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Cultural cognition in artificial intelligence generated content adoption among visual designers

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ABSTRACT

Artificial intelligence generated content (AIGC) is transforming visual arts by automating image design, illustration, and interface composition. Extending beyond traditional technology acceptance models (TAM), this study integrates cultural memory (CM) theory to develop a four-layer pathway model comprising CM perception, cultural cognition evaluation (cultural preservation (CP) and cultural transformation (CT)), functional assessment, and behavioral intention. Using partial least squares structural equation modeling (PLS-SEM) in SmartPLS, data from 238 visual designers were analyzed. The results show that CM significantly influences CP (β=0.564, $p<0.001$) and CT (β=0.166, $p<0.01$). CP strongly predicts CT (β=0.768, $p<0.001$), which in turn significantly affects perceived usefulness (PU) (β=0.423, $p<0.001$). However, CT does not directly predict adoption intention (UI) (β=0.069, p=0.158), indicating full mediation through PU (indirect effect =0.359, $p<0.001$). The model explains 81.4% of the variance in UI. These findings demonstrate that AIGC adoption is grounded in a hierarchical cultural cognitive process, which must be translated into functional utility perceptions before it can shape behavioral intention.

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1. INTRODUCTION

Artificial intelligence generated content (AIGC) is reshaping artistic creation by automating image design, illustration, and interface composition, redefining originality, authorship, and creative practice [1], [2]. As it spreads through visual design, it creates tensions around creative authority and cultural belonging-seen as both a threat to authenticity and a tool for reinterpretation [3], [4]; yet most acceptance studies emphasize functional cognition and overlook cultural dimensions [1], [5]. Having shifted designers from creators to cultural mediators [6], [7], AIGC expands creative possibilities but can weaken traditional design's contextual depth and, through dataset dependence, introduce bias favoring dominant cultural patterns [8]–[11]; it thus acts as both cultural amplifier and homogenizer [12]–[14].

These dynamics can be understood through cultural memory (CM) theory, which views culture as continuously reconstructed rather than passively stored [15]. AIGC introduces algorithmic participation into symbol reconstruction, broadening participation while risking narrative dominance [10], [16]–[20]. Prior studies remain largely descriptive, underexplaining the cultural mechanisms of adoption [21]–[28], though acceptance in creative industries is tied to cultural identity and legitimacy [29]–[32]. This study therefore integrates CM theory with the technology acceptance model (TAM), proposing a culturally grounded pathway from CM through preservation, transformation, and perceived usefulness (PU) to adoption intention (UI) [33], [34]. Based on the theoretical foundations, eight hypotheses are proposed:

– CM positively influences cultural preservation (CP) (H1).
– CM positively influences cultural transformation (CT) (H2).
– CP positively influences CT (H3).
– CP positively influences PU (H4).
– CT positively influences PU (H5).
– CT positively influences UI (H6).
– Perceived ease of use (PEOU) positively influences PU (H7).
– PU positively influences UI (H8).

The proposed model inserts a pre-functional cultural cognition layer upstream of PU, identifying it as the gating mechanism-a falsifiable, culturally sensitive TAM refinement transferable to other heritage-rich AIGC contexts.

2. RESEARCH METHOD

2.1. Research design

This study used a quantitative cross-sectional survey design to examine factors influencing AIGC adoption among visual designers, grounded in CM theory and the TAM to explain how cultural cognition and functional perceptions shape behavioral intention [35]–[37]. The model was analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4.0, preferred over covariance-based SEM because the study is prediction-oriented and exploratory, extends TAM with cultural cognition constructs, is structurally complex (six constructs, eight paths, and multiple mediations), suits non-normal Likert data, and has a sample of 238 exceeding standard power requirements [35], [36]. The standard two-stage procedure was followed [35].

2.2. Participants

The target population was visual designers in Sichuan, China-professionals, freelancers, educators, and students-exposed to both design practice and AIGC, with the individual designer as the unit of analysis. Purposive sampling required at least one year of design experience or current enrolment, familiarity with Chinese traditional graphic design and AIGC, and working or studying in Sichuan, China; this non-probability design may bias toward AIGC-engaged designers, so findings are analytic and need probability-based testing. Data were collected via Wenjuan Xing (January-March 2025) through design communities, alumni networks, and WeChat and Weibo groups, with snowball referral; IP and device-fingerprint restrictions and three attention-check items ensured quality. Of 279 responses, 238 valid cases were retained (85.3%). Ethical clearance came from Universiti Teknologi MARA, with informed consent and anonymous storage.

2.3. Instruments

The structured questionnaire had two sections: demographics (age, gender, experience, education, specialization, and AIGC usage) and the six latent constructs, all rated on a 5-point Likert scale. CM (5 items) drew on Assmann [38]; CP (5) on heritage literature [39]–[42]; CT (5) on cultural innovation studies; PU and PEOU (5 each) on Davis's TAM scales [33]; and UI (4) on Venkatesh and Davis [34]. Items were expert-reviewed, translated into simplified Chinese via forward-backward procedure, and pilot-tested with 30 designers (12-15 minutes; Cronbach's alpha above 0.80 for all constructs).

2.4. Data analysis

Data analysis was conducted using two-stage PLS-SEM procedure. In the first stage, the measurement model was evaluated to assess internal consistency reliability and construct validity. Reliability was examined using Cronbach's alpha and composite reliability (CR), while convergent validity was assessed through average variance extracted (AVE). Discriminant validity was evaluated using the Fornell-Larcker criterion.

In the second stage, the structural model was analyzed to test the hypothesized relationships among constructs. Path coefficients, mediating effects, and significance levels were assessed using bootstrapping with 5,000 resamples. Model fit was examined using the standardized root mean square residual (SRMR), while the explanatory power of the model was assessed through the coefficient of determination (R^2) for endogenous constructs. Given that the study used a cross-sectional, single-source, self-reported survey, common method bias (CMB) was assessed. Harman's single-factor test showed the first unrotated factor explained 32.4% of total variance, below the 50% threshold, and all construct-level full collinearity variance inflation factor (VIF) values were below 3.3 (maximum 3.14), together indicating that CMB was unlikely to be a serious concern. As these are diagnostic rather than corrective procedures, procedural remedies were also implemented at the design stage: respondent anonymity, construct items visually separated, neutral wording, and predictor and outcome items placed in different sections.

3. RESULTS

The final sample of 238 respondents showed diverse demographics. Participants were concentrated in the 18-25 (39.5%) and 36-45 (38.7%) age groups, with a balanced gender split (47.1% male, 46.2% female, and 6.7% undisclosed). Professionally, the sample comprised working designers (53.8%), design educators (20.2%), freelance designers (16.4%), and design students (9.7%), with design experience ranging mainly from one to ten years. The full demographic profile is presented in Table 1.

Table 1. Demographic characteristics of respondents

Demographic variable	Category	Frequency (n)	Percentage (%)
Age	18–25 years	94	39.5
	26–35 years	38	16.0
	36–45 years	92	38.7
	46–55 years	11	4.6
	Over 55 years	3	1.3
Gender	Male	112	47.1
	Female	110	46.2
	Prefer not to disclose	16	6.7
Professional role	Working designers	128	53.8
	Design educators	48	20.2
	Freelance designers	39	16.4
	Design students	23	9.7
Design experience	1–3 years	73	30.7
	4–6 years	47	19.7
	7–10 years	52	21.8

3.1. Measurement model assessment

The results in Table 2 demonstrate that the measurement model achieves strong reliability and validity across all constructs. The measurement model is robust: factor loadings (0.838–0.931) exceed 0.70, Cronbach's alpha (0.925-0.943) and CR (0.944-0.959) confirm internal consistency, AVE values (0.770-0.853) support convergent validity, and all VIFs (2.46-4.46) stay below 5.0, indicating no multicollinearity.

Table 2. Construct reliability and convergent validity

Construct	Items	Item (description)	Loading	α	CR	AVE	VIF
CM	CM1	Cultural heritage importance	0.895	0.937	0.952	0.800	3.38
	CM2	Cultural identity maintenance	0.919				4.29
	CM3	Continuity priority	0.838				2.46
	CM4	Historical value protection	0.923				4.46
	CM5	Knowledge preservation	0.894				3.53
CP	CP1	Accuracy maintenance	0.854	0.932	0.949	0.787	2.49
	CP2	Cultural meaning protection	0.891				3.30
	CP3	Authenticity assurance	0.888				3.20
	CP4	Tradition fidelity	0.888				3.30
	CP5	Heritage integrity	0.914				3.77
CT	CT1	Innovation facilitation	0.911	0.939	0.953	0.804	4.12
	CT2	Contemporary adaptation	0.918				4.44
	CT3	Reinterpretation convenience	0.855				2.60
	CT4	Creative transformation	0.896				3.33
	CT5	Cultural renewal	0.903				3.49
PEOU	PEOU1	Learning ease	0.888	0.937	0.952	0.798	3.78
	PEOU2	Interaction clarity	0.891				3.19
	PEOU3	Operational flexibility	0.876				2.96
	PEOU4	Overall usability	0.908				3.94
	PEOU5	Skill transfer	0.904				3.58
PU	PU1	Productivity enhancement	0.878	0.925	0.944	0.770	3.75
	PU2	Performance improvement	0.860				2.86
	PU3	Efficiency increase	0.878				3.24
	PU4	Overall usefulness	0.905				3.82
	PU5	Work quality enhancement	0.867				3.11
UI	UI1	Future use intention	0.929	0.943	0.959	0.853	4.24
	UI2	Usage prediction	0.928				4.37
	UI3	Integration planning	0.905				3.39
	UI4	Technology adoption readiness	0.931				4.37

Note: All factor loadings significant at $p<0.001$. All constructs exceed recommended thresholds (CR>0.70, AVE>0.50, α>0.70).

For discriminant validity in Table 3, heterotrait-monotrait (HTMT) values ranged from 0.584 to 0.963. Only CT–CP (0.920) and UI–PU (0.963) exceeded 0.90, but both bootstrapped confidence intervals exclude 1.0, confirming distinctness. The elevated PU–UI value reflects the well-documented TAM tendency for utility beliefs and intentions to converge when a technology is professionally indispensable; cross-loadings in Table 2 confirm each item loads strongest on its own construct, indicating PU and UI are distinct yet adjacent rather than redundant.

Table 3. HTMT discriminant validity matrix with bootstrapped confidence intervals

Construct pair	HTMT	95% CI	Conclusion
CP↔CM	0.600	[0.464, 0.727]	Acceptable (<0.90)
CT↔CM	0.635	[0.496, 0.764]	Acceptable (<0.90)
CT↔CP	0.920	[0.865, 0.960]	Acceptable (CI excludes 1.0)
PEOU↔CM	0.584	[0.462, 0.694]	Acceptable (<0.90)
PEOU↔CP	0.705	[0.587, 0.804]	Acceptable (<0.90)
PEOU↔CT	0.727	[0.628, 0.811]	Acceptable (<0.90)
PU↔CM	0.710	[0.578, 0.816]	Acceptable (<0.90)
PU↔CP	0.767	[0.678, 0.845]	Acceptable (<0.90)
PU↔CT	0.826	[0.743, 0.898]	Acceptable (<0.90)
PU↔PEOU	0.804	[0.729, 0.866]	Acceptable (<0.90)
UI↔CM	0.700	[0.556, 0.819]	Acceptable (<0.90)
UI↔CP	0.661	[0.551, 0.755]	Acceptable (<0.90)
UI↔CT	0.767	[0.664, 0.849]	Acceptable (<0.90)
UI↔PEOU	0.756	[0.670, 0.828]	Acceptable (<0.90)
UI↔PU	0.963	[0.929, 0.992]	Acceptable (CI excludes 1.0)

Note: HTMT values<0.90 indicate discriminant validity.
Pairs exceeding 0.90 remain acceptable as their 95% bootstrapped CI excludes 1.0.

3.2. Structural model assessment

Figure 1 shows the complete structural equation model with standardized coefficients. Table 4 presents the complete structural equation model with standardized path coefficients, factor loadings, and explained variance (R^2) for endogenous constructs. The measurement model shows strong factor loadings (0.838–0.931). The structural model reveals R^2 values of 0.318 (CP), 0.761 (CT), 0.689 (PU), and 0.814 (UI), demonstrating robust explanatory power. The saturated model yielded an SRMR of 0.047, well below the 0.08 threshold [43], indicating acceptable global model fit.

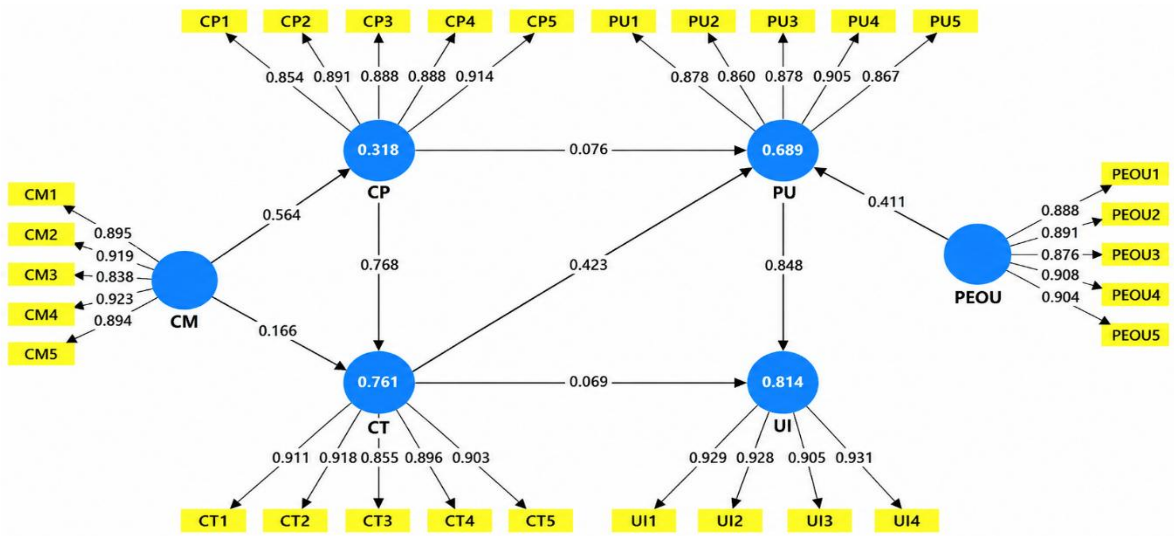

Figure 1. Conceptual framework: complete structural equation model with standardized coefficients

CM had a strong positive effect on CP ($\beta = 0.564, p < 0.001$), explaining 31.8% of its variance, which supports H1 and confirms CM's foundational role. It also significantly influenced CT ($\beta = 0.166$, $p < 0.01$), supporting H2. The strongest cultural path was from CP to CT ($\beta = 0.768, p < 0.001$); together, CM and CP explained 76.1% of the variance in CT, supporting H3. However, CT did not directly influence UI ($\beta = 0.069, p = 0.158$), despite a strong correlation, indicating that its effect is mainly mediated through other variables; thus, H6 was not directly supported. Likewise, CP did not significantly affect PU ($\beta = 0.076$, $p = 0.423$) so H4 was not supported. In contrast, CT significantly increased PU ($\beta = 0.423, p < 0.001$), supporting H5. PEOU also positively affected PU ($\beta = 0.411, p < 0.001$), supporting H7. Finally, PU had the strongest direct effect on UI ($\beta = 0.848, p < 0.001$), confirming H8. The supported paths also show practically meaningful effects: Cohen's f^2 values indicate large effects for the core paths (CP→CT, 1.685; PU→UI, 1.570; CM→CP, 0.465) and smaller effects for the remainder. The R^2 of 0.814 for UI indicates the model accounts for 81.4% of the variance in designers' intention to adopt AIGC, a high level of explanatory power for behavioral intention research. As a purely descriptive observation, the standardized path coefficients across respondent subgroups (by professional role and by design experience) shared the same direction for all eight structural paths. As no formal multi-group analysis (PLS-MGA, permutation test) or measurement invariance assessment (MICOM) was conducted, these are not interpreted as group-level equivalence; formal invariance testing is identified as a priority for future replications.

Table 4. Structural model path analysis results

H	Path	Coeff.	SE	t-value	p-value	95% CI	Support	f^2
H1	CM→CP	0.564***	0.063	8.893	0.000	[0.440, 0.688]	Supported	0.465
H2	CM→CT	0.166**	0.060	2.754	0.006	[0.048, 0.284]	Supported	0.079
H3	CP→CT	0.768***	0.049	15.562	0.000	[0.672, 0.864]	Supported	1.685
H4	CP→PU	0.076	0.095	0.801	0.423	[-0.111, 0.263]	Not supported	0.005
H5	CT→PU	0.423***	0.098	4.319	0.000	[0.231, 0.615]	Supported	0.135
H6	CT→UI	0.069	0.049	1.411	0.158	[-0.027, 0.165]	Not supported	0.011
H7	PEOU→PU	0.411***	0.062	6.627	0.000	[0.289, 0.533]	Supported	0.278
H8	PU→UI	0.848***	0.043	19.695	0.000	[0.764, 0.932]	Supported	1.570

Note: ***p<0.001, **p<0.01. Bootstrap resampling: 5,000 iterations.

3.3. Mediation analysis and mechanism pathways

Indirect effects analysis showed that cultural cognition influences UI mainly through mediation pathways. CM had significant indirect effects on PU ($\beta = 0.296, t = 5.019, p < 0.001$) and UI ($\beta = 0.293, t = 4.924, p < 0.001$) through the sequential path CM→CP→CT→PU, indicating indirect-only mediation, in line with the typology proposed by Zhao *et al.* [44] and the PLS-SEM mediation guidelines of Hair *et al.* [35]. CP also had a strong indirect effect on UI through PU ($\beta = 0.539$), accounting for 93.4% of the total effect. Most importantly, CT influenced UI only indirectly through PU ($\beta = 0.359, t = 4.206$, $p < 0.001$), while its direct effect was non-significant, confirming indirect-only mediation (i.e., full indirect pathway dominance in the absence of a significant direct effect) [35], [44]. This shows that CT affects adoption only when translated into perceived functional value. By contrast, PEOU showed partial mediation through PU, with 74.9% of its effect on UI transmitted indirectly, consistent with the traditional TAM pathway. The complete mediation results are summarized in Table 5.

Table 5. Mediation effect testing results

Mediation pathway	Total effect	Direct effect	Indirect effect	Bootstrap 95% CI	Mediation type
CP→PU→UI	0.565***	0.026	0.539***	[0.447, 0.631]	Indirect-only mediation
CT→PU→UI	0.633***	0.036	0.597***	[0.498, 0.696]	Indirect-only mediation
PEOU→PU→UI	0.671***	0.088†	0.583***	[0.489, 0.677]	Partial mediation

Note: ***p<0.001. † Direct effect not significant (p>0.05). Bootstrap resampling: 5,000 iterations.

4. DISCUSSION

This study shows that AIGC adoption among visual designers follows a hierarchical process in which cultural cognition shapes functional evaluation. First, the significant effect of CM on CP ($\beta = 0.564, p < 0.001$) supports CM theory, which holds that cultural identity and collective memory shape how cultural forms are protected and reproduced [15]. Designers with stronger heritage awareness are therefore more likely to judge AIGC by its capacity to preserve cultural meaning, extending earlier AIGC studies by showing that cultural values are foundational rather than peripheral in professional evaluations [1], [5], [20]. Second, the strong effect of CP on CT ($\beta = 0.768, p < 0.001$) indicates that preservation and innovation are complementary rather than opposing dimensions, consistent with studies arguing that AIGC can revitalize traditional culture through reinterpretation when cultural integrity is maintained, and with the view that heritage is continuously reconstructed through media and practice [8], [11], [14], [15], [30], [31].

However, although CT significantly affected PU ($\beta = 0.423, p < 0.001$), its direct effect on UI was not significant ($\beta = 0.069, p = 0.158$). This suggests that CT alone does not drive adoption. Instead, designers adopt AIGC only when its cultural potential is translated into practical value, such as improving efficiency, quality, or workflow performance. This fully mediated result is especially relevant in professional design contexts, where adoption decisions are often more instrumental than emotional [3], [5], [32]. In the visual design profession, adoption decisions are typically embedded in client briefs, deadlines, and quality benchmarks, which privileges utilitarian over symbolic considerations. Cultural enthusiasm for innovation must therefore pass through a "professional usefulness filter" before it converts into intention to use. The non-significant H6 path is thus not a null finding to be discounted; it is theoretically informative because it identifies PU as the gating mechanism through which cultural meaning becomes adoption behavior, refining how cultural variables should be positioned in extended TAM frameworks.

Similarly, the non-significant path from CP to PU ($\beta = 0.076, p = 0.423$) shows that cultural legitimacy does not automatically become functional endorsement. This supports prior work suggesting designers evaluate AI not only by symbolic alignment, but also by whether it provides concrete control, workflow support, and performance value [13], [17], [20]. Notably, among the two cultural cognition dimensions, only CT, not CP, directly affects PU: designers appear to associate functional value with what AIGC enables them to create and reinterpret rather than what it conserves, treating preservation as an ethical prerequisite and transformation as a productivity-relevant capability. This extends TAM by showing that conservation-oriented and innovation-oriented cultural beliefs enter the cognitive chain at different points, repositioning cultural cognition as a pre-functional layer that selectively channels cultural meaning into PU. The strongest path in the model was PU→UI ($\beta = 0.848, p < 0.001$), confirming TAM's core proposition that utility is the most immediate driver of adoption [33], [34]. The significant path from PEOU to PU ($\beta = 0.411, p < 0.001$) further supports TAM, while also suggesting that ease of use in AIGC involves compatibility with culturally grounded creative practice, not just technical simplicity [26], [28], [29].

5. CONCLUSION

This study extends the TAM by integrating CM theory and testing a culturally grounded pathway model among 238 visual designers. The results show that CM shapes CP and CT; that CP strongly predicts CT; and that cultural cognition reaches UI almost exclusively through PU, with the model accounting for 81.4% of the variance in UI. Theoretically, this repositions cultural variables from peripheral moderators to a pre-functional cognition layer that organizes upstream cultural meaning and channels it, via PU, into behavioral intention, clarifying the boundary conditions under which TAM applies in culturally embedded creative industries. Practically, AIGC developers should surface cultural provenance and style controls so cultural respect is experienced as a productivity gain; design education should link cultural intent, generated outputs, and joint functional and cultural evaluation; and policymakers should require auditable provenance standards for AIGC tools in heritage and educational settings. The study is limited by its focus on Chinese traditional graphic design, its cross-sectional single-source self-report design, and online purposive sampling. Future research should test the pathway with probability-based, cross-cultural, longitudinal designs, conduct formal multi-group and measurement invariance analyses, and incorporate transparency and ethical-governance variables.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflicts of interest. All participants acknowledged and consented to participating in this research. The authors declare that AI-assisted tools were used solely to extract information during the literature review and to improve grammar and language (e.g., Quill Bot). All scientific interpretations, analyses, and conclusions were developed and verified by the authors.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has complied with all the relevant national regulations and institutional policies, in accordance with the tenets of the Helsinki Declaration, and has been approved by the research ethics committee of Universiti Teknologi MARA.

DATA AVAILABILITY

The data that support the findings of this study are available from the main author upon reasonable request.

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