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Acceptance of Generative AI in the creative industry: the role of UTAUT, brand recognition and trust in adoption

Aceptación de la Inteligencia Artificial Generativa en la industria creativa: el rol del modelo UTAUT, reconocimiento y la confianza de marca en su adopción

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Abstract: this study explores the factors influencing the adoption of Generative AI in the creative industry, focusing on the Unified Theory of Acceptance and Use of Technology (UTAUT) factors: performance expectancy, effort expectancy, facilitating conditions, social influence, and consumer-based brand equity factors: brand recognition and brand trust. While previous research has emphasized the importance of UTAUT constructs in technology adoption, the influence of brand equity factors remains underexplored. This study bridges this gap and provides insights to enhance adoption strategies. Standardized questionnaires were used, incorporating UTAUT constructs and brand-related variables such as Brand Recognition and Brand Trust. A sample of 208 creative professionals from the US and Spain validated the proposed model using PLS-SEM. Results reveal that performance expectancy, facilitating conditions, and brand trust positively influence the behavioral intention to use Generative AI tools, while brand recognition negatively influences behavioral intention. Social influence and effort expectancy did not present statistically significant results. The model explains 67 % of the variance in behavioral intention ($R^2 = 0.679$), indicating strong predictive power. These insights contribute to developing effective adoption strategies for Generative AI in the creative industry.

Keywords: Generative artificial intelligence, UTAUT, recognition, trust, creative industries, Adobe, brand equity, technology adoption.

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Resumen: el estudio explora los factores que influyen en la adopción de la inteligencia artificial (IA Gen) en la industria creativa, tomando como referencia la Teoría Unificada de Aceptación y Uso de Tecnología (UTAUT), y la teoría del capital de marca. Numerosos estudios han demostrado la capacidad explicativa del modelo UTAUT en la adopción tecnológica en diferentes sectores; sin embargo, no se había analizado cómo el capital de marca, especialmente el conocimiento y la confianza influye a la adopción de la Inteligencia Artificial Generativa. El capital de la marca es especialmente relevante en la industria creativa, donde el bajo conocimiento tecnológico hace que la marca de IA sea una fuente clave de información e influencia en la toma de decisiones. Una muestra de 208 profesionales creativos de EE. UU. y España validó el modelo propuesto utilizando PLS-SEM. Los resultados indican que la expectativa de rendimiento, las condiciones facilitadoras y la confianza en la marca influyen positivamente en la intención de uso de la IA Generativa, mientras que el reconocimiento de marca tiene un efecto negativo. La influencia social y la expectativa de esfuerzo no presentaron resultados estadísticamente significativos. El modelo explica el 67 % de la varianza en la intención de uso ($R^2 = 0.679$), indicando un alto poder predictivo. Se destaca la importancia del desempeño, soportes accesibles y confianza en la marca, abordando los desafíos de la percepción y reconocimiento de marca.

Palabras clave: Inteligencia Artificial Generativa, UTAUT, reconocimiento, confianza, industrias creativas, Adobe, capital de marca, adopción de tecnología.

Introduction

Currently, the creative industry is marked by the rapid changes in the wake of the digital revolution. The increased interaction of the creative sector with technologies has led to new forms of artistic expression (Abbasi *et al*., 2017). Through Generative Artificial Intelligence (Gen AI) we are experiencing transformative advancements, enabling unprecedented levels of efficiency, and creativity. Understanding the adoption criteria among professionals is crucial for the success of this innovation, especially in those industries that use it intensively. The creative sector is grounded in originality and the production of imaginative ideas, requiring human involvement. Gen AI is being integrated into creative workflows, offering potential benefits in productivity and time efficiency (Vinchon *et al*., 2023). The expanding role of Gen AI has prompted a research agenda to explore its impact on the creative workforce. Although we are witnessing the rise of Gen AI in 2024, one of the first takes on AI deployment in the creative sector took place in 2016. The Next Rembrandt was created, and the three-dimensional printed painting was produced only based on training data from Rembrandt's portfolio.

Figure 1
El Next Rembrandt

Note. Wunderman Thompson, 2016.

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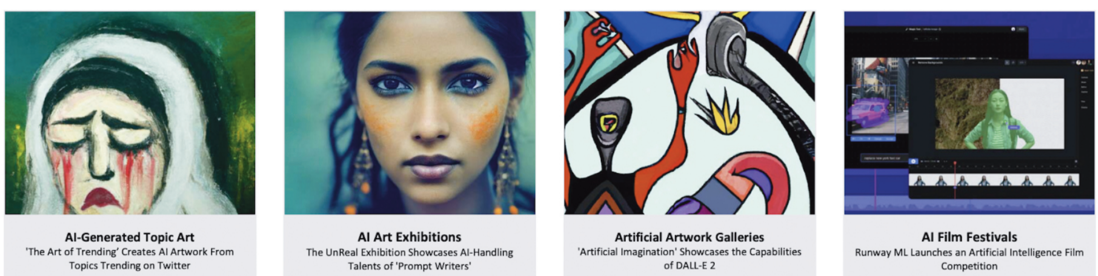
Gen AI adoption has increased exponentially since the launch of the Next Rembrandt. This is shown by embracing of AI art as a new discipline. With the boom of Gen AI-generated arts, galleries and curators are adapting by showcasing this art and their prompt writers. For example, The UnReal Exhibition, part of NSDM Fuse in Amsterdam showcases a wide variety of AI art and the prompt writers as artists, exploring the boundaries of creativity and the latest technology. Another gallery showcasing Gen AI art opened in December 2023 in New York. Artechouse- World of AI-Imagination is a captivating art installation blending human creativity and cutting-edge AI computer graphics (Artechouse, 2023). The Artechouse exhibition is built on the foundation of NVIDIA hardware and its generative AI tool. These exhibitions are a way to showcase the potential of Gen AI in the creative industry and tame its capabilities because AI is becoming an integral part of the artistic process (Smith, 2022). They satiate desires for new art forms while providing thoughtful discussion regarding art production and the meaning of creativity, providing a new perception of using Gen AI as a creative tool in the digital artistry era (Smith, 2022). The creative community embraces Gen AI in many ways, from content creation to streamlining tasks.

Figure 2

Examples of AI exhibitions



Note. Smith, 2022.

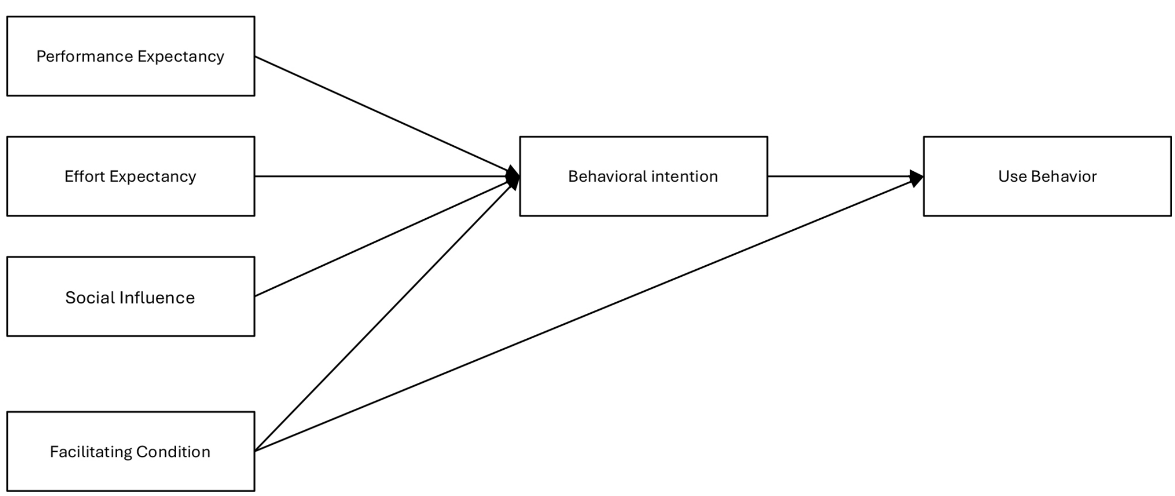
Figure 3

Artechouse-World of AI-Imagination, NewYork, 2023

As professionals in creative industries leverage Gen AI to streamline tasks and enhance their work, its adoption is growing (Sanchez, 2023). Research suggests that Gen AI could automate up to 26% of functions in the arts, design, entertainment, media, and sports sectors (Hatzius *et* *al*., 2023). Similarly, other findings indicate that 75% of creative professionals consider Gen AI useful for tasks such as image editing and search, emphasizing its role as a facilitator rather than a creator (Anantrasirichai and Bull, 2022). Since the launch of ChatGPT, Gen AI has enabled original content creation using natural language prompts and has gained rapid prominence due to its user-friendly interfaces (Chui, 2023; Anantrasirichai and Bull, 2020). Amidst the growing adoption, ethical concerns arise. They are rooted in originality, authorship, and the potential for job displacement. As AI systems increasingly produce creative works, questions arise regarding ownership and can lead to ethical dilemmas and technology rejection (Chen, 2024; Caporusso, 2023). Addressing these concerns is crucial to foster the adoption. The Unified Theory of Acceptance and Use of Technology (UTAUT) model has become a useful framework for understanding and predicting the adoption of this technology (Yin *et al*., 2023, Menon and Shilpa, 2023, Cabrera-Sánchez, 2021). The UTAUT model integrates eight foundational theories, including the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and Innovation Diffusion Theory (IDT). UTAUT considers four key factors; performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) (Venkatesh *et al*., 2003). According to this model, PE represents individuals' perceptions of the benefits and usefulness they expect to derive from using new technology, EE is defined as the degree of ease associated with the use of new technology, SI is the degree to which an individual perceives that significant others believe she or he should use the latest technology, and FC is the degree to which an individual believes that technological infrastructure exists to support the use of new technology (Venkatesh *et al*., 2003). Figure 4 presents the original UTAUT model.

Figure 4

Model of Unified Theory of Acceptance and Use of Technology



Note. Venkatesh *et al*., 2003.

UTAUT has been used to examine Gen AI adoption in various industries such as health and safety (De Almeida *et al*., 2023), financial services (Jiang *et al*., 2024), and lastly creative industries (Yin *et al*., 2023, Menon and Shilpa, 2023). The results highlight performance expectancy, effort expectancy, and social influence as significant predictors of Gen AI use, with no notable impact from facilitating condition (Yin *et al*., 2023; Menon and Shilpa, 2023; Cabrera-Sánchez, 2021). Despite its benefits, limitations of this technology, such as lack of authenticity and personal touch, remain concer-

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ns for users in the creative industry (Wang *et al*., 2023). However, most creative professionals view Gen AI as a tool to complement their skills rather than replace them, underscoring the importance of fostering understanding and acceptance (Yin *et al*., 2023). Yin *et al*. (2023) applied the UTAUT2 model, incorporating hedonic motivation, price value, and habit, while Zhang (2020) focused on music, examining factors like performance expectancy, effort expectancy, social influence, individual innovation, and perceived value. Notably, Zhang found that perceived innovativeness had the strongest impact on AI music adoption, followed by performance expectancy and effort expectancy. However, these findings are geographically constrained and fail to provide universal insights. The creative industry in Western cultures may demonstrate distinct patterns influenced by individualism, creative autonomy, and differing attitudes toward emerging technologies (Cabrera-Sánchez, 2021). As stated in the previous research behavioral intention, which determines the acceptance of AI use, can be attributed strongly to performance expectancy (Maican *et al*., 2023, Menon and Shilpa, 2023, Cabrera-Sánchez, 2021). effort expectancy (Zhang, 2020, Menon, Shilpa, 2023), facilitating condition (Menon and Shilpa, 2023), and social influence (Maican *et al*., 2023, Menon and Shilpa, 2023). The research showed that the impact of effort expectancy is more pronounced in cases of low creativity (Maican *et al*., 2023). While these studies enhance the UTAUT framework by incorporating variables such as user trust and emotional responses, they overlook additional factors that could support users in industries characterized by limited technological expertise.

Creative Industries often lack good knowledge of innovation, different levels of maturity, and lack of skills which presents a barrier to the rapid adoption of technology (Abbasi *et al*., 2017). This gap necessitates reliance on different ways to find reassurance of quality. In industries with limited technological knowledge, consumer-based brand equity is a substitute for direct quality evaluation. The confidence provided by brand factors supports decision-making and reduces uncertainty (Abbasi *et al*., 2017). Brand recognition and trust are essential components of consumer-based brand equity, shaping consumer behavior across the consumer journey. Brand recognition refers to the ability of consumers to recall or identify a brand within a product category. It progresses through three stages: recognition (aided awareness), recall (unaided awareness), and top-of-mind (preferred choice) (Kathuria *et al*., 2018). Strong brand recognition is crucial in the early stages of the consumer journey, where it ensures the brand's inclusion in consideration sets during the need recognition, information-seeking, and evaluation phases (García and Yábar, 2023). High recognition facilitates decision-making, fosters loyalty, and increases purchase intentions (Izza *et al*., 2024; Rubio *et al*., 2014). Brand trust builds upon recognition, representing confidence in a brand's ability to deliver on promises and meet expectations (García and Yábar,2023). Trust moderates risk perception, promotes customer commitment, and deepens emotional connections with a brand (Hess and Story, 2005). Trust is critical in service-based industries, where emotional evaluations and repeated positive interactions drive long-term relationships (Bowden, 2014). Both recognition and trust impact brand use. Recognition simplifies decisions by creating familiarity and positive associations (Rios and Riquelme, 2010). Trust reinforces loyalty by aligning brand values with consumers' values, fostering commitment, and reducing perceived risks (Roets *et al*., 2014).

This study seeks to address the research gap by investigating the role of brand-related factors in shaping the acceptance of Gen AI among individuals in creative industries, particularly to enhance quality assurance in sectors with limited technological expertise. This research is grounded in the UTAUT model because its validity has been proven in professional, business settings (Chatterjee *et al*., 2021; Zhang, 2020). It aims to address this gap by exploring how brand equity factors interact with established UTAUT constructs to shape user behavior and help creative professionals to adapt Gen AI effectively.

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Materials and methods

Theoretical model and hypotheses

Based on the research questions the following theoretical model and hypotheses for the study were established:

Performance expectancy

Performance expectancy is the degree to which an individual working in the creative industry believes that the Gen AI text-to-image tools will help him or her to attain gains in job performance. Gen AI tools can significantly impact workflows by automating repetitive tasks and enabling ideation or content creation. Previous studies showed that performance expectancy strongly predicts behavioral intention to use AI (Maican *et al*., 2023; Menon and Shilpa, 2023; Cabrera-Sánchez, 2021). Individuals are expecting that the use of AI technology will enhance their job performance (Yin *et al*., 2023). Hence, the hypothesis is structured as follows:

> *H1: Performance expectancy positively influences the increase of behavioral intention of use of the Generative Artificial Intelligence text to image service-based brand.*

Effort expectancy

Effort expectancy is the degree of ease associated with using Gen AI text-to-image tools by individuals working in the creative industry. Gen AI tools, while able to enhance work effectiveness, require user-friendly interfaces and intuitive usage to gain adaptation among new users. Previous studies confirm that effort expectancy positively impacts behavioral intention, especially in fields where complex or non-intuitive interfaces may deter regular use (Chuyen and Vinh, 2023). We believe that creative industry professionals prefer tools with minimized education effort (Bravo *et al*., 2020). The ease of using a new tool reduces barriers to adoption, making effort expectancy an important predictor in dynamic sectors, such as creative industry (Zhang, 2020; Menon and Shilpa, 2023). Hence, the hypothesis is structured as follows:

> *H2: Effort expectancy positively influences the increase of behavioral intention of using the Generative Artificial Intelligence text to image service-based brand.*

Social influence

Social influence is the degree to which an individual working in the creative industry perceives that people of importance believe he or she should use Gen AI text-to-image tools. Creative professionals might rely on external opinions from clients, coworkers, or industry leaders. Studies on AI adoption in the design industry demonstrated that individuals are likely to adopt such technologies if they perceive that influential peers or leaders endorse their use (Chuyen and Vinh, 2023). Additionally, other studies found that professionals in the music industry often adopt AI tools based on industry-wide trends, reflecting the impact of social influence on AI adoption (Maican *et al.*, 2023). Hence, the hypothesis is structured as follows:

> *H3: Social influence positively influences the increase of behavioral intention of use of the Generative Artificial Intelligence text to image service-based brand.*

Facilitating condition

Facilitating condition is the degree to which an individual working in the creative industry believes that the organization's technical infrastructure exists to support the use of Gen AI text-to-image tools. It encompasses the organizational, training, and technical support available to the user. Facilitating condition has been proven to improve the strategies that promote the acceptance of Gen AI (Menon and Shilpa, 2023). The availability of robust training and learning positively impacts user confidence, indicating that facilitating condition is a predictor of Gen AI adoption (Chuyen, Vinh, 2023). Hence, the hypothesis is structured as follows:

H4: Facilitating condition positively influences the increase of behavioral intention of use of the Generative Artificial Intelligence text to image service-based brand.

Brand recognition

Brand recognition is the ability of individuals working in the creative industry to recall the brand in a Gen AI text-to-image services category. Brand recognition is the first step in the consumer journey and the decision to start using a product (Sasmita and Suki, 2015). Moreover, consumers prefer to use only recognizable brands with a good performance history (Kathuria *et al.*, 2018). Therefore, the hypothesis is structured as follows:

H5: The more recognized the brand of Generative Artificial Intelligence text to image, the more positive influence it has on behavioral intention of use.

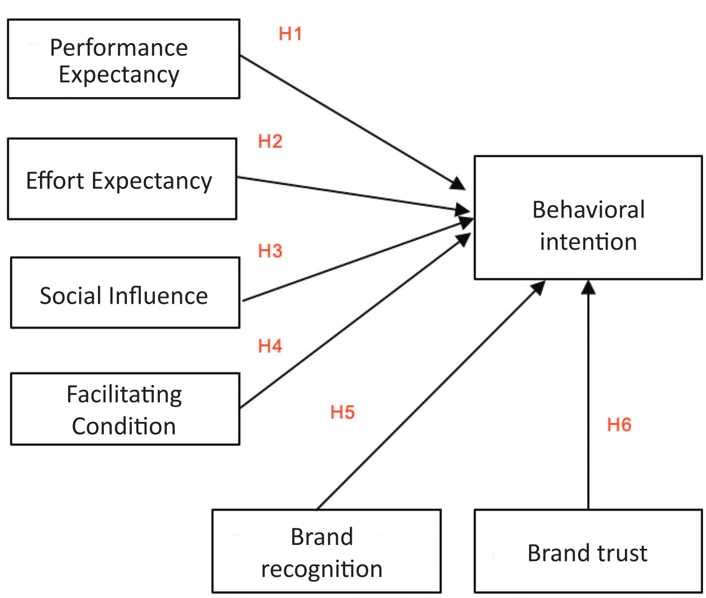
Trust of the brand

The trust of the brand is the confidence that individuals working in the creative industry have in the brand's ability to deliver on its promises. In previous studies we saw that trust in the ability of the AI tool to provide the best task performance and trust in compliance with the service promise are predictors of AI adoption (Cabrera-Sánchez, 2021). Additionally, satisfaction and service quality impacts positively on AI service adoption (Chatterjee *et al.*, 2021). Hence, the hypothesis is structured as follows:

H6: The more trusted the brand of Generative Artificial Intelligence text to image, the more positive influence it has on behavioral intention to use it.

Our theoretical model is presented in Figure 5:

Figure 5
Theoretical model and hypotheses



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Data collection

Hypotheses were validated using standardized Qualtrics questionnaire, adopting items suggested by Venkatesh *et al*. (2012) in Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. Additionally, two brand-related variables were introduced: brand recognition and brand trust adopting items suggested by Wang *et al* (2008), in *"Global brand equity model: combining customer-based with product-market outcome approaches"*. Adobe Firefly's text-to-image platform was specified as the subject for the consumer-based brand equity variables. The questionnaire comprised two sections: Sociodemographic (gender, age, place of residence, occupation- creative profile, experience with Gen AI) and factors influencing the use intention. Selected items for constructs of performance expectancy, effort expectancy, social influence, facilitating conditions, brand recognition, brand trust, and brand equity. Each construct consisted of 5 items, adapted from the original scales mentioned above. No pretest was conducted, as these items have been widely used and adapted by other researchers. Respondents evaluated each variable using a 7-point Likert scale (1: "Totally disagree" to 7: "Totally agree"). The study focused on a sample of individuals working in the creative industry in the US and Spain. The questionnaire was distributed through online creative communities using a survey link. The sample was randomly drawn from a creative collective of professionals in advertising, marketing, and other creative industries. This random selection aimed to minimize bias and enhance the generalizability of the findings. Following Westland (2010) and Soper (2024) conditions to perform PLS-SEM a total of 224 responses were collected and 208 were complete and valid responses. This number of responses provides us with an above the minimum sample size required for the model structure and the margin of error is less than 5% as desired.

Results and discussion

Data analysis

In the first instance, descriptive statistics of the sample were analyzed. The total sample of 224 has the following characteristics presented in Table 1. From the total sample, 208 were valid responses that serve as a base for the measurement model analysis.

Table 1

Description of the sample

Age	**Sample**	%
Less than 35	103	46
More than 35	121	54
Gender		
Female	93	41.5
Masculine	130	58
Prefer not to say	1	0.5
Place of residency		
Spain	104	46.5
USA	104	46.5
Others	16	7

Experience with Gen AI		
Yes	138	62
No	86	38
Experience with Gen AI text to image		
Yes	88	39
No	136	61

To validate the proposed model, the data was subjected to analysis using the Partial Least Squares (PLS) method. It allows the analysis of complex relationships between variables and puts them into practice (Hair *et al*., 2017). The data was analyzed using the SmartPLS 4.0 software. The data analysis was structured into two key phases: assessing the measurement model and analyzing the structural model.

In the first phase, we assessed the measurement model's reliability and validity, by calculating Cronbach's Alpha (α), composite reliability (CR), and average variance extracted (AVE). Factor loadings (λ) were examined to determine individual item reliability, and discriminant validity was evaluated using the Fornell-Larcker criterion, ensuring that the square root of a construct's AVE exceeded its correlations with other constructs (Hair *et al*., 2017). Additionally, we analyzed the individual validity for the formative construct- facilitating condition. A comprehensive literature review was performed to ensure the validity of the facilitating condition as a formative construct. Studies applying UTAUT to domains like education, mobile banking, and digital libraries consistently highlight that facilitating condition captures distinct enabling factors (e.g., technical and organizational support), justifying a formative specification (Sanmukhiya, 2020, Handayani, 2023). The value of convergent validity in Sanmukhiya's study confirms that facilitating conditions are measured effectively as a formative construct (Sanmukhiya, 2020). We assessed the multicollinearity using the Variance Inflation Factor (VIF), with values below the recommended threshold of 3 (Hair *et al*., 2019). Outer weights and loadings were then evaluated to measure each indicator's contribution to the latent construct. Finally, discriminant validity was verified using the HTMT ratio. In the second phase, the structural model was analyzed using the bootstrapping technique to test the proposed hypotheses. This included estimating the significance of variable relationships through t-statistics, p-values, and path coefficients (β), leading to the study's conclusions.

Measurement model evaluation

First, the validity of all individual items from the original model was assessed. Outer loadings should ideally be 0.708 or higher (Bagozzi and Yi, 1988; Hair *et al*., 2019). This indicates that the indicator explains at least 50% of the variance in the construct (since $0.708^2 \approx 0.50$). We use the theoretical model to validate the measurement model through PLS-SEM, focusing on assessing all latent variables for reliability and validity. Once validated we adjusted our measurement model shown in Figure 6.

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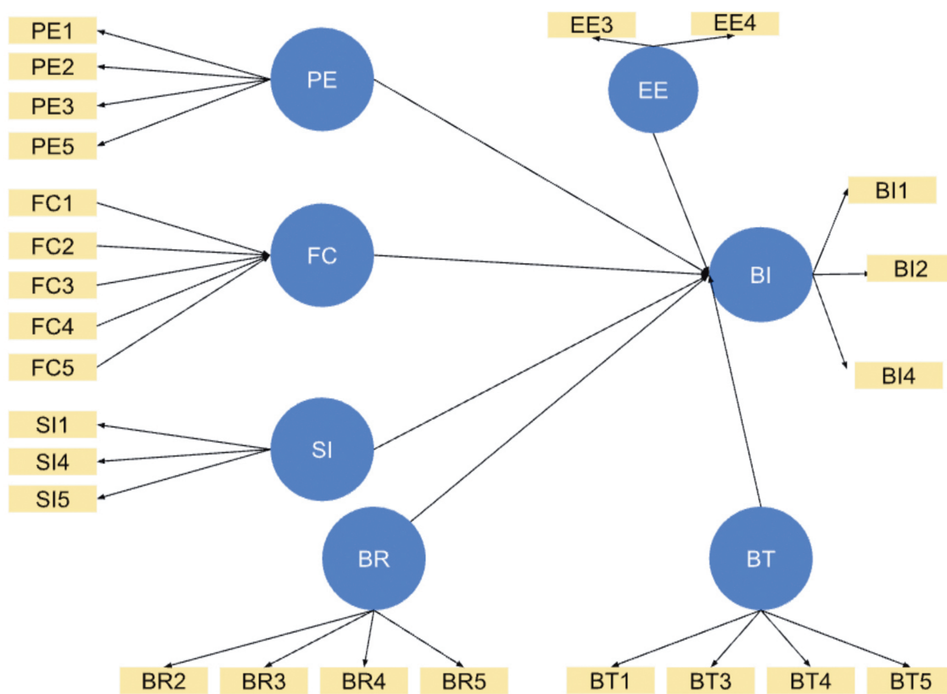
Figure 6
Measurement model



As shown in Table 2 the validity of the individual items was determined. All the outer loading for reflective constructs PE, EE, SI, BR, BT, and BI are well above 0.708, suggesting sufficient levels of indicator reliability. Only the outer loadings for FC don't meet the criteria because it is a formative construct. Composite reliability, indicating internal consistency, was deemed acceptable with all construct loadings exceeding the 0.7 threshold. Convergent validity, ensuring indicators measure the same concept, was evaluated using the AVE method. Following Fornell and Larcker's criteria of a minimum AVE value of 0.5, all constructs surpassed this threshold, indicating that each construct explains at least 50% of the variance in its indicators, demonstrated in Table 2.

Table 2
Overview of construct reliability and validity

	Outer loading		Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
PE	PE1	0.908	0.905	0.917	0.906	0.709
	PE2	0.842				
	PE3	0.900				
	PE5	0.877				
EE	EE3	0.899	0.775	0.776	0.775	0.633
	EE4	0.908				

	Outer loading		Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
PE	PE1	0.908	0.905	0.917	0.906	0.709
	PE2	0.842				
	PE3	0.900				
	PE5	0.877				
SI	SI1	0.820	0.768	0.786	0.760	0.520
	SI4	0.827				
	SI5	0.824				
BR	BR2	0.863	0.919	0.933	0.917	0.738
	BR3	0.909				
	BR4	0.892				
	BR5	0.920				
BT	BT1	0.880	0.906	0.914	0.902	0.700
	BT3	0.874				
	BT4	0.873				
	BT5	0.902				
BI	BI1	0.909	0.872	0.876	0.874	0.698
	BI2	0.914				
	BI4	0.854				

A discriminant validity test was performed using the Fornell-Larcker criterion and Heterotrait-Monotrait Ratio. Table 3 shows the results, notably, the correlations between the constructs are lower than the square root of the AVE, indicating that each construct shares more variance with its indicators than with any other constructs in the model. Consequently, all six reflective constructs exhibit strong internal consistency and convergent validity.

Table 3

Discriminant validity- Fornell-Larcker Criterion and Heterotrait-Monotrait ratio (HTMT)

	Fornell-Larcker criterion					Heterotrait-monotrait ratio (HTMT)					
	PE	**EE**	**SI**	**BR**	**BT**	**PE**	**EE**	**SI**	**BR**	**BT**	**BI**
PE	0.842										
EE	0.637	0.795				0.639					
SI	0.711	0.517	0.721			0.713	0.515				
BR	0.324	0.340	0.474	0.859		0.332	0.332	0.494			
BT	0.337	0.287	0.512	0.809	0.837	0.347	0.285	0.532	0.827		
BI	0.892	0.613	0.679	0.290	0.384	0.890	0.612	0.669	0.288	0.382	

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The assessment of the formative construct started by assessing multicollinearity for the FC variable using the VIF, with values below the recommended threshold of 3 (Hair *et al.*, 2019), confirming no critical multicollinearity issues as demonstrated in Table 4. Outer weights and loadings were then evaluated to measure each indicator's contribution to the latent construct. While 4 of 5 indicators showed strong contributions (loadings > 0.5), FC1 displayed low contribution but was retained for conceptual importance. Bootstrapping confirmed that 4 indicators were statistically significant ($p < 0.05$).

Table 4

Multicollinearity evaluation - VIF

	VIF
FC1	1,022
FC2	1,314
FC3	1,280
FC4	1,223
FC5	1,127

Finally, discriminant validity was verified using the HTMT ratio, which fell within acceptable thresholds, validating the construct as shown in Table 5.

Table 5

Heterotrait-Monotrait ratio

	01.PE	02.EE	03.SI	04.FC	05.BR	06.BT	08.BI
01.PE							
02.EE	0.639						
03.SI	0.713	0.515					
04.FC	0.577	0.620	0.509				
05.BR	0.332	0.332	0.494	0.333			
06.BT	0.347	0.285	0.532	0.377	0.827		
08.BI	0.890	0.612	0.669	0.608	0.288	0.382	

Structural model evaluation

The model was assessed by obtaining path coefficients, p-values, T-values, Coefficient of determination (R2), and predictive relevance (Q2). Path coefficients of Performance Expectancy and Behavioral Intention of use of Gen AI text to image (H1), Facilitating Condition and Behavioral Intention of use of Gen AI text to image (H4), Brand Recognition and Behavioral Intention of use of Gen AI text to image (H5), and Brand Trust and Behavioral Intention of use of Gen AI text to image (H6) were 0.638, 0.137, -0.134, 0.147 with p-values 0.000, 0.011, 0.019, 0.017 respectively. Table 6 presents the path coefficients along with their corresponding p-values. Four path coefficients are statistically significant out of the six hypothesized relationships, thereby supporting four of the six proposed hypotheses.

Table 6

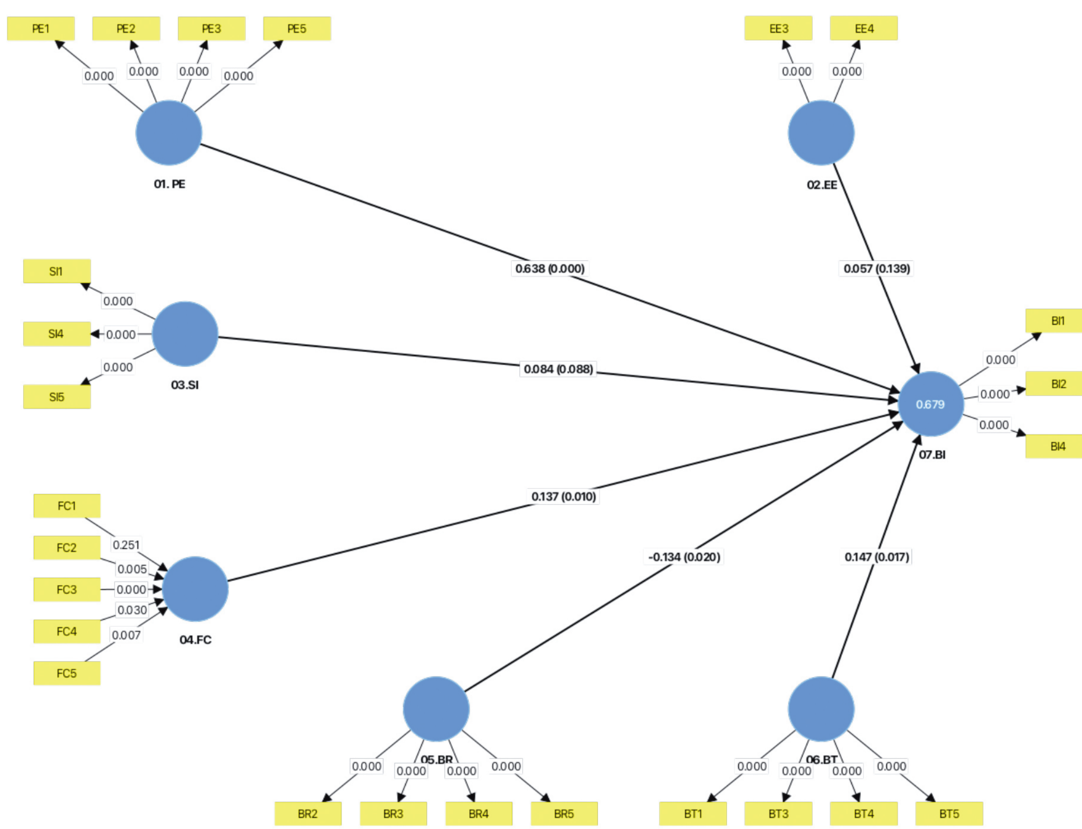
Path coefficients

Model R^2=0,679 (67%)		Model Q^2 = 0,649 (64%)	
	Path coefficients	**P Values**	**Support**
H1: PE ->BI	0.638	0.000	H1 accepted
H2.EE -> BI	0.057	0.139	H2 rejected
H3 SI ->BI	0.084	0.088	H3 rejected
H4 FC ->BI	0.137	0.010	H4 accepted
H5. BR ->BI	-0.134	0.020	H5 partially accepted
H6.BT ->BI	0.147	0.017	H6 accepted

As indicated in Table 6 (R^2), the model accounts for 67% of the variance in Behavioral Intention to use Gen AI text-to-image services in creative industries, driven by the factors of Performance Expectancy, Facilitating Condition, Brand Recognition, and Brand Trust. Performance Expectancy is identified as the strongest predictor ($\beta = 0.638$, $p < 0.001$). According to established thresholds for explained variance, this effect can be classified as moderate, suggesting that the model provides a substantial explanation of the variation in users' intentions to adopt the technology.

Figure 7

Final structural model with Path coefficients, p values and R square



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The Q^2 value of 0.649 presented in Table 6, indicates that the model has substantial predictive relevance for Behavioral Intention. Values of Q^2 greater than zero suggest that the model has predictive power, and a value of 0.649 implies a strong ability of the model to predict BI based on the predictors used.

Discussion

This study aimed to identify the primary factors influencing the adoption of Gen AI text-to-image tools in the creative industry, extending the UTAUT model by incorporating Brand Recognition and Brand Trust. The findings highlight Performance Expectancy as the strongest predictor of Behavioral Intention, with Facilitating Conditions and Brand Trust also showing positive influence. However, Brand Recognition has a negative influence on Behavioral Intention, potentially due to Adobe's established brand identity in traditional creative services conflicting with its new generative AI offerings. Effort Expectancy and Social Influence show no significant influence, resulting in four out of six hypotheses being supported.

The findings align with existing literature on technology adoption, particularly the predictive power of Performance Expectancy (Maican *et al.*, 2023; Upadhyay *et al.*, 2022) and Facilitating Condition in behavioral intention (Anantrasirichai and Bull, 2020). It reinforces Performance Expectancy as the strongest predictor of Behavioral Intention to adopt Gen AI tools. Creative professionals increasingly see value in Gen AI tools that enhance productivity and workflows, aligning with previous research (Maican *et al.*, 2023; Menon and Shilpa, 2023). For professionals in the creative industry Performance Expectancy is the most significant adoption driver. Emphasizing how Gen AI tools streamline workflows, enhance efficiency, and improve output quality is critical, particularly in high-pressure environments. Facilitating Conditions, such as resource availability, external support, and hardware compatibility (Anantrasirichai and Bull, 2020), also positively impact adoption. Comprehensive support systems and resources allow creatives to navigate the learning curve, develop new skills, and remain competitive in a rapidly evolving industry. Tools that offer robust support and align with professional goals are more likely to succeed. However, Effort Expectancy and Social Influence showed no significant effect on Behavioral Intention, which contradicts previous research where these factors were found to positively influence Behavioral Intention (Alhwaiti, 2023; Maican *et al.*, 2023; Menon and Shilpa, 2023; Upadhyay *et al.*, 2022). Previous studies confirm that Effort Expectancy has a positive impact on behavioral intention, especially in fields where complex or non-intuitive interfaces may deter regular use (Chuyen and Vinh, 2023). Similarly with social influence, studies on AI adoption in the design industry demonstrated that individuals are more likely to adopt such technologies if they perceive that influential peers or leaders endorse their use (Chuyen and Vinh, 2023). Additionally, other studies found that professionals in the music industry often adopt AI tools based on the industry-wide trends, reflecting the impact of Social Influence on AI adoption (Maican *et al.*, 2023).

When it comes to consumer-based brand equity, it provides reassurance of quality in industries with limited specialized knowledge. The confidence provided by brand factors supports decision-making and reduces uncertainty (Abbasi *et al.*, 2017). Familiarity with the brand increases the chance to engage with its AI offerings, especially when talking about new, non-renewed technologies (Cabrera-Sánchez *et al.*, 2021). However, our findings suggest a contrary relationship within the context of Adobe's Gen AI text-to-image tools. Individuals familiar with Adobe as a brand were less likely to adopt these tools. This finding contradicts prior research which generally supports a positive association between brand recognition and behavioral intention to use a new product (García and Yábar,2023, Izza *et al.*, 2024). This suggests that strong brand associations with traditional creative tools may create resistance toward adopting Gen AI solutions. Future studies should explore this phenomenon further, potentially incorporating qualitative research to understand the cognitive biases and brand perceptions affecting adoption. Our research, focusing on the Adobe Firefly, suggests that this negative influence might stem from misalignments between the parent brand's established identity and the new product offering (Hem *et al.*, 2003).

For Adobe the negative influence of Brand Recognition on the behavioral intention to use Gen AI tools might stem from the lack of authenticity in the generative AI field. Gen AI is an emerging and nascent field, therefore when the new technology is attached to a well-established brand in another field, these new tools might appear as a non-secure deviation from the brand's core. Familiarity with a reputable brand like Adobe can paradoxically increase scrutiny and raise expectations for new products. While Brand Recognition negatively influences adoption, likely due to misalignment between established brand identity and new product offerings, Brand Trust mitigates this barrier. Trusted brands alleviate concerns about data security, reliability, and output quality, fostering sustained use and loyalty. Professionals prefer tools from brands they trust, which reduces perceived risks and encourages long-term adoption. Our findings corroborate these insights, demonstrating that Brand Trust has a positive, significant relationship with Behavioral Intention to use Gen AI text to image. Users who trusted Adobe as a Gen AI text-to-image service provider were likely to adopt and engage with this service. Prior research also demonstrates that trust in a brand has a positive influence on Behavioral Intention when the users trust the brand behind the technology to fulfill its promises and offer a positive user experience (Ameen *et al.*, 2021).

Additionally, there is a risk that Gen AI technology may be perceived as overshadowing human creativity, leading to a decline in adoption (Caporusso, 2023). However, trusted brands could help mitigate these negative perceptions and foster a more positive view of Gen AI's contribution to creative fields.

From a brand management perspective, marketing strategies should emphasize performance benefits and align brand communications with user expectations. Sub-branding can address misalignment by differentiating AI services from traditional offerings, as seen in Adobe's case. Building Brand Trust through ethical practices, partnerships with industry influencers, and transparent messaging can further enhance adoption, ensuring Gen AI integrates seamlessly into creative workflows.

The methodology employed in this research offers several strengths and limitations that must be considered. The use of PLS-SEM provided robust validation of the research model, ensuring reliability and validity of findings. However, the sample selection process, which relied on online surveys targeting creative professionals in Spain and the US, may have introduced selection bias. The sample size only slightly exceeded the required minimum to apply the PLS-SEM statistical technique. Additionally broader representation across different creative sectors and geographical regions would strengthen generalizability. Investigating how different creative disciplines (e.g., design, advertising, filmmaking) engage with Gen AI could yield more nuanced insights. Second, no multigroup analysis was performed, leaving a research gap in understanding differences between groups based on age, gender, place of residence, or prior experience with Gen AI. This suggests a direction for further research. Another limitation is the representativeness of the sample within the broader creative industry. Although random sampling was used, the sample is skewed towards creative direction and content creation, with limited diversity in creative profiles in music, or writing. This may impact the generalizability of the findings. Future studies should also examine how brand fit and perceived AI ethics influence adoption, given the growing discourse around ethical AI practices. Methodologically, employing experimental designs to test causality or conducting longitudinal studies to assess evolving perceptions over time could further

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enrich the understanding of Gen AI adoption trends. Another limitation relates to brand fit: Adobe was chosen as the primary subject for brand factors. However, the results indicated a negative influence of Brand Recognition on Behavioral Intention. This suggests that selecting different brands for future studies may help generalize findings. Additionally, further research could expand the measurement model by incorporating other consumer-based brand equity variables, such as Brand Loyalty and Perceived Quality. It could benefit from understanding specific users' expectations and branding aspects that are not aligned with their perception. Despite these limitations, this study provides a foundation for advancing theoretical and practical insights into the adoption of Gen AI in the creative industries. While this focus provides valuable insights into how AI tools are adopted in creative fields, this may not fully capture the views of professionals in other sectors with less familiarity with AI.

Conclusions

In conclusion the study contributes to the growing body of knowledge on Gen AI adoption in the creative industries, by offering a nuanced understanding of the influences of Consumer Based Brand Equity factors. The findings highlight that Performance Expectancy and Facilitating Conditions significantly drive adoption, while Brand Trust also plays a crucial role. Interestingly, Brand Recognition negatively impacted adoption, suggesting that strong associations with traditional creative tools may create resistance to Gen AI.

While Gen AI service-based brands are gaining traction in the market, the academic landscape is still developing a robust framework to help understand the adoption process and mitigate the barriers. This research contributes to the growing body of evidence on Gen AI adoption, particularly in the creative industry. The study also provides practical implications for both professionals in the creative industry and brand managers of AI service-based brands. From a practical perspective, these insights help creative professionals, AI developers, and policymakers understand key adoption drivers and barriers. For the empirical field, this research contributes by extending the UTAUT framework with brand-related constructs, offering a novel perspective on technology acceptance in creative industries. Future research can build on these findings by exploring industry-specific variations, cross-cultural differences, and the evolving role of AI ethics in adoption decisions. This research lays the foundation for future studies on Gen AI adoption and offers insights that could guide both theoretical advancements and practical strategies for promoting AI tools in creative industries.

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