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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 16 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i16.57603

PAPER

Evaluating the Impact of Mobile-Based Generative AI Tools on Visual Design Education

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ABSTRACT

Mobile-based generative artificial intelligence (AI) tools have been increasingly adopted in visual design education. These tools have introduced multidimensional impacts on traditional educational models. However, significant gaps remain in current research regarding their application in visual design education. Existing studies have predominantly addressed the general educational use of generative AI tools, while the specific affordances of mobile platforms and the disciplinary characteristics of visual design have not been sufficiently integrated. Furthermore, research methodologies have largely relied on surveys and interviews, with acceptance modeling limited to surface-level analysis. Some critical factors have been underexplored, resulting in constrained accuracy and comprehensiveness in predicting user acceptance. Centering on the context of visual design education, this study investigated the acceptance of mobile-based generative AI tools among teachers and students. The study was conducted in two parts. First, an acceptance model was constructed by incorporating technological attributes, pedagogical demands, and disciplinary background to identify key influencing factors and their underlying mechanisms. Second, based on the proposed model, scientific prediction methods were employed to dynamically forecast acceptance levels among different types of teachers and students across various teaching stages. This study aims to provide a theoretical foundation for the deep integration of mobile-based generative AI tools in visual design education, thereby supporting the refinement of instructional strategies and fostering the cultivation of high-caliber design professionals equipped to adapt to technological transformation.

KEYWORDS

mobile-based generative artificial intelligence (AI) tools, visual design education, acceptance modeling, acceptance prediction

1 INTRODUCTION

Amid the rapid evolution of digital technologies, generative artificial intelligence (AI) [1–4] has been recognized as a transformative technology that is fundamentally reshaping operational paradigms across various fields. In the domain of visual design,

Meng, L. (2025). Evaluating the Impact of Mobile-Based Generative AI Tools on Visual Design Education. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(16), pp. 189–203. https://doi.org/10.3991/ijim.v19i16.57603

Article submitted 2025-05-03. Revision uploaded 2025-07-01. Final acceptance 2025-07-05.

mobile-based generative AI tools [5, 6] have increasingly emerged as essential assistive technologies for both professional designers and design learners, owing to their convenience, efficiency, and creative potential. These tools enable the rapid generation of images, graphics, layouts, and other design solutions, thereby introducing novel modes of creative production and expanding the boundaries of visual expression. With the widespread adoption of mobile devices such as smartphones and tablets [7–9], the application scenarios of mobile-based generative AI tools have been significantly diversified [10, 11]. These tools are not only being extensively utilized in professional design practice but are also gaining prominence within the context of visual design education, exerting multidimensional influences on traditional pedagogical models.

Although the educational applications of generative AI tools have been extensively explored, research focusing specifically on the influence of mobile-based generative AI tools within visual design education remains limited. Previous studies [12, 13] have mainly used questionnaires and interviews to explore teachers' and students' initial views and experiences with these tools. However, they lack in-depth modeling and systematic analysis of user acceptance. Although some research [14–16] has applied technology acceptance models in education, they often overlook the unique features of mobile-based generative AI tools [17] and the specific professional and educational needs of teachers and students in visual design [18]. As a result, predictions of user acceptance are often neither accurate nor comprehensive. These studies' limited methods and narrow focus have made it difficult to uncover the deeper mechanisms and patterns shaping the impact of such tools on visual design education.

This study consists of two main parts. The first part focuses on modeling how teachers and students accept mobile-based generative AI tools in visual design education. The model was designed specifically for this context, combining factors such as technology features, teaching needs, and the professional backgrounds of teachers and students. Key factors and their relationships were analyzed to understand how these tools are adopted in education. The second part involves predicting acceptance levels among teachers and students. Using the established model and empirical data, suitable prediction methods were applied to estimate acceptance at different teaching stages and for different user types. These insights aim to guide the development of targeted teaching strategies. Overall, this study offers a thorough understanding of how mobile-based generative AI tools are currently used and how they are evolving in visual design education. It provides both theoretical and practical guidance to help the field adapt to new technological trends.

2 ACCEPTANCE MODELING OF MOBILE-BASED GENERATIVE AI TOOLS AMONG TEACHERS AND STUDENTS

In various application contexts, the acceptance of mobile-based generative AI tools by teachers and students is commonly evaluated using two scoring models.

a) Five-point model: A multidimensional evaluation index system can be developed based on five key dimensions: 1) technological attributes, 2) professional adaptability, 3) pedagogical value, 4) creative impact, and 5) risk perception. In the technological attributes dimension, indicators include whether the mobile interface fits established visual design workflows and whether the tool's response speed meets the fast-paced needs of design tasks. These are rated on a 5-point Likert scale (1–5). The professional adaptability dimension assesses how well the tool meets the specific needs of visual design education, such as whether it supports export in PSD/AI formats or offers a dedicated visual design resource library. The pedagogical value dimension examines practical teaching and learning benefits, including support for faster idea generation in sketching and multi-version design iteration. The creative impact dimension focuses on professional skill development, evaluating whether the tool limits original thinking or inspires cross-media creativity. The risk perception dimension considers concerns like copyright issues with AI-generated content and the potential decline of manual design skills due to overreliance on the tool. This model refines the structure of user acceptance in a professional education context and provides a layered framework for quantitatively analyzing teacher and student attitudes toward mobile-based generative AI tools.

b) Binary model: Acceptance indicators can be simplified into a two-part evaluation system based on behavioral intention and barrier factors. Key indicators of positive behavioral intention include actions such as "willingness to use the tool for coursework" and "recommending it for design instruction." On the other hand, barrier factors include reasons for rejection like "abandoning the tool due to complex operations" or "perceiving the output as lacking professional quality." In this model, binary judgments (accept/do not accept) must be considered within the context of visual design education. For example, "using the tool continuously in design projects for over three months" can indicate long-term acceptance. Barrier factors should reflect discipline-specific challenges, such as "whether generated typography meets visual communication standards" or "whether automated layout interferes with layout design teaching goals." By clearly dividing responses into "accept" and "do not accept," this model helps quickly identify key influencing factors and lays the groundwork for analyzing how acceptance correlates with user characteristics. It is particularly useful for comparing acceptance levels between teachers with different experience levels and students at various academic stages.

The acceptance rate can be calculated using the following formula:

$$Accept\ Ratio = \frac{Number\ of\ Accept}{Number\ of\ Accept + Number\ of\ Not\ Accept} \tag{1}$$

2.1 Acceptance indicators based on operational data

Acceptance indicators derived from operational data can be categorized into three dimensions as follows:

a) Acceptance indicators based on direct counting of single operations: In the context of visual design education, single-operation counting indicators related to mobile-based generative AI tools must be closely aligned with core pedagogical and learning behaviors. The frequency of tool activation can be adopted as a fundamental indicator of acceptance. This metric captures the average weekly number of times the tool is launched by teachers and students across scenarios such as course preparation, assignment creation, and project-based learning. Higher activation frequencies are generally indicative of deeper integration of the tool into routine instructional or learning practices. The usage frequency of core functions focuses on operations directly relevant to visual design tasks, including intelligent poster layout generation, automated color scheme optimization, and batch export of vector graphic assets. The average monthly invocation of these functions can be measured, as these actions correspond to key stages in the design workflow. Their frequencies serve as direct indicators of the tool's effectiveness in supporting professional tasks. In terms of the task-specific operation counts in instructional settings, indicators include the number of assignments issued using AI-assisted design tasks and the frequency of real-time design demonstrations during class using the tool on the teacher side. On the student side, indicators include the number of initial drafts generated using AI tools in coursework and the quantity of submitted works incorporating AI-assisted design elements. These indicators capture scenario-specific behaviors in the educational environment, providing quantitative evidence of the degree to which the tool has been integrated into instructional processes. Let the usage volume of a specific teacher or student group H_u be denoted as $DL(H_u)$, and the total usage across all groups as $\Sigma DL(H_u)$. The usage proportion of each group is then defined as:

$$DS(H_u) = \frac{DL(H_u)}{\sum DL(H_u)} \tag{2}$$

Let a set of v instructional tasks be ranked by tool usage in descending order. For a given task u, let its rank be $rank_u$. The usage percentile rank of task u is calculated as:

$$DP(i) = \frac{v - rank_i}{v} \tag{3}$$

b) Acceptance indicators based on the relative scale of operational volume: The calculation of relative scales across different operational quantities reveals user behavior preferences and underlying needs during tool usage by teachers and students. The functional usage structure ratio can be employed to assess the proportional use of discipline-specific features versus general-purpose functions. For example, in terms of the ratio of "visual design-specific features" to "general assistive functions," a higher proportion of specialized function usage can be interpreted as indicative of stronger alignment between the tool and the instructional requirements of visual design education. The cross-platform operation correlation can be used to measure the frequency of interaction between mobile-based tools and professional design software such as PS and AI. For instance, the proportion of "instances where AI-generated design drafts are imported into PS for further refinement" to the "total number of exported files from the mobile tool" reflects the degree to which the tool is embedded within the end-to-end design workflow. The inter-group operational divergence ratio compares the frequency of identical operations performed by teachers and students. This comparison facilitates the identification of differentiated usage patterns among user groups and provides a data-driven foundation for optimizing instructional strategies.

In scenarios where significant differences in usage scale exist between teachers and students, direct comparison using absolute values is deemed inappropriate. For such cases, the uninstallation rate, a relative indicator, can be adopted to reflect the proportion of tool uninstallations relative to total usage volume. This metric can be calculated using the following formula:

$$U - IRatio = \frac{Number\ of\ Uninstalls}{\sum DL(H_u)} \tag{4}$$

Similarly, following the release of a new version of a mobile-based generative AI tool, the update rate can be used to indicate the proportion of users (teachers or students) who have adopted the update. The calculation is given by:

$$Update\ Ratio = \frac{Number\ of\ Updates}{Number\ of\ Installs} \tag{5}$$

c) Acceptance indicators based on operational sequence analysis: Acceptance indicators derived from user operation sequences can reveal how deeply users rely on and regularly use a tool. The complexity of these sequences—measured by the number of functional steps taken to produce a design—can reflect user proficiency and acceptance, especially when the sequences are both complex and coherent. Frequent operation patterns help identify behavior models unique to teachers and students. For example, teachers might follow instructional workflows such as "input course topic → AI generates design options → select and annotate → present in class," while students might follow learning-focused steps such as "analyze design brief → AI-assisted sketching → refine manually → submit assignment." The consistency of these patterns over time indicates sustained acceptance.

Operational continuity across different periods can be evaluated by looking at how often the tool is used and how advanced features are adopted during various teaching or learning stages. For instance, increased use of features such as "AI-generated 3D visuals" or "cross-media design solutions" in advanced phases suggests that the tool continues to meet users' evolving needs, reflecting ongoing acceptance throughout the learning process.

3 ACCEPTANCE PREDICTION OF MOBILE-BASED GENERATIVE AI TOOLS AMONG TEACHERS AND STUDENTS

In the context of visual design education, four distinct states of decision-making regarding the use of mobile-based generative AI tools by teachers and students can be defined in relation to specific instructional and learning scenarios:

a) Non-cognitive state: This state refers to a condition in which teachers and students lack basic awareness of the functions, value, or application scenarios of mobile-based generative AI tools. Such unawareness typically results from the absence of relevant technologies in the curriculum, limited dissemination of the tools, or a mismatch with users' fields of interest. Individuals in this state have not yet encountered functions such as intelligent layout generation or color scheme recommendations, placing them in the initial "technology blind zone."

b) Cognitive state: In this stage, basic understanding of the tools' fundamental capabilities and potential applications in education has been formed through exposure to classroom lectures, industry news, or peer discussions. However, no active intention to use the tools has yet emerged. Users in this state are aware of the existence of the tools but have not explored their compatibility with coursework or instructional practices in depth.

c) Willingness-to-use state: This state is characterized by a subjective inclination to incorporate the tool into instructional or learning activities, driven by a recognition of its professional relevance. At this stage, teachers and students are mentally prepared to experiment with the tool—for example, by planning to use

AI-generated design outputs in assignments or preparing to demonstrate tool operations during class sessions.

d) Decision-to-use state: In this stage, the tool has been integrated into practical design or teaching behaviors. Through continued usage, a stable pattern of technical reliance has been established, with tool engagement increasingly linked to the development of professional competencies. Users in this state are regarded as active implementers of the technology.

These four states represent a progressive decision-making continuum, ranging from technological unfamiliarity to deep integration. Collectively, they delineate the evolving trajectory of acceptance of mobile-based generative AI tools among teachers and students in visual design education. Figure 1 shows the flowchart of acceptance prediction for mobile-based generative AI tools among teachers and students.

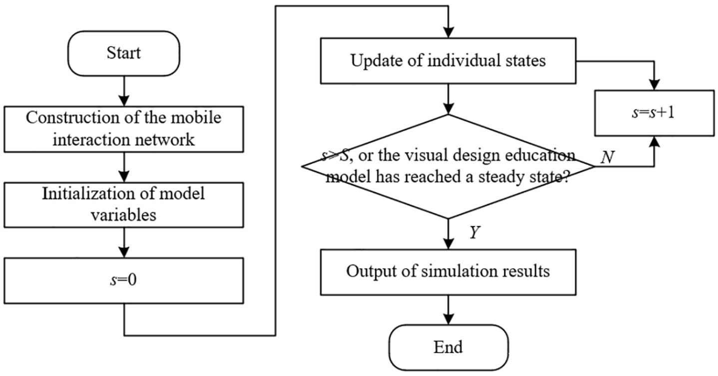

Fig. 1. Flowchart of acceptance prediction for mobile-based generative AI tools among teachers and students

For clarity within the model, the variables and parameters are defined below.

In terms of core variables, U represents the total duration of an individual's continuous involvement in visual design education, reflecting the potential influence of professional educational background on technology acceptance. L denotes the average daily usage time, distinguished between teachers and students, indicating the depth of integration of the tool into teaching or learning practices. V refers to the scale of the mobile interaction network, defined as the total number of individuals within the user's visual design education-related social network, serving as a measure of the foundational structure for technology diffusion. The state variables $b_k(s)$, $a_k(s)$, and $c_u(s)$ correspond to an individual's status at time step s, representing whether the user is in the cognitive state, willingness-to-use state, or decision-to-use state, respectively, thereby enabling precise tracking of technology adoption stages within educational scenarios.

In terms of key parameters, the adoption period s is discretized into units such as weeks or semesters in accordance with instructional cycles. A maximum adoption period S is defined based on the pedagogical rhythm of visual design education, ensuring comprehensive coverage from initial exposure to the formation of stable usage habits. X_{uk} and j_u denote, respectively, the strength of professional communication links between individuals and the degree of individual engagement within the professional network. $X_f(s)$ represents the promotion intensity, encompassing education-specific strategies such as tool integration in classroom instruction, requirements in design competitions, and the incorporation of industry case studies, all of which influence individual cognition. T_u defines the cognitive threshold, influenced by factors such as technological sensitivity and curriculum-tool alignment. S_u denotes the willingness threshold, shaped by the tool's capability to address domain-specific problems and its relevance to instructional evaluation systems. E_u captures the initial effect, reflecting inherent predispositions toward generative technologies. $W(s)$ denotes the global network effect, capturing macro-level influences such as institution-wide promotion policies and industry trends. $H_u(s)$ indicates the local network effect, emphasizing peer-driven behaviors observed in mentoring systems and collaborative learning environments. O_u is defined as the probability of transitioning from willingness to actual usage, which is governed by practical factors such as the operational complexity of the tool and its fit with instructional contexts. Together, these variables and parameters constitute a predictive model framework that is specifically aligned with the educational ecology of visual design.

The evolution rule governing the transition of four states among teachers and students was defined as follows:

a) Transition from non-cognitive state to cognitive state: A state transition occurs when the combined influence of promotional intensity $X_f(s)$ within professional educational scenarios and the perceived reputation effect from interpersonal networks surpasses an individual's cognitive threshold T_u. For example, a student, who first encounters the tool during an in-class demonstration in a UI design course and simultaneously receives usage recommendations from three peers that have participated in digital design competitions, may undergo a state change. If the cumulative influence of these two channels exceeds the individual's acceptance threshold for new technologies, the student transitions from a non-cognitive state (i.e., unaware of the tool) to a cognitive state, in which the tool is recognized as capable of generating interface prototypes. Similarly, a teacher repeatedly exposed to application cases of the tool in guiding capstone design projects during professional development programs—combined with widespread adoption by colleagues in the same department—may surpass the threshold T_u and enter the cognitive state once the cumulative recognition exceeds their individual acceptance barrier. This rule emphasizes the synergistic effect between formal dissemination channels and domain-specific social networks within educational settings. It also highlights how individual professional characteristics modulate the threshold level. This dynamic evolution logic provides an education-ecology-based framework for predicting the transition into the cognitive state.

$$X_f(s) + \sum_{k=1}^{V} X_{uk}\left[a_k(s) + b_k(s) + c_k(s)\right] \geq T_u, a_u(s+1) = 1 \tag{6}$$

b) Transition from cognitive state to willingness-to-use state: A transition from the cognitive state to the willingness-to-use state occurs when the total utility evaluation of the mobile-based generative AI tool by an individual, denoted as $I_u(s)$, exceeds their willingness threshold S_u. In this state change, the individual shifts from understanding the tool's basic functions to developing an intention to actively incorporate it into teaching or learning processes. The individual professional utility evaluation centers on the alignment between the tool and the needs of visual design education. This includes the tool's efficiency in supporting domain-specific tasks, its effectiveness in promoting instructional or learning objectives, and the individual's subjective disposition toward technological innovation. The mobile interaction network effects consist of two components. The global network effect $W(s)$ captures macro-level influences, such as institution-wide promotion strategies or prevailing industry standards.

The local network effect $H_u(s)$ represents peer-driven influence within professional social networks, where tool adoption by colleagues generates reputation-based diffusion. For instance, a visual communication teacher, who discovers that the “intelligent layout generation” feature reduces lesson preparation time by 40%, observes that 80% of early-career colleagues have already incorporated the tool into coursework, and recognizes that AI-assisted design has been embedded into the institution’s updated curriculum guidelines, may reach a total utility evaluation that surpasses their personal threshold S_u for integrating new technologies into instruction. This would result in the formation of an intention to demonstrate the tool in the upcoming layout design course. Similarly, a student who notes that peers using the tool achieve higher efficiency ratings in coursework—and that the tool supports export formats compliant with assignment specifications—may exceed the threshold of perceived learning costs associated with adopting new technology, thereby entering the willingness-to-use state. This transition rule highlights the synergistic role of professional function alignment and social network influence in decision-making within visual design education. Additionally, it emphasizes the moderating effect of individual instructional or learning goals on the willingness threshold. Taken together, these dynamics offer an education-driven framework for modeling the formation of tool adoption intent among teachers and students. Assuming that the utility function is a weighted combination of the individual initial effect E_u, global network effect $W(s)$, and local network effect $H_u(s)$, with corresponding weight parameters β_u, α_u, and ε_u, the expression is as follows:

$$I_u(s) = \beta_u E_u + \alpha_u W(s) + \varepsilon_u H_u(s),\ \beta_u + \alpha_u + \varepsilon_u = 1 \tag{7}$$

It is assumed that, at the initial stage, the mean perceived utility of mobile-based generative AI tools among teachers and students is denoted by ω_1, and the degree of variation in perceived utility is represented by δ_1. The initial individual utility E_u for teachers and students regarding mobile-based generative AI tools is assumed to follow a normal distribution, expressed as:

$$E_u \sim V(\omega_1, \delta_1^2) \tag{8}$$

The global network utility $W(s)$ is the proportion of individuals within the entire mobile interaction network who are using mobile-based generative AI tools. This is computed as:

$$W(s) = \frac{1}{V}\sum_{k=1}^{V} c_k(s) \tag{9}$$

The local network effect $H_u(s)$ captures the influence exerted by other individuals within a teacher’s or student’s social network who are aware of mobile-based generative AI tools on an individual’s acceptance of the tool. Let the influence weights associated with peers in the cognitive state, willingness-to-use state, and decision-to-use state be denoted by ω, ϑ, and δ, respectively, where $\omega < \vartheta < \delta$. Then, the local network effect is calculated using the following expression:

$$H_u(s) = \frac{1}{j_u}\sum_{k=1}^{V} X_{uk}\left[\omega a_k(s) + \vartheta b_k(s) + \delta c_k(s)\right] \tag{10}$$

c) Transition from willingness-to-use state to decision-to-use state: Following the exceedance of the willingness threshold S_u by the individual's total utility evaluation $I_u(s)$, the actual use of the mobile-based generative AI tool is governed by the adoption probability O_u. This probability is influenced by both domain-specific contextual factors and individual behavioral inertia. Domain-specific contextual factors include: a) Teaching task coupling strength, such as whether the submission of AI-assisted design outputs is explicitly required in coursework, or whether AI-generated content has been incorporated into the grading criteria for final design projects. b) Operational threshold of the tool, wherein advanced features such as 3D visual element generation may involve complex parameter configurations, which could lower immediate willingness to use and extend the transition period from intention to action. c) Workflow compatibility, where incompatibility between output formats and professional design software (e.g., PS/AI) may result in delayed tool usage due to anticipated costs in secondary editing. Behavioral inertia factors include teachers' dependence on traditional instructional models and students' aversion to perceived technological risks. For instance, a student in a UI design course may recognize the efficiency of the tool's intelligent prototype generation feature, yet experience an initial reduction in O_u due to incompatibility between exported code and the development platform. The adoption probability may increase only after the release of an updated tool version or the provision of instructional support from the teacher. Similarly, a teacher who identifies that the tool's case library can address 80% of in-class demonstration needs may still be constrained by limited weekly lesson preparation time. In such cases, the adoption probability may increase incrementally—initially through basic tool trials in theory-based sessions, followed by gradual incorporation of advanced features in practical courses. This rule emphasizes the interplay among task-driven instructional demands, technological adaptability, and habitual behavior within visual design education. A probabilistic model was employed to quantify delayed adoption effects, offering a dynamic analytical framework tailored to the rhythms of professional education. Specifically, the cumulative number of adopters is obtained by summing the number of individuals entering the decision-to-use state during each adoption cycle s. The total number of adopters is thus computed as:

$$E(s) = \sum_{u}^{V} c_u(s), 0 < s \leq S \tag{11}$$

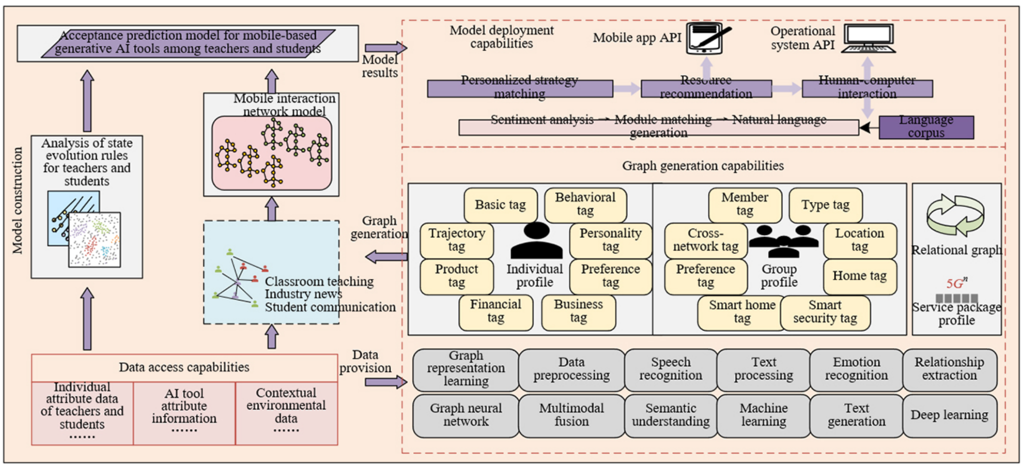

Fig. 2. Architecture of the acceptance prediction model for mobile-based generative AI tools among teachers and students

Figure 2 shows the complete architecture of the acceptance prediction model for mobile-based generative AI tools among teachers and students. The model takes as input three categories of information: individual attributes of teachers and students, attributes of the AI tool, and contextual environmental data. Through the analysis of individual state evolution and the interaction network model, supported by multi-modal technologies, the model enables the contextual adaptation of the tool within instructional settings and facilitates the dynamic prediction of user acceptance.

4 EXPERIMENTAL RESULTS AND ANALYSIS

As shown in the data presented in Figure 3, the acceptance of mobile-based generative AI tools among teachers and students—when 5% of initial adopters are randomly selected—follows a characteristic S-shaped growth curve over increasing time intervals. In the initial phase, acceptance increases slowly, corresponding to the early stage of innovation diffusion during which awareness and trial usage remain limited. In the middle phase, a rapid rise in acceptance is observed, indicating that the tool has undergone effective dissemination and has entered a phase of accelerated adoption among the teacher and student population. In the late phase, the growth trend gradually stabilizes, and the acceptance rate approaches approximately 40%, reflecting a saturation point in the educational context. The experimental results not only provide a clear visualization of the evolutionary trajectory of acceptance in visual design education scenarios but also validate the scientific robustness and predictive reliability of the proposed methodology to simulate the behavioral diffusion process of teachers and students in response to mobile-based generative AI tools through the strong fit to the S-shaped adoption curve.

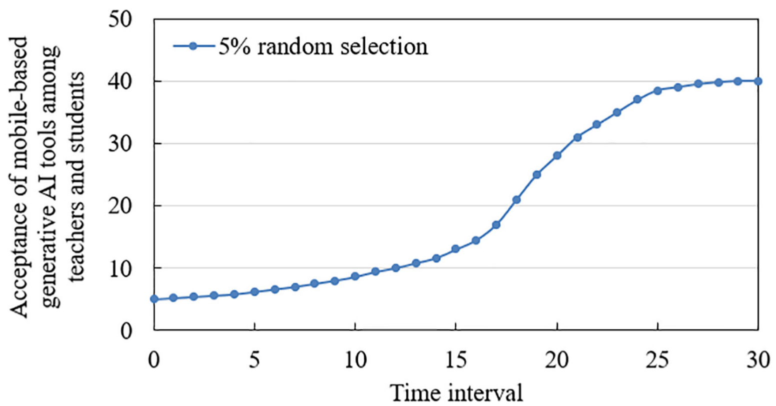

Fig. 3. Simulation results of the mobile interaction network

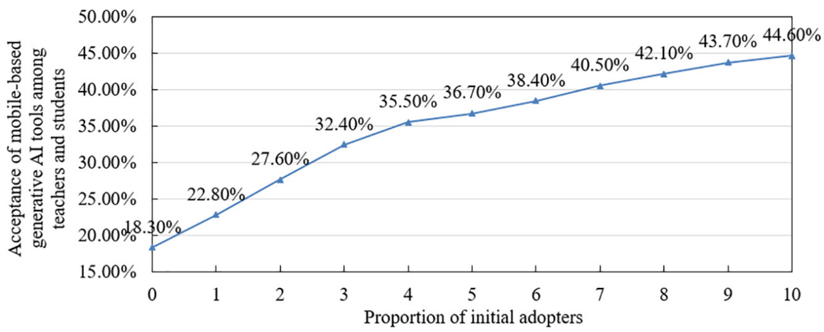

Fig. 4. Relationship between the proportion of initial adopters and the acceptance of mobile-based generative AI tools among teachers and students

As shown in Figure 4, a clear positive correlation can be observed between the proportion of initial adopters and the acceptance of mobile-based generative AI tools among teachers and students. As the initial adopter ratio increases from 0% to 10%, the overall acceptance rate gradually rises from 18.30% to 44.40%. The data points have been fitted to a smooth growth curve, demonstrating the linear influence of the initial adopter proportion on overall acceptance. In relation to the objectives of this study, the results confirm that the proposed prediction method effectively captures the dynamic relationship between early adoption levels and subsequent acceptance behavior. When the proportion of initial adopters is low, acceptance growth remains modest. As the proportion increases, the rate of adoption accelerates while still maintaining a predictable trend. Furthermore, the continuity of the fitted curve and the high degree of alignment with empirical data validate the model's ability to quantitatively predict how acceptance evolves as initial adopters expand.

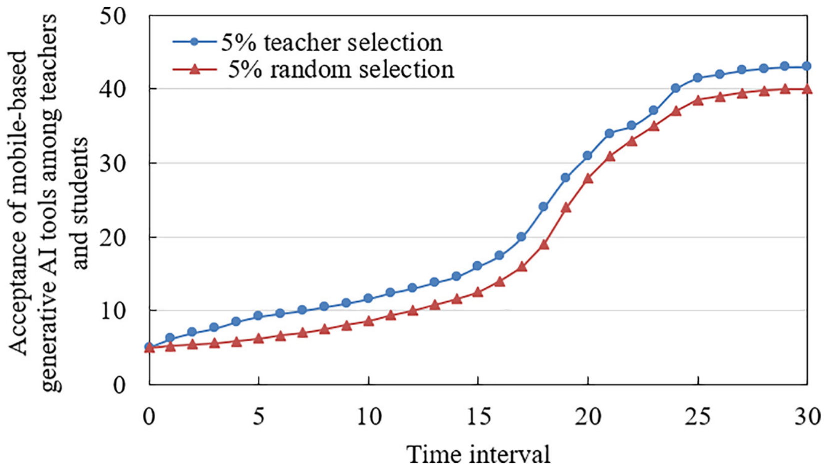

Fig. 5. Influence of initial adopter type on the acceptance of mobile-based generative AI tools among teachers and students

As shown in Figure 5, the influence of initial adopter type—specifically, selecting 5% of teachers versus randomly selecting 5% of users—on the acceptance of mobile-based generative AI tools among teachers and students can be examined. Both groups exhibit S-shaped adoption curves that rise with increasing time intervals. However, the adoption curve associated with "selecting 5% of teachers" consistently shows higher acceptance levels than that of "random selection of 5%." For example, at time interval 25, the acceptance rate under the teacher-based seeding scenario is approximately 43%, compared to 40% for the random selection scenario. This finding indicates that teachers, when chosen as initial adopters, serve as more effective catalysts for the diffusion of the tool within the educational setting. The observed difference between the two adoption curves demonstrates that, once the user type variable is incorporated into the prediction model, the simulated technology diffusion process reflects educational dynamics with greater realism, improving predictive accuracy and practical guidance.

Figure 6 and Table 1 illustrate the differences in the evolution of acceptance levels under various weight parameter combinations. For instance, the green curve, corresponding to the weight set (0.2, 0.2, 0.6), achieves a final acceptance level of 51.3% with a steady-state time of 21 cycles. In contrast, the red curve, associated with the weight set (0.6, 0.2, 0.2), results in a lower acceptance level of 27.5% and requires 28 cycles to reach steady state. These results indicate that weight parameters exert a significant influence on the growth of acceptance: assigning higher weights to key influencing factors accelerates the diffusion process, whereas lower weights suppress it. In alignment with the study's objectives, this outcome validates the effectiveness of incorporating multidimensional weight parameters into the model. It also demonstrates the model's capability to simulate the dynamic variation of acceptance over time and accurately reflect the multivariable interactions underlying teacher and student behavior. In addition, Figure 7 presents the trend of acceptance under varying levels of initial utility variance. All three S-shaped curves show an upward trajectory as time progresses. However, the acceptance curve associated with a variance of 0.1 increases most rapidly, while those with variances of 0.5 and 1.0 exhibit slower growth. This finding suggests that smaller variance in initial utility leads to more efficient diffusion of acceptance.

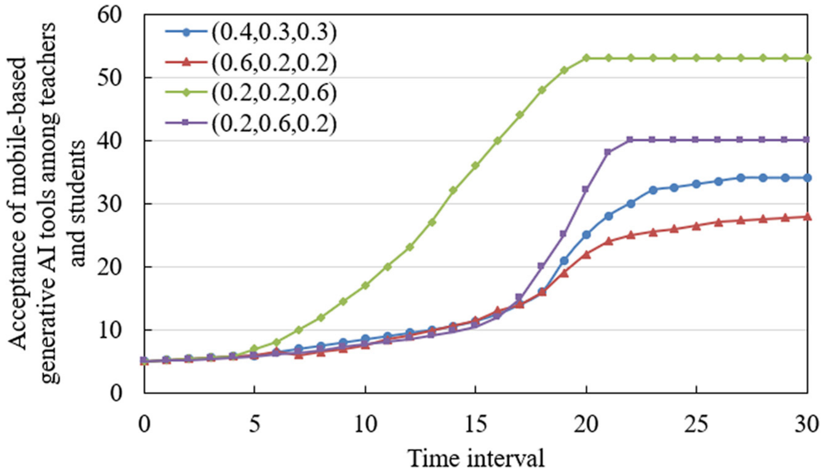

Fig. 6. Influence of weight parameters on the acceptance of mobile-based generative AI tools among teachers and students

Table 1. Relationship between weight parameters and the acceptance of mobile-based generative AI tools among teachers and students

	(0.4, 0.3, 0.3)	(0.6, 0.2, 0.2)	(0.2, 0.2, 0.6)	(0.2, 0.6, 0.2)
Acceptance of mobile-based generative AI tools among teachers and students (%)	35.6	27.5	51.3	42
Time to reach steady state (cycle)	26	28	21	22

As shown in Figure 8, distinct adoption trajectories emerge under different purchase intention threshold scenarios. A greater reduction in the threshold corresponds to a faster rate of adoption and a higher final steady-state value. Specifically, the curve representing a 0.05 reduction in the threshold exhibits an intermediate adoption rate and acceptance level, falling between the initial state and the curve for a 0.1 reduction. These results indicate that lowering the purchase intention threshold significantly promotes the acceptance of mobile-based generative AI tools among teachers and students and that the magnitude of threshold reduction is positively correlated with the degree of acceptance improvement. The experimental results not only visually depict the dynamic relationship between the purchase intention threshold and acceptance levels but also emphasize, through comparative analysis of the adoption curves, the predictive model's scientific validity and practical applicability to accurately simulate the diffusion process under the influence of multiple variables.

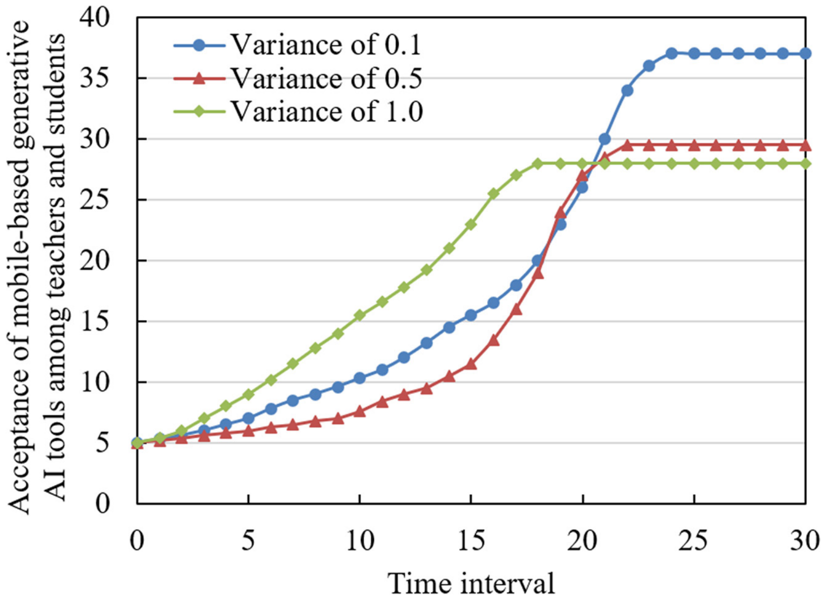

Fig. 7. Influence of initial utility variance on the acceptance of mobile-based generative AI tools among teachers and students

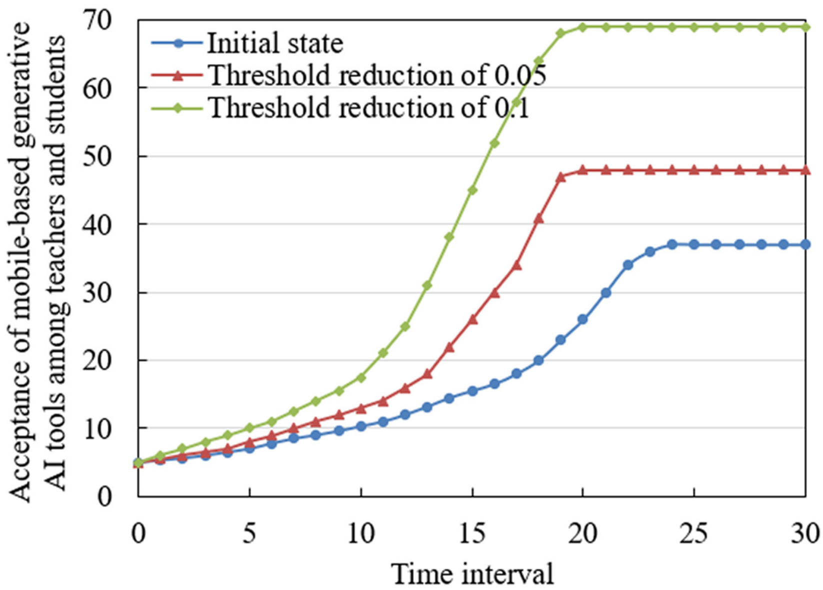

Fig. 8. Influence of purchase intention threshold on the acceptance of mobile-based generative AI tools among teachers and students

5 CONCLUSION

In this study, a model of acceptance toward mobile-based generative AI tools among teachers and students in visual design education was constructed. By integrating technical characteristics, instructional demands, and user-specific background factors, the model revealed the mechanisms by which variables such as initial adopter type, weight parameters, initial utility variance, and purchase intention thresholds influence acceptance dynamics. A theory-driven technology diffusion framework tailored to educational contexts was thereby established. Through an S-curve fitting–based prediction approach, the dynamic evolution of acceptance over time and across variable conditions was accurately simulated. The validity and effectiveness of the proposed method in quantifying the diffusion of adoption behaviors were empirically demonstrated, thereby providing a robust foundation for the formulation of instructional strategies and dissemination plans in educational practice. The findings not only deepen the understanding of educational technology adoption but also offer a practical analytical framework for the integration of AI tools in visual design instruction, contributing both theoretical innovation and actionable insights.

Several limitations should be acknowledged. The simulation data were derived from hypothetical scenarios, and the alignment with real-world educational environments remains to be improved. The generalizability of the model has yet to be empirically verified. Future research may be extended in three directions: a) Real-world instructional data should be collected to optimize model parameters and enhance contextual adaptability, thereby reducing the bias inherent in simulated assumptions; b) dynamic variables should be incorporated to refine temporal prediction capabilities and improve long-term adoption trajectory modeling; and c) empirical studies should be conducted to track the impact of adoption levels on instructional outcomes, forming a closed-loop system of modeling, prediction, and performance evaluation, thereby further validating the practical value of the theoretical model. These advancements are expected to facilitate the transition from theoretical framework to practical educational application, providing more robust support for the innovative deployment of mobile-based generative AI tools in visual design education and promoting the integrated development of educational technology and design pedagogy.

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