Exploring Human-AI Collaboration in Creative Workflows: A Case Study on Acceptance and Efficiency in Brand Design

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***Abstract*—Creative workflows are increasingly shaped by Generative AI (GenAI) tools supporting the ideation and design process. This is also relevant for brand design. Here, tools like DALL-E 3 (Deep Artificial Language Learning for Embedding - Version 3) enable designers to generate visual logo ideas from textual prompts, offering new levels of speed and inspiration. However, it is unclear to what extent such tools are accepted and perceived as efficient by designers. This study investigates Human-AI collaboration (HAIC) in the ideation phase of logo design by applying a research approach based on the Technology Acceptance Model (TAM) and the Task-Technology Fit model (TTF). A quantitative empirical study was conducted to analyze how perceived ease of use, usefulness, and task-technology fit influence the acceptance and efficiency of using the text-to-image GenAI tool DALL-E 3. The data of this study was collected through an online survey among students and professionals in the field of design in Germany. The results confirm that task fit and usability significantly impact the acceptance of the GenAI tool DALL-E 3, while task alignment contributes to increased efficiency in creative workflows.**

Keywords-Human-AI Collaboration (HAIC); Creative Workflows, Logo Design; Generative Artificial Intelligence (GenAI); Technology Acceptance Model (TAM); Task-Technology Fit (TTF).

I. INTRODUCTION

GenAI tools are transforming creative workflows by enabling the automated generation of visual content based on text prompts. Within the design field, particularly in logo development, these tools offer new ways to explore ideas quickly and efficiently [1]. Unlike traditional software, text-to-image GenAI tools, such as DALL-E 3, combine machine learning with large-scale image data sets to help designers in the early ideation phase of the design process [2]. DALL·E 3 is a GenAI model developed by OpenAI that transforms natural language prompts into images by leveraging a multimodal architecture combining text and image embeddings, enabling users to generate detailed visuals from textual descriptions [3].

In the context of Human-AI Collaboration (HAIC), this development represents a shift from automation, where tasks are entirely delegated to machines, to augmentation, where Artificial Intelligence (AI) enhances human creativity without replacing it [4]. In creative design, a shift from linear AI tools toward nonlinear Human-AI collaboration, aligning better with designers' iterative and exploratory workflows, is seen. AI agents are increasingly perceived not just as tools but as opinionated collaborators who support creative reflection and remixing [5]. Studies have shown that such collaboration can improve creative output by combining human intuition with AI's generative capabilities [6]. However, the technology acceptance of these technologies is shaped mainly by designers' perceptions, particularly regarding the capabilities of AI and its integration into existing creative workflows [7].

Our empirical study investigates technology acceptance and efficacy using the GenAI tool DALL-E 3 in the ideation phase of logo design. We apply the xTAM-TTF model as proposed by [8], combining the TAM by [9] and the TTF model by [10]. We adopted the research model to the creative domain in early-stage design workflows, particularly logo design ideation, to analyze acceptance and perception on efficiency, regarding AI Tools in logo design. Against this background, we address the following research questions:

- **RQ1:** How do perceived ease of use and usefulness of DALL-E 3 influence its acceptance in the ideation phase of logo design?
- **RQ2:** To what extent does the task-technology fit of DALL-E 3 contribute to efficiency gains in creative workflows?

This article is structured as follows: Section II introduces the theoretical background on the TAM and the TTF, followed by a Section III on related work on HAIC in creative workflows. Section IV describes the methodology and approach of our study. The results are presented in Section V. Finally, a conclusion is given in Section VI, including a discussion, limitations, and outlook.

II. THEORETICAL FOUNDATION

In this section, we provide the theoretical background concerning this study by introducing the creative design process and HAIC (II-A and II-B). Moreover, we explain the TAM (II-C), followed by the TTF model (II-D).

A. Creative Workflows in the Design Process

Creative workflows describe a structured and dynamic process to generate, develop, and refine ideas. Especially in design, these workflows are essential for translating abstract concepts into concrete outcomes. Creative workflows typically consist of iterative phases supported by collaboration and feedback loops [11].

A fundamental characteristic of creative workflows is their non-linear nature. They adapt flexibly to evolving project goals, integrating new insights or shifts in direction. This dynamic balances structure and creative freedom, fostering innovation through exploration [12]. To support this, various methods and frameworks are often applied to clarify objectives and guide problem-solving activities [13].

An early model on creative workflows by [14] distinguishes four stages: ***(1) preparation***, ***(2) incubation***, ***(3) illumination***, and ***(4) verification*** [14]. These stages describe the path from initial problem definition and subconscious idea development to moments of insight and final evaluation. Additional research has identified an intermediary "intimation" phase, which bridges unconscious processing and conscious realization [15].

Modern approaches emphasize the relevance of social and contextual factors that shape creativity throughout the workflow. For example, studies have shown that factors, such as team dynamics, cultural background, and motivational drivers significantly influence the creative process, particularly in collaborative environments on design tasks [16]–[18].

For logo design, this creative process is described as ideation. Ideation is a central step in brand design and forms the bridge between the initial research and the final realization of the logo. In this phase, designers devote themselves intensively to the systematic exploration and development of concepts and sketches that are intended to express the identity and core values of the brand. This step in the creative workflow of brand designers follows a structured framework that includes the definition of brand values, the brainstorming of visual elements and the iterative refinement of ideas through feedback loops. Without AI support, brainstorming sessions are often held at the beginning to encourage creativity and collaboration between the designers. This open environment enables the development of different concept ideas. Visual elements, typography and symbols that specifically harmonize with the brand's mission and target group are analyzed [19]. Using GenAI tools as support of design activities can be classified to HAIC described in the following.

B. Human-AI Collaboration (HAIC)

HAIC describes a dynamic, interactive process in which humans and AI systems jointly contribute to task completion by combining their respective strengths [4]. Unlike fully automated systems, the HAIC model emphasizes augmentation, enhancing human capabilities through AI support [20].

Users rely on AI for data-driven input but retain control over decisions, ensuring that human expertise remains central [21]. In practice, this is reflected in forms such as task delegation, where AI takes over specific routine components, allowing users to focus on higher-level creative work [22].

AI can also support decision-making by offering context-relevant recommendations. The extent to which users accept these suggestions depends on the system's transparency and its ability to inspire trust [23] [24]. In creative fields, such as design, HAIC enables faster idea generation without replacing human judgment. This illustrates the difference between using AI for automation, which aims to replace human labor, and augmentation by AI according to the HAIC model [25].

C. Technology Acceptance Model (TAM)

The TAM by [9] is a foundational framework for analyzing user acceptance of new technologies. It builds on the Theory of Reasoned Action (TRA) and focuses on two key constructs: *Perceived Usefulness (PU)* and *Perceived Ease of Use (PEOU)*. PU refers to the degree to which a person believes that using technology enhances their job performance, while PEOU describes how effortless the technology appears to be in use [9]. The TAM is illustrated in Figure 1.

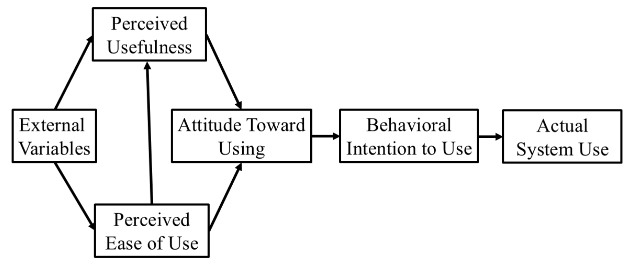

Figure 1. Technology Acceptance Model (TAM) by [9]

TAM suggests that both constructs influence the user's attitude toward using a system (AT), which in turn predicts behavioral intention. Moreover, PEOU indirectly impacts PU, as systems perceived as easy to use are often judged more useful. These interrelations have been confirmed across multiple domains, including mobile apps, online banking, and e-learning environments [26][27] [28].

Despite its wide application, TAM has been criticized for oversimplifying acceptance processes by excluding emotional, contextual, or experiential factors [29] [30]. In response, later extensions, such as the TAM3 incorporated constructs like Social Influence (SI) and facilitating conditions to enhance explanatory power [30]. Recent studies have also explored, for example, how individual differences and motivational factors affect acceptance across diverse cultural and technological contexts [31], [32]. In this study, we additionally included SI and Social Recognition (SR) as external variables to TAM. These factors are often examined in extended models to capture social dynamics that may shape users' attitudes towards technology adoption [30].

The continued evolution of the TAM results from the need for adaptive models that reflect the complexity and the context of user-technology interaction and motivational dimensions.. The TTF model, which describes such a context for the task environment, is described in the following.

D. Task-Technology Fit (TTF)

The TTF model developed by [10] provides a framework to assess how well a technology supports the tasks it is intended to facilitate. The core assumption is that a good match between task requirements and technological capabilities leads to higher performance and user satisfaction [10].

TTF distinguishes between the *Task Characteristics*, such as complexity and cognitive demand, and *Technology Characteristics*, like functionality and usability, illustrated in Figure

2. The better these two dimensions align, the more likely it is that users can accomplish their goals efficiently [33].

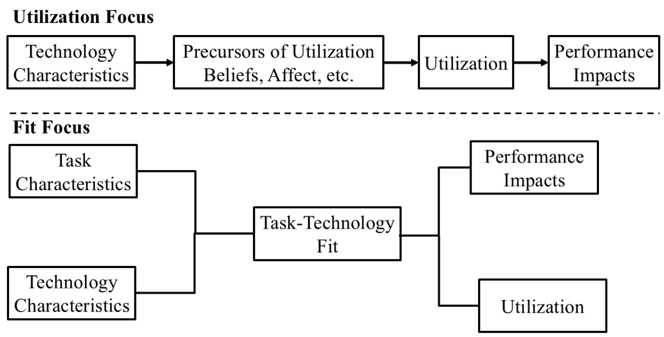

Figure 2. Task-Technology-Fit Frameworks by [10]

Although initially part of the broader Technology-to-Performance Chain (TPC), TTF has been widely adopted as a standalone approach due to its practical applicability. Empirical studies have confirmed its relevance across domains—for example, in healthcare systems where alignment between tools and clinical workflows improved user satisfaction, and in education where matched learning technologies enhanced engagement and outcomes [34][35].

In the context of creative work, TTF can be applied to evaluate whether generative AI tools meaningfully support design-specific tasks. The TTF can also be combined with the TAM, resulting in the xTam-TTF Model, later utilized for the research model. This enables the assessment of the perceived efficiency of AI on the process of logo design.

III. Related Work on HAIC in Creative Workflows

Research on generative AI in creative workflows is still in its early stages, particularly regarding domain-specific applications such as logo design.. While the number of studies is growing, most focus on technical capabilities or general user perceptions rather than domain-specific applications such as logo design. For example, the study conducted by [36] discusses ethical concerns and opportunities associated with DALL-E yet provides limited insight into workflow integration [36]. Similarly, [37] highlights the relevance of AI-generated content in creative industries but does not explore concrete use cases in branding [37]. To date, few empirical studies have examined how generative AI tools are integrated into the specific tasks and decision points of visual identity design, such as logo ideation.

Recent research on HAIC emphasizes the potential of AI to augment creative thinking and enhance task performance. However, it also stresses the importance of trust, transparency, and user-centered design in determining actual adoption [4][21]. These insights underline that beyond technical quality, the perceived integration into existing workflows plays a decisive role in acceptance.

Despite these contributions, a research gap remains regarding the evaluation of generative AI in specific phases of the creative process, especially early-stage ideation in visual design. This study aims to address this gap by analyzing the use of DALL-E 3 in the ideation phase of logo creation.

IV. Methodological Approach

We conducted a comprehensive study examining the technology acceptance, and efficiency using the GenAI tool **DALL-E 3** for supporting designers in the idea generation phase and logo design. DALLE-E 3 is the image generation tool from the company Open-AI [38]. It can be used to generate images based on textual prompts. The technology is included in the flagship product of Open-AI, ChatGPT. Here, DALL-E 3 can be accessed with a text request. DALL-E 3 is chosen as a research object based on the relevance of Chat-GPT, in which it is integrated. In 2024, 48% of German respondents stated to have used the tool within the last year.

For the analysis, we applied the *xTAM-TTF* model by [8], measuring its core constructs based on 21 validated items. It is chosen because the expansion on external factors enables a more differentiated analysis of user acceptance and ensures the fit between the tasks and the characteristics of the technology, making it eligible for acceptance and perceived efficiency increase in the design phases.

Here the TTF is applied. Within this model efficiency is assessed via the areas of speed, time-save, resources, quality, productivity, results and human factor. The research model and its respective hypotheses and constructs are explained in IV-A and IV-B. The study procedure is described in IV-C.

A. Research Model

The *xTAM-TTF* Model integrates the Technology Acceptance Model (TAM) proposed by [9] with the Task-Technology Fit (TTF) model developed by [10]. The xTAM-TTF model was developed to better explain user acceptance and effective use of gamified, technology-enabled training by integrating motivational, task-related, and technological factors [8].

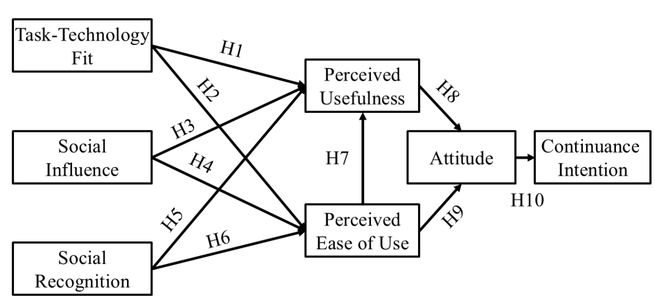

Figure 3. xTAM-TTF Model by [8]

The *xTAM-TTF* Model is illustrated in Figure 3. It further incorporates the factors of SI and SR contributing to social motivation. In particular, SI describes the influence of the social environment, such as colleagues or friends, on the acceptance and continuance intention (CI) to use a technology. It analyzes the extent to which the behavior or recommendations of others influence the decision-making processes of users. SR measures the importance of recognition users receive through the use of a technology. This includes aspects such as increased self-perception, social affirmation, and the feeling of being valued by the environment. By integrating these factors with the core constructs of the TAM and the TTF, the research model enables a comprehensive analysis of both individual and social acceptance. Based on the proposed model, we provide the respective hypotheses in the following.

B. Model Constructs and Hypotheses

The xTAM-TTF model applied in our study comprises the following seven constructs and their corresponding measurement items as defined by [8]:

- **TTF**: Perceived alignment between technology features and task requirements
- **SI**: Influence of the social environment on tool adoption
- **SR**: Visibility and perceived ease of tool
- **PEOU**: Perceived effort required to use the tool
- **PU**: Perceived value in improving productivity or creativity
- **AT**: Users' general stance toward using the tool
- **CI**: Intention to keep using the tool over time

Based on these constructs, ten hypotheses were formulated, indicating the causal relationship between the constructs in the research model (See Table I). In addition, the hypotheses were adapted to the object of the study–logo design ideation.

TABLE I: OVERVIEW OF MODEL HYPOTHESES

Nr.	Hypothesis	Variables
H1	TTF positively affects the perceived usefulness of DALL-E 3 in logo design ideation.	TTF → PU
H2	TTF positively affects the perceived ease of use of DALL-E 3 in logo design ideation.	TTF → PEOU
H3	SI positively affects the perceived usefulness of DALL-E 3 in logo design ideation.	SI → PU
H4	SI positively affects the perceived ease of use of DALL-E 3 in logo design ideation.	SI → PEOU
H5	SR positively affects the perceived usefulness of DALL-E 3 in logo design ideation.	SR → PU
H6	SR positively affects the perceived ease of use of DALL-E 3 in logo design ideation.	SR → PEOU
H7	PEOU positively affects the perceived usefulness of DALL-E 3 in logo design ideation.	PEOU → PU
H8	PU positively affects the attitude toward using DALL-E 3 in logo design ideation.	PU → A
H9	PEOU positively affects the attitude toward using DALL-E 3 in logo design ideation.	PEOU → A
H10	Attitude toward using DALL-E 3 in logo design ideation positively affects continued use intention.	A → CI

C. Study Approach

We conducted a quantitative study using an online survey based on a convenience sample regarding individuals with experience in brand and visual design. The survey was deployed digitally using the platform *Unipark* [39] and remained accessible from *December 16, 2024* until *January 10, 2025*. Participants were recruited as a convenience sample from various channels, including social media, academic networks, mailing lists, academic networks, and professional communities.

Participants were selected based on predefined criteria to ensure domain relevance regarding logo design: Only individuals with either academic or professional experience in design-related fields or specific expertise in branding were included. Respondents who did not meet these qualifications were excluded from the analysis to ensure the validity of the results.

To standardize participants' understanding of the study context, a design scenario involving using DALL-E 3 for a fictional brand was presented. Participants were introduced to the tool via a short explanation and a demonstration video, followed by a detailed use case description. This was done to align their responses with a consistent frame of reference. The use case is described in the following:

> A brand designer has been tasked with creating a logo for a new client. The client is the brand "BubbleBloom", which stands for refreshing, botanical-inspired craft soft drinks made from natural ingredients. The brand is aimed at a young, creative audience that values aesthetics, sustainability, and enjoyment. The logo should appear playful, modern, and authentic. The designer would like to develop initial visual concepts for the logo during the brainstorming phase. To support his creative approach, he decides to use Dall-E

Examples of possible logo designs created for this use case with DALL-E, were shown to respondents of the survey to assess to potential of the tool. One example is shown in Figure 4.

Figure 4. Exemplary AI-generated Logo-Design

Based on the contextualization of the application area of DALL-E in the logo design process, the supplementary description of the use case on the use case of logo design

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ideation to be evaluated, and the exemplary results of the DALL-E tool, the participants were asked to complete a questionnaire. This online questionnaire contained the following sections:

- Demographic questions, prior experience with brand design, perception of and collaboration with GenAI tools.
- Validated items adopted from the xTAM-TTF model by [8] to evaluate factors for HAIC acceptance of DALL-E as presented in Section IV-A.
- Additional questions to access the expected efficiency of using DALL-E in the design process based on [16].

To assess efficiency, respective aspects concerning the logo design process (see Section II-A) are conceptualized based on relevant criteria from different research articles. In particular, the five aspects simplicity [40], memorability [41], relevance [42], versatility [43] and uniqueness [44] were applied. All items are based on a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5).

V. RESULTS

This section summarizes the empirical evaluation results of this study. In V-A, demographic information regarding the convenience sample and general insights into the perception and usage of GenAI tools are provided. Concerning the research model, we applied a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach following the standard procedure by [45] using SmartPLS4 software [46] for the statistical evaluation of both, the measurement and the structural model. Section V-B presents the empirical findings.

A. Descriptive Evaluation Results

1) Sample Demographics: A total of 135 responses were collected, with 109 completed questionnaires. The final sample of 83 valid cases was determined by filtering based on the proposed eligibility criteria. Concerning their background, most identified as either students in design-related programs or professionals in the creative industry. Participants were well-distributed across age groups, with the highest representation in the 25–34 age range. Nearly half of the respondents were actively employed in design-related fields, while around a third were current students. The sample demographic is shown in Table II.

Moreover, we examined the participants' experience in brand design, aiming to contextualize their familiarity with the tasks relevant to the study. Over three-quarters (64 out of 83) reported direct experience with branding processes, including logo creation, concept development, and brand communication. Regular involvement in brand-related tasks (23 out of 32) and over five years of experience were common among professionals (10 out of 23).

2) Perception and Usage of GenAI Tools in Brand Design: We further explored the use and perception of AI tools in design contexts, particularly on generative image models such as DALL-E 3. Results revealed that nearly half of the participants had already used DALL-E 3 (43%), primarily for ideation and concept development, followed by Adobe Firefly (40%). The most common use cases for GenAI tools among respondents included idea generation and concept development (63%), creating visual drafts (36%), and modifying designs (36%).

TABLE II: DEMOGRAPHIC OVERVIEW OF THE SAMPLE

Category	Attribute	Count
Gender	Female	46
	Male	37
	Diverse	0
Age Group	18–24 years	26
	25–34 years	29
	35–44 years	15
	45–54 years	6
	55+ years	7
Occupational Status	Working in design-related field	40
	Studying design-related subject	29
	Neither	14
Study Field	Media Management	13
	Media Design	9
	UX/UI Design	2
	Other / No response	5
Job Field	Graphic Design	10
	UX/UI Design	9
	Illustration	7
	Branding / Corporate Design	4
	Product Design	4
	Fashion / Textile Design	3
	Other Design-Related	3

Participants expressed their attitude on a scale of 1 (strongly disagree) to 5 (strongly agree), shown in Table III. Overall, participants expressed a positive attitude toward the tool's usefulness and ease of integration (3,9) while remaining cautious about issues such as output quality (3,0) and legal implications (3,5). Nevertheless, the participants acknowledged the tool's capacity to enhance efficiency in the initial creative phases (3,8). However, they also emphasized the necessity of human judgment in refining and evaluating design outcomes (4,1).

TABLE III: PARTICIPANTS' PERCEPTION OF EFFICIENCY GAINS THROUGH AI TOOLS

No.	Statement	M
1	AI tools can accelerate ideation and lead to quicker first concepts.	4.0
2	Using AI tools can save time and resources during creative work.	3.7
3	AI tools improve the quality of generated designs.	2.9
4	I believe AI tools can boost my personal productivity during ideation.	3.7
5	While AI makes brand design more efficient, the results become more interchangeable.	3.6
6	Despite AI, humans remain essential for efficient brand design.	4.1

Approximately half of the participants emphasized data privacy as a significant concern for the effective use of AI in design (49%). Additionally, ease of use (41%), along with the transparency and explainability of AI systems (40%) were regarded as important factors. In contrast, the availability of training offers or the exclusive use of ethically sourced data for AI training was not considered essential (31%).

TABLE IV: RELIABILITY AND VALIDITY EVALUATION RESULTS

Construct	Item	Loading	Cronbach's α	rho_A	rho_C	VIF	AVE
TTF	TTF1	0.860	0.809	0.821	0.875	2.029	0.637
	TTF2	0.772				1.695	
	TTF3	0.709				1.360	
	TTF4	0.844				1.949	
SI	SI1	0.816	0.883	0.916	0.927	1.870	0.810
	SI2	0.948				4.072	
	SI3	0.931				3.596	
SR	SR1	0.887	0.878	0.893	0.925	2.407	0.804
	SR2	0.887				2.756	
	SR3	0.877				2.231	
PU	PU1	0.903	0.868	0.870	0.919	2.461	0.791
	PU2	0.872				2.104	
	PU3	0.894				2.327	
PEOU	PEOU1	0.869	0.851	0.878	0.908	2.233	0.767
	PEOU2	0.886				1.845	
	PEOU3	0.873				2.356	
A	A1	0.874	0.858	0.858	0.913	2.057	0.778
	A2	0.865				2.063	
	A3	0.907				2.584	
CI	CI1	0.929	0.848	0.848	0.929	2.178	0.868
	CI2	0.934				2.178	

B. Empirical xTAM-TTF Model Evaluation

1) Measurement Model: The evaluation of the measurement model included the analysis of indicator reliability, internal consistency, convergent validity, and discriminant validity following the standard procedure as defined by [45].

First, indicator reliability was evaluated based on the standardized outer loadings, all exceeding the recommended threshold of 0.708. Internal consistency was validated by Cronbach's Alpha, composite reliability (rho_c), and reliability coefficient (rho_a), all of which were within the acceptable range of 0.60 to 0.90. Table IV shows the evaluation results regarding the quality criteria.

Convergent validity was assessed using the average variance extracted (AVE), with all constructs exceeding the minimum requirement of 0.50. Although the Heterotrait-Monotrait (HTMT) ratio exceeded the critical value of 0.90 (illustrated in *cursive*) in two cases (see Table V), the Fornell-Larcker criterion and cross-loading analysis indicated sufficient discriminant validity. Consequently, no changes to the measurement model were required.

TABLE V: HTMT EVALUATION RESULTS

	A	CI	PEOU	PU	SI	SR	TTF
A	1						
CI	*0.949*	1					
PEOU	0.561	0.519	1				
PU	0.885	0.840	0.769	1			
SI	0.569	0.697	0.327	0.408	1		
SR	0.734	0.681	0.369	0.572	0.651	1	
TTF	0.894	0.771	0.838	*1.037*	0.340	0.588	1

2) Structural Model: The structural model was analyzed to examine the relationships between the latent variables. All variance inflation factor (VIF) values were below the critical threshold of 5, indicating no serious multicollinearity issues.

Path coefficients, t-values, and p-values were calculated using bootstrapping with 5,000 iterations and a significance level of 5%. A visual representation of the structural model and its path coefficients is shown in Figure 2.

TABLE VI: STRUCTURAL MODEL EVALUATION RESULTS

H.	Relationship	VIF	Coeff.	t-Val.	p-Val.	Sig.
H1	TTF → PU	1.000	0.758	10.025	0.000	Yes
H2	TTF → PEOU	1.855	0.716	8.654	0.000	Yes
H3	SI → PU	2.078	0.086	1.594	0.111	No
H4	SI → PEOU	1.855	0.111	1.207	0.227	No
H5	SR → PU	1.487	0.047	0.631	0.528	No
H6	SR → PEOU	1.512	-0.071	0.572	0.567	No
H7	PEOU → PU	1.787	0.097	1.900	0.058	No
H8	PU → A	1.797	0.794	10.341	0.000	Yes
H9	PEOU → A	1.323	-0.042	0.453	0.651	No
H10	A → CI	2.388	0.809	15.990	0.000	Yes

TTF showed significant positive effects on both PU and PEOU, supporting hypotheses H1 and H2. This indicates that a higher alignment between the tool's features and the requirements of the ideation task is associated with more positive evaluations regarding usefulness and usability.

PU also had a significant effect on AT, confirming H8. Additionally, ATshowed a strong and significant effect on CI, confirming H10. These two relationships complete the model's output side, connecting perceptions of usefulness to long-term use intentions via user attitude.

No significant relationships were observed for SI or SR on PU or PEOU (H3 to H6). Similarly, PEOU did not significantly affect PU or A (H7, H9), and those hypotheses were rejected.

In total, four out of ten hypotheses (H1, H2, H8, and H10) can be confirmed by the statistical analysis.

VI. Conclusion

A. Discussion and Implications

This study examined the acceptance and perceived efficiency of the AI-based image generator DALL-E 3 in the ideation phase of logo design. The perception of efficiency gains through AI tools shows the potential for AI-Tools in ideation, saving resources and increasing productivity. However, since quality of output of AI tools is not seen as beneficial. Human impact on the design process is still needed to benefit from efficiency gains. By applying the extended xTAM-TTF model, key factors influencing user perception and tool adoption were identified. In particular, **TTF** positively influences both Perceived Usefulness and Perceived Ease of Use. Moreover, Perceived Usefulness has a positive influence on Attitude, which in turn positively influences CI, thus confirming the core constructs of the TAM. To conclude, using DALL-E 3 in the ideation phase of logo design is generally accepted positively. Moreover, the findings show that the alignment between the tool's functionalities and task requirements plays a central role in shaping perceived usefulness and ease of use. Regarding practical implications, designers are likelier to adopt and use GenAI tools like DALL-E 3 when tailored to specific design tasks and seamlessly integrate into creative workflows.

In contrast, social factors such as SI and SR did not show significant effects. This result suggests that individual and task-related assessments are more relevant for tool adoption in creative workflows than external opinions. Overall, the results underline that functional value and task relevance are more decisive for designers than social dynamics when considering the use of generative AI tools.

B. Limitations

However, several limitations must be drawn. Although the study targeted participants with relevant design experience, the sample size was relatively small (n = 83), limiting the statistical power and generalizability of the findings. Moreover, the convenience sampling approach merges two distinct user groups—students and professionals—who may differ significantly in design experience, technological familiarity, and attitudes toward GenAI tools. This may affect the generalizability of the results. Using a hypothetical case study ("BubbleBloom") and a predefined DALL-E 3 interaction provided a controlled basis for evaluation. Still, it may not fully capture the complexity and variability of real-world design processes. Participants did not actively use the tool themselves, which may have influenced their evaluation of efficiency and creative potential. By focusing solely on DALL-E 3, the findings are limited in scope and may not be directly transferable to other generative AI tools or domains beyond logo design. Differences in capabilities, UI, and output quality across different tools were not explored.The study relies on established acceptance models (TAM and TTF) and did not include qualitative methods such as interviews or diary studies. While effective for quantifying relationships, this reduces the methodological novelty and limits the depth of contextual understanding. Although ethical concerns such as copyright and data privacy were briefly addressed in the survey, these aspects were not explored in detail.

C. Outlook & Future Research

The study results provide valuable insights into the factors influencing the acceptance and perceived efficiency of AI-based tools, such as DALL-E 3, in creative workflows for practitioners and researchers. However, GenAI evolves rapidly, as recent ChatGPT 4o Image Generation developments show [38]. Thus, further research is needed to deepen our understanding of its role in design practice. Future research could also examine how the rise of autonomous AI agents may affect established HAIC models, particularly in terms of user trust, role delegation, and co-creative dynamics in complex design processes.

The study should be replicated with a broader and more diverse sample. In addition, different creative domains, such as advertising, product design, or illustration, can be targeted. Furthermore, combining quantitative results with qualitative methods, such as interviews or observational studies, could deepen the understanding of how designers interact with AI tools in practice.

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