not solely depend on its inherent qualities, but rather on whether we can build corresponding organizational wisdom and management capabilities. This is the core insight this study offers.

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