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Smart Learning with Generative AI Tools in Higher Education: An Integrated SOR–SDT Model of Student Creative Confidence and Engagement

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Abstract

We investigate how generative AI tools function in smart learning by estimating a structural path model that combines the Stimulus–Organism–Response (SOR) framework with Self-Determination Theory (SDT). Using survey data from N = 540 university students and covariance-based SEM, we examine whether perceptions of these tools—usefulness (PU), ease of use (PEU), creative benefit (PCB), and personalization (PP)—align with SDT's motivational states of perceived autonomy (PA) and perceived competence (PC) and, in turn, relate to creative confidence (CC) and creative engagement (CE). All four perceptions show positive links to PA and PC, with PP exhibiting the largest association with PA. PA precedes PC, indicating a sequential motivational route. At the behavioral level, PC relates more strongly to CC, whereas PA shows a comparatively larger association with CE. In aggregate, the results support integrating SOR with SDT to explain students' psychological responses to generative AI tools and inform course designs that cultivate autonomy and competence to sustain creative confidence and engagement in smart-learning contexts.

Keywords: smart learning; generative AI tools; stimulus–organism–response (SOR); self-determination theory (SDT); creative confidence; creative engagement

1. Introduction

In recent years, generative artificial intelligence (AI) has reconfigured both the tooling and the classroom routines of creative education [1]. Platforms such as ChatGPT (GPT-4), Midjourney, and Runway now sit inside routine coursework across a range of AI-assisted tasks. In higher-education classrooms, they are used for image generation, textual ideation, style transfer, and video synthesis [2,3]. Early uptake has concentrated in visual arts, design methods, and new-media communication, where the tools support sketching, ideation, and cross-modal expression, enabling more experimental, interactive studio settings [4]. For example, Midjourney often anchors composition and style exercises [5]; ChatGPT supports copywriting and narrative development [6]; and Runway extends practice into digital imagery, animated scenes, and visual storytelling [7]. These tools increasingly function as co-creative collaborators rather than mere assistive technologies [8]. Studies also report personalized responsiveness and user-defined control in smart-learning settings, challenging the limits of traditional media workflows [9].

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Despite broad expectations about creativity gains, students respond unevenly when they work with generative tools [10]. Some learners treat the tools as catalysts for inspiration and collaboration, showing strong participation in image generation, linguistic sketching, and style adaptation [11,12]; others report lower motivation, tool dependence, or aesthetic confusion, and at times resistance tied to loss of control or de-individualization [13,14]. Such patterns are clearest in artistic design and visual production—domains that depend on personal expression—where trust in AI-generated content, perceived control, and fit with expressive intent shape participation [15]. Much of the literature tracks functionality or adoption, but less is known about how subjective perceptions are internalized into motivation and then into behavior [16,17]. As integration deepens, whether students read AI as an enabler appears to hinge on functionality, feedback responsiveness, and personalization. This motivates an integrated model that traces perceptions → motivational states → participation—with creative confidence (CC) and creative engagement (CE) as focal outcomes—to guide both theory and course design.

Prior work often draws on Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) to explain technology uptake, emphasizing perceived usefulness (PU) and behavioral intention [18,19]. These accounts center on intention formation, offering less traction on intrinsic motivation or sustained creativity. The Stimulus–Organism–Response (SOR) framework instead models how external stimuli channel through internal states to produce behavioral responses, and it has been applied to generative-AI use in education [20]. However, SOR's organism layer is often treated abstractly, which limits precision. We address this by specifying the organism via Self-Determination Theory (SDT), focusing on autonomy and competence. At the stimulus level, we combine TAM-based perceptions (PU, ease of use) with creative-affective affordances (personalization, perceived creative value). On this basis, we develop and validate a structural model in which students' perceptions inform autonomy and competence, and these organismic states subsequently shape CC and CE. Structural modeling and empirical analyses are used to trace the motivational pathways by which generative AI supports active participation in creative education.

Anchored in the SOR perspective, autonomy and competence are taken as the central organismic states. In our model, students' perceptions of AI tools—covering functional evaluations (usefulness, ease of use) and creative-affective affordances (personalization, perceived creative value)—shape autonomy and competence, which then align with CC and CE. Rather than predicting intention as in TAM, the emphasis is on how these perceptions are internalized into motivational states that sustain participation. Usefulness and ease are necessary, yet durable engagement depends on the extent to which the tool supports autonomy and competence and, through personalization and perceived creative value, activates intrinsic motivation. Accordingly, this study offers a motivation-oriented account that complements the TAM within a SOR and SDT specification of the motivational pathway.

The paper proceeds as follows: Section 2 reviews the educational applications of generative AI, the theoretical foundations of the SOR model and SDT, and the study's key variables and hypothesized pathways. Section 3 formulates the hypotheses and sets out the conceptual model. In Section 4, we describe the questionnaire design and outline the data-collection procedures. In Section 5, we present the empirical findings. In Section 6, we discuss theoretical and practical implications. We also state the study's limitations and suggest avenues for future work. Section 7 concludes by distilling the study's core insights and contributions (see Figure 1).

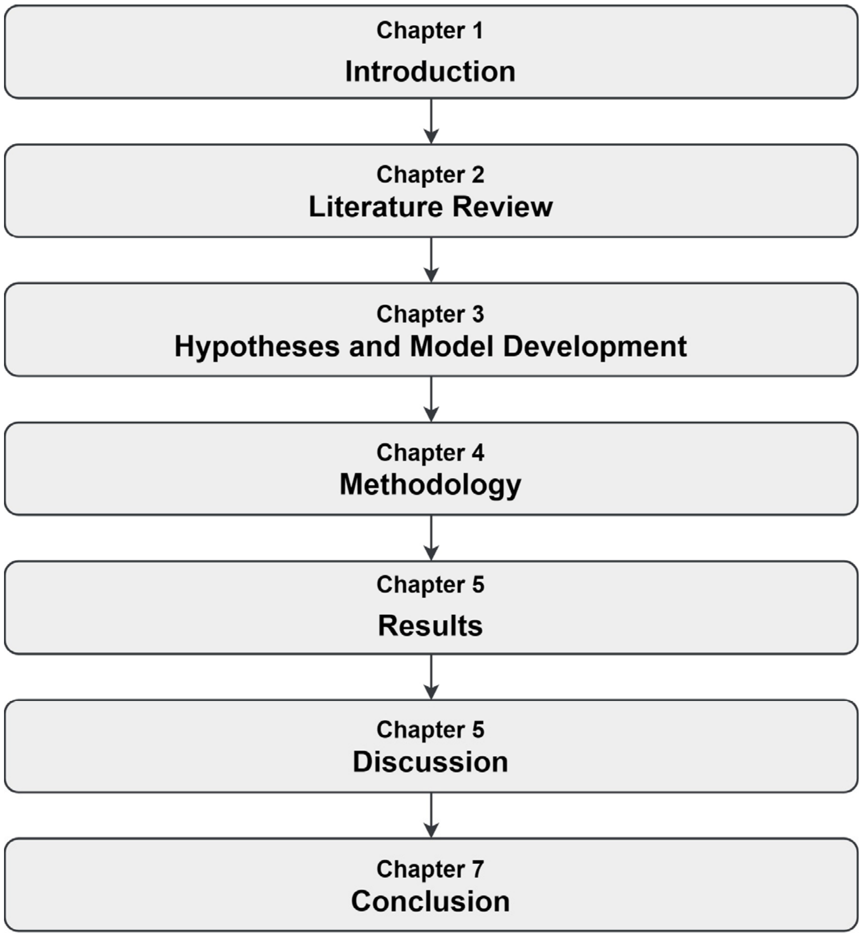

Figure 1. Overview of the Paper Structure.

2. Literature Review

2.1. The Stimulus–Organism–Response Model

The SOR model—proposed by Mehrabian and Russell (1974) [20]—models how environmental stimuli pass through internal organismic states to yield behavioral responses [21]. It comprises three parts: stimuli (S)—external inputs (e.g., technological features, interface design); organisms (O)—internal states (e.g., psychological, emotional, or cognitive responses); and responses (R)—observable outcomes (e.g., usage intention, sustained participation, overt actions).

Because of its explicit path structure, SOR has been used in consumer psychology, service marketing, social platforms, and digital education to examine how technology experience engages internal mechanisms and culminates in behavioral outcomes [22–24]. In education specifically, SOR helps analyze how digital games, blended platforms, and online course systems stimulate learning motivation and shape participation [25].

With AI more deeply embedded in classrooms, recent work applies SOR to generative tools to study creative behavior in learning contexts [26]. For example, studies model interface responsiveness and content diversity as stimuli, treat emotional engagement/immersion as organismic states, and test links to learning outcomes [27]. In smart learning, SOR traces how perceptual input is internalized into motivation and then expressed as creative action, providing a workable lens on input $\rightarrow$ state $\rightarrow$ output processes [28].

However, SOR's explanatory power is constrained when the organism is left generic (e.g., broad affect or perception), which can blur the motivational drivers of students' expressive processes. To address this, recent studies specify the organism with motivational theory—most notably SDT—so that autonomy and competence render the internal layer more precise and thus more informative for educational research.

2.2. Self-Determination Theory

In this study, SDT is used to articulate the organism layer within the SOR framework. Originally developed by Deci and Ryan, SDT explains how motivation emerges and how behavior is regulated in learning contexts [29]. It posits that intrinsic motivation and sustained, goal-directed activity are more likely when three basic psychological needs—autonomy, competence, and relatedness—are adequately supported. In the present study, we concentrate on autonomy and competence, as they are most directly tied to students' perceptions of control and capability in AI-supported creative work. Rather than emphasizing external rewards or sanctions, SDT foregrounds the volitional, internally driven activation of behavior. In this framework, perceived autonomy refers to the experience of acting with a sense of volition and self-endorsement, whereas perceived competence refers to feeling effective and capable of mastering challenging tasks. Accordingly, we define Perceived Autonomy (PA) as the extent to which students feel they can freely choose, initiate, and adjust how they use generative AI tools in creative tasks, and Perceived Competence (PC) as students' belief that they can successfully accomplish AI-assisted creative work and handle difficulties with these tools. These need-related perceptions form the core organismic states in our model and are conceptually distinct from CC, which reflects students' confidence in producing creative outcomes with AI support rather than their basic sense of autonomy or competence.

In educational research, SDT has been widely used to analyze persistence, self-efficacy, and motivational engagement across classroom, online, and game-based learning environments [30]. In more open-ended tasks—notably in arts and design—autonomy and competence needs have been linked to creative intention, risk-taking, and expressive engagement [31,32]. When learners feel that they can decide how to approach tasks and that they are capable of meeting creative demands, they are more willing to explore unconventional ideas and to invest effort in refining their work.

Recent work has begun to integrate SDT with technology-adoption research to examine how digital and AI-based tools shape learner motivation [33]. For example, personalized content delivery, controllable task structure, and real-time feedback have been shown to strengthen perceptions of control and competence [34]. When generative AI is framed and used as a supportive collaborator rather than a controlling agent, students report greater expressive freedom and more autonomous forms of participation [35]. Moreover, adaptive system responses that align with learners' expressive intent tend to activate intrinsic motivation and deepen emotional engagement [36].

Building on studies that embed SDT within the SOR framework, we treat PA and PC as the core organismic states that link students' perceptions of generative AI tools to their behavioral responses through motivational processes [37,38]. This pathway view is particularly pertinent to AI-mediated creative education: students first derive internal motivation from their perceptions of AI performance and personalized responsiveness, and then convert that motivation into tangible creative behavior and sustained creative engagement [39].

2.3. Perceptual Dimensions of Generative AI Tools in Smart Learning

In smart learning, we organize students' perceptions of generative tools into two classes: functional evaluations (usefulness, ease of use) and creative–affective affordances (personalization, perceived creative value), which together feed the Stimulus layer in the SOR model. Prior work shows that perceptions of technological efficacy, operational fluency, creative experience, and personal relevance shape behavioral pathways in AI-supported learning [40–42].

This study selects four stimulus variables to construct the perception structure. Among them, PU and Perceived Ease of Use (PEU) are two foundational constructs derived from the TAM, which has been extensively applied in technology adoption, information system studies, and various educational contexts to predict users' attitudes toward and adoption of emerging technologies [43–45]. PU refers to the extent to which students believe that a tool can improve the efficiency and outcomes of their creative tasks [43], while PEU reflects the ease with which the tool can be understood and operated [45]. In AI-supported learning studies, these two constructs have consistently demonstrated strong predictive power in explaining students' willingness to adopt technologies, including mobile learning platforms, virtual labs, and AI-based writing assistants [46,47]. In this model, PU is treated as an instrumental appraisal of performance and efficiency, rather than an evaluation of the tool's creative affordances.

Although this study adopts PU and PEU from TAM as input variables in the perception layer, it does not employ the complete TAM structure. Instead, these variables are embedded into the SOR framework as rational cognitive perceptions that initiate the first stage of the path model. This integration helps to clarify the functional role of performance-based perceptions within the motivational chain.

A central appraisal concerns whether a tool enhances creative potential in smart-learning tasks. We therefore introduce Perceived Creative Benefit (PCB) as a third stimulus: students' belief that generative tools enrich expressive depth, improve creative quality, and stimulate ideation. Whereas PU concerns whether tools help students complete creative assignments more efficiently and effectively, PCB focuses on whether they expand the space of possible ideas and expressions [48,49]. When tools are seen as enablers of inspiration and expression, students show stronger intrinsic drive and more sustained creative involvement [50].

Perceived Personalization (PP) also shapes interaction in creative-learning environments. Given their adaptive functionality, generative tools can tailor outputs to individual style, pace, and content preferences [51]. In this study, PP captures whether students feel able to adjust and steer the tool—by refining prompts, selecting options, and iterating on outputs—and whether the system responsively aligns with their creative intent and preferences [52]. Evidence from adaptive learning systems, recommendation platforms, and AI-driven artistic tools links PP to higher satisfaction and engagement [53]. When students perceive high responsiveness and preference alignment based on their own choices, autonomy and motivation for self-expression are more readily activated [54].

Overall, PU/PEU index instrumental appraisals of efficiency and usability, whereas PCB/PP index creative empowerment and personal resonance. Together, these four stimuli form the perception structure that feeds the stimulus layer and, in our model, flows into autonomy and competence as the basis for motivational activation.

2.4. Behavioral Responses to Generative AI Tools in Smart Learning

Within SOR, response variables (R) capture behavioral outcomes that arise when external stimuli are processed through internal states. In AI-augmented smart learning, we operationalize participation with two indicators: CC and CE.

CC denotes students' confidence in handling uncertain, open-ended creative challenges and achieving meaningful results. It is used to assess self-efficacy and creative preparedness across expressive domains [55,56]. Prior work shows that perceived AI support—e.g., style alignment, sketch assistance, compositional guidance—strengthens students' sense of control and process confidence. Students then take greater creative risks and stay involved [57,58]. The tools' adaptability and flexibility widen the early-stage exploratory space. That, in turn, reduces hesitation under uncertainty. In line with this literature, we treat CC primarily as creative self-efficacy—an internally anchored belief that students can generate valuable ideas and artifacts with AI support—rather than as dependence on external approval. The item that refers to others' recognition of creativity is intended to capture students' confidence that their AI-assisted work will meet widely shared standards of creativity, and is interpreted as an expression of self-belief rather than a separate need for social validation.

CE indexes the behavioral side of creative activity and signals the depth of participation. It is used in art education, immersive learning, and media production as an indicator of creative engagement and involvement [59,60]. In AI-enhanced settings, perceived interactivity and responsiveness—e.g., real-time adjustment and iterative support—make it likelier that students develop emotional attachment to the process. They also enter immersive states. Such emotional engagement prolongs participation. It supports persistence and sustained effort on complex creative tasks and is closely tied to creative performance in these domains [61].

3. Research Model and Hypotheses Development

In this section, we lay out the research model. The model links students' perceptions of AI tools to motivational states and creative behaviors. We build on the model and state the hypotheses. The hypotheses address how generative-AI contexts activate creative drive and foster behavioral engagement.

3.1. Hypotheses Related to Perception Variables

3.1.1. The Influence of Perceived Usefulness on Perceived Autonomy and Perceived Competence

In creative-learning settings, students' use of AI tools tracks their judgments of usefulness. PU is the belief that the tool raises creative efficiency and helps pursue expressive goals.

When students see practical gains in their workflows, goal alignment increases, and PA rises [62]. Better output quality builds confidence in one's abilities, raising PC [63].

PU functions as a stimulus. It speaks to the core needs of autonomy and competence, consistent with SDT.

H1. *PU positively influences PA.*

H2. *PU positively influences PC.*

3.1.2. The Influence of Perceived Ease of Use on Perceived Autonomy and Perceived Competence

In generative-AI learning, operational simplicity and interface clarity shape engagement. PEU is how intuitive the tool is and how little effort it takes to understand and apply. Beyond initial acceptance, PEU is associated with motivation and later participation [47].

Prior work shows that easy-to-use tools make students feel more in control during creation. This strengthens PA and encourages task involvement [64]. Smooth interaction and real-time feedback limit technical interruptions in smart learning. They free attention for expressive work. This seamless use builds self-perceived capability. It raises PC [65].

PEU acts as a stimulus. It activates motivation and supports creative participation.

H3. *PEU positively influences PA.*

H4. *PEU positively influences PC.*

3.1.3. The Influence of Perceived Creative Benefit on Perceived Autonomy and Perceived Competence

Creative education centers on personal expression and intrinsic motivation, not on productivity-first tools. In this setting, the empowering potential of generative tools—beyond convenience—shapes motivation [66]. PCB is the belief that AI tools enhance originality, expressiveness, and narrative coherence [67]. Students treat AI as a supportive partner, not a substitute. They report greater authorship and deeper involvement. This raises PA [68]. Tools that expand expressive range and depth lead students to rate their capabilities more positively. This strengthens PC [69].

Creative-empowerment experiences link to the activation of intrinsic motivation.

H5. *PCB positively predicts PA.*

H6. *PCB positively predicts PC.*

3.1.4. The Influence of Perceived Personalization on Perceived Autonomy and Perceived Competence

Creative work varies from person to person. Students vary in style, pace, and modes of expression. They respond to customizability. Generative systems adapt well, unlike fixed-procedure tools. Students feel more accurately represented in interactions [70]. PP means the belief that the system matches a student's style and intent. It offers bespoke support.

This sense of personalization creates psychological resonance. It eases restricted autonomy from low tool control. The tool accommodates instructions and preferences. Students then report greater agency throughout creation. This supports PA [71]. Dynamic interaction and timely feedback cut frustration and trial-and-error fatigue. They build task-management confidence and raise PC [61].

Customized interactions raise the chance that students view the system as a reliable creative partner.

H7. *PP positively predicts PA.*

H8. *PP positively predicts PC.*

3.2. Hypotheses Related to Motivational Variables

3.2.1. The Influence of Perceived Autonomy on Perceived Competence

Autonomy and competence serve as basic needs within SDT. They sustain intrinsic motivation. Prior work treats them as parallel. It positions autonomy as a precursor in motivational pathways [72].

Perceived choice and control in creative activity connect to active engagement and sustained effort. Autonomy-driven engagement gathers positive feedback. It supports self-efficacy and competence beliefs [73]. Students customize tool functions in AI-assisted creative learning. This raises perceived control and lifts PC [74].

PA works as a motivational enabler. It builds PC through engagement and performance confidence.

H9. *PA positively influences PC.*

3.2.2. The Impact of Perceived Autonomy and Perceived Competence on Creative Confidence and Creative Engagement

Motivation appears in internal states and observable participation during AI-enhanced creative learning. It also shows in creative behavior. Meeting autonomy and competence needs under SDT leads to intrinsic motivation. It produces sustained, proactive, expressive engagement.

Students perceive autonomy in the creative process. They treat the activity as self-expression and build stronger beliefs about their creative ability. This internal validation cuts reliance on external approval. It supports CC. Meeting autonomy needs aids deep engagement with complex tasks. It raises persistence and CE [75,76].

PC drives active participation in creative work. Students who trust their capability are more likely to set ambitious goals and sustain commitment. Such self-perceptions foster confidence [77], and sustain active involvement across the creative process [48,78].

Together, PA and PC form the psychological base of creative motivation, shaping confidence and behavioral engagement in AI-supported learning.

H10. *PA positively predicts CC.*

H11. *PA positively predicts CE.*

H12. *PC positively predicts CC.*

H13. *PC positively predicts CE.*

3.3. Model Structure and Path Diagram

To test the hypotheses, we estimate a structural path model that depicts the links among perception characteristics, motivational states, and creative behavioral outcomes (see Figure 2).

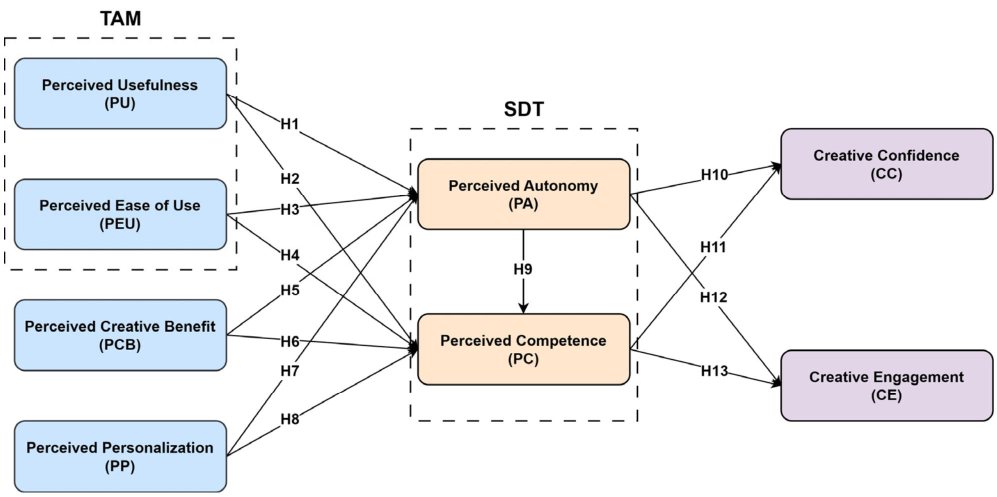

Figure 2. The Proposed Research Model.

4. Methodology

4.1. Measures

To ensure content validity, we drew items from empirically validated scales in prior work. We measured eight latent variables: PU, PEU, PCB, PP, PA, PC, CC, and CE. Most constructs used three items; CC and CE each used four, reflecting their behavioral emphasis. All items were semantically adapted and localized to the AI-assisted educational context. Table 1 lists the English labels, example items, and primary references for each latent variable.

Table 1. Measurement Items and References for Latent Variables.

Variables	Items	References
PU	Using AI tools makes my creative tasks more efficient. AI tools are useful for improving my creative performance. AI tools help me achieve meaningful creative goals.	[79–81]
PEU	It is straightforward to become familiar with generative AI tools. I can become proficient quickly in using generative AI tools. AI tools are easy to navigate and operate.	[1,82,83]
PCB	AI tools help me generate more original or expressive outputs. Using AI enhances my creative imagination and ideation. AI tools help me explore new creative possibilities.	[84–86]
PP	AI tools adapt to my personal creative preferences. The AI output reflects my personal style. AI tools allow me to create in my own way.	[87–89]
PA	I feel free to decide whether or not to use AI in my creative work. I can make independent decisions while using AI in my work. I can autonomously define goals and methods when using AI tools.	[90–92]
PC	I feel capable of producing quality creative work with AI tools. I am able to overcome creative challenges using AI tools. I have confidence in using AI tools for creative work.	[93–95]
CC	I am confident in my ability to develop original ideas with the assistance of AI tools. I feel confident in my creative skills when working with AI. I expect others to recognize the creativity in my AI-assisted work. I feel confident addressing creative challenges when using AI tools.	[96–98]
CE	I focus deeply when creating with AI tools. Doing creative work with AI is absorbing and enjoyable for me. I see AI-assisted creative tasks through to completion. When creating with AI, time often slips by unnoticed.	[11,75,99]

4.2. Data Collection

To adapt the measures for Chinese-speaking students, we used a forward–backward translation procedure to ensure both linguistic precision and cultural appropriateness. A panel of five experts (creative education and educational technology) and two doctoral students conducted several rounds of revision to improve item clarity and contextual relevance. These steps helped ensure that the questionnaire captured students' perceptions and experiences with generative AI tools accurately.

Before the main fieldwork, we conducted a pilot study (N = 50 university students) to assess reliability and validity.

The pilot results indicated good internal consistency and initial construct validity, and inter-variable correlations were in line with theoretical expectations. On this basis, the final instrument was deemed suitable for large-scale administration.

The finalized questionnaire consisted of two sections. Section 1 collected demographic information (gender, age, education level, and field of study) as well as self-reported familiarity with generative AI tools. Section 2 contained 32 items mapped to the model's eight latent variables, all rated on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree).

Data collection was carried out in May 2025 using the Wenjuanxing online survey platform. The target population comprised students in mainland China enrolled in upper-secondary (high school/vocational) and post-secondary (associate, bachelor's, and master's) programs that included courses related to creative practice, design, or AI-supported learning. The questionnaire link was distributed through academic networks connected to these programs, including online course communities, class chat groups, and creative-learning platforms. Respondents came from a range of fields of study, including arts and design, science and engineering, social sciences, management and business, and other majors. We obtained 540 valid responses that met the inclusion criterion of having prior experience with generative AI tools. Responses with unrealistically short completion times, straight-line answering patterns, or failed attention checks were removed before analysis. As summarized in Table 2, 22.78% of participants were in high school or vocational tracks, while the majority were enrolled in associate, bachelor's, or master's programs.

Table 2. Participant Demographics and Background Characteristics.

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	258	47.78%
	Female	282	52.22%
Age	16–18	85	15.74%
	19–22	210	38.89%
	23–26	147	27.22%
	27 or above	98	18.15%
Education Level	High School/Vocational	123	22.78%
	Associate Degree	182	33.70%
	Bachelor's Degree	163	30.19%
	Master's Degree or above	72	13.33%
Field of Study	Arts & Design	136	25.19%
	Science & Engineering	99	18.33%
	Social Sciences	109	20.19%
	Management & Business	99	18.33%
	Other	97	17.96%
Familiarity with Generative AI Tools	First-time user	110	20.37%
	Aware but rarely use	142	26.30%
	Occasionally use for learning/creation	168	31.11%
	Frequently use for learning/creation	120	22.22%

4.3. Analytical Approach

Given the model's structural complexity and our focus on fit and path significance, we adopted structural equation modeling (SEM) as the core framework, as it accounts for measurement error and estimates latent-variable relations in theory-driven designs.

First, we conducted confirmatory factor analysis (CFA) to assess the measurement model, examining convergent and discriminant validity. Second, we estimated the structural model using maximum likelihood (ML) to test the hypothesized paths. Model fit was evaluated with GFI, CFI, TLI, and RMSEA (Goodness-of-Fit, Comparative Fit, Tucker–Lewis, and Root Mean Square Error of Approximation). Path significance was assessed via critical ratios (C.R.) and *p*-values.

5. Results

5.1. Reliability Analysis

To assess scale reliability, we examined internal consistency for each construct. Internal consistency indicates how well the items in a scale tap the same latent variable. Higher values imply a more stable and reliable scale.

As Table 3 shows, Cronbach's α exceeds 0.70 for all constructs (0.822–0.927), showing adequate internal consistency and justifying their use in subsequent CFA/SEM analyses.

Table 3. Reliability Analysis Results.

Construct	Number of Items	Cronbach's Alpha
PU	3	0.882
PEU	3	0.897
PCB	3	0.822
PP	3	0.855
PA	3	0.870
PC	3	0.876
CC	4	0.891
CE	4	0.927

5.2. Confirmatory Factor Analysis

We evaluated the measurement model on two dimensions: content validity and construct validity. Content validity drew on a literature synthesis and pilot feedback, confirming that items adequately represented the theoretical domains of their constructs. Construct validity was tested via CFA; Figure 3 shows the standardized path diagram.

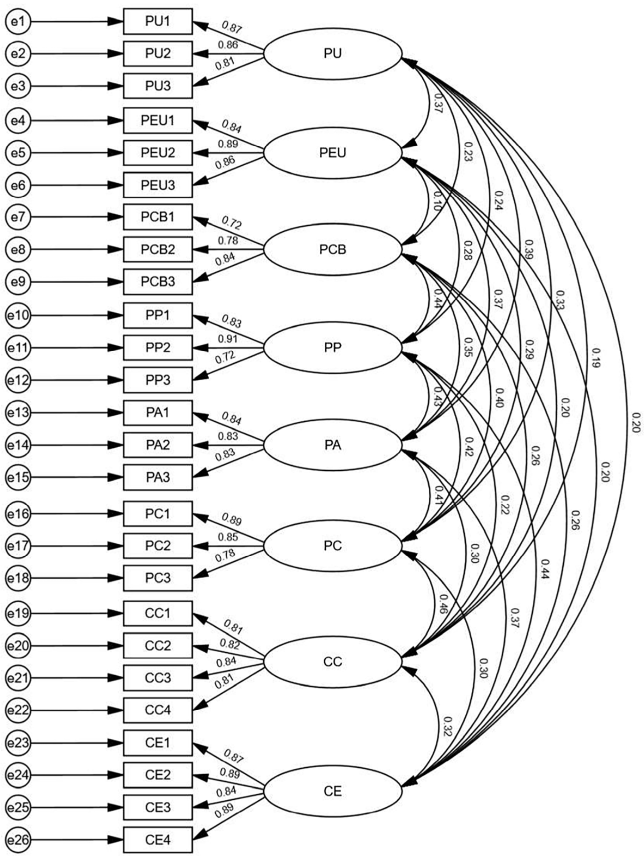

Figure 3. Path Diagram of the Confirmatory Factor Analysis Model.

Model-fit results indicate an acceptable overall fit. Absolute fit indices—CMIN/DF = 2.109, GFI = 0.926, AGFI = 0.904, RMSEA = 0.045—fall within recommended thresholds. Incremental fit indices—NFI = 0.938, IFI = 0.966, TLI = 0.959, CFI = 0.966—are satisfactory. Parsimony indices (PNFI = 0.782, PCFI = 0.805) exceed conventional benchmarks. Taken together, the indices support the adequacy and structural validity of the model; Table 4 provides details.

Table 4. Model Fit Indices for the CFA Model.

Fit Index	Recommended Threshold	Actual Value	Fit Evaluation
Absolute Fit Indices			
CMIN/DF	<3	2.109	Good
GFI	>0.80	0.926	Good
AGFI	>0.80	0.904	Good
RMSEA	<0.08	0.045	Good
Incremental Fit Indices			
NFI	>0.9	0.938	Good
IFI	>0.9	0.966	Good
TLI	>0.9	0.959	Good
CFI	>0.9	0.966	Good
Parsimonious Fit Indices			
PNFI	>0.5	0.782	Good
PCFI	>0.5	0.805	Good

5.3. Convergent Validity

We assessed convergent validity using two indicators: Average Variance Extracted (AVE) and Composite Reliability (CR). All AVE values exceeded 0.50 (0.609–0.761), and all CR values surpassed 0.80 (0.823–0.927). Standardized factor loadings ranged 0.721–0.914 and were significant at $p < 0.001$. Overall, the results support the convergent validity and measurement consistency of all constructs (see Table 5).

Table 5. Results of Confirmatory Factor Analysis.

Construct	Item	Loading	S.E.	C.R.	*p*	CR	AVE
PU	PU1	0.872				0.883	0.716
	PU2	0.858	0.043	23.398	***		
	PU3	0.808	0.044	21.940	***		
PEU	PEU1	0.843				0.898	0.746
	PEU2	0.885	0.043	24.492	***		
	PEU3	0.862	0.041	23.859	***		
PCB	PCB1	0.725				0.823	0.609
	PCB2	0.777	0.068	15.863	***		
	PCB3	0.836	0.073	16.314	***		
PP	PP1	0.830				0.864	0.681
	PP2	0.914	0.045	22.783	***		
	PP3	0.721	0.047	18.243	***		
PA	PA1	0.835				0.871	0.692
	PA2	0.826	0.053	21.030	***		
	PA3	0.834	0.052	21.226	***		
PC	PC1	0.888				0.879	0.708
	PC2	0.851	0.042	23.848	***		
	PC3	0.780	0.044	21.363	***		
CC	CC1	0.810				0.891	0.672
	CC2	0.824	0.049	21.050	***		
	CC3	0.835	0.047	21.409	***		
	CC4	0.810	0.045	20.618	***		
CE	CE1	0.871				0.927	0.761
	CE2	0.894	0.038	28.610	***		
	CE3	0.838	0.039	25.395	***		
	CE4	0.886	0.037	28.180	***		

Note: *** indicates $p < 0.001$.

5.4. Discriminant Validity

We evaluated discriminant validity with the Fornell–Larcker criterion: for each construct, the square root of its AVE should exceed its largest inter-construct correlation. Before applying the criterion, we examined the correlation matrix; all coefficients were significant ($p < 0.001$). This condition held for every construct, supporting discriminant validity.

As shown in Table 6, each construct met measurement benchmarks: standardized loadings > 0.60, CR > 0.70, and AVE > 0.50, consistent with convergent-validity criteria. Additionally, the square root of each AVE exceeded its largest inter-construct correlation, affirming discriminant validity. On balance, the evidence indicates that the measurement model is adequate and appropriate for hypothesis testing.

Table 6. Discriminant Validity Analysis.

	PU	PEU	PCB	PP	PA	PC	CC	CE
PU	**0.846**							
PEU	0.375 ***	**0.864**						
PCB	0.235 ***	0.101 *	**0.78**					
PP	0.240 ***	0.277 ***	0.440 ***	**0.825**				
PA	0.389 ***	0.365 ***	0.352 ***	0.432 ***	**0.832**			
PC	0.329 ***	0.294 ***	0.404 ***	0.417 ***	0.409 ***	**0.841**		
CC	0.187 ***	0.201 ***	0.264 ***	0.224 ***	0.303 ***	0.462 ***	**0.82**	
CE	0.197 ***	0.204 ***	0.260 ***	0.437 ***	0.373 ***	0.303 ***	0.318 ***	**0.873**

Note. Diagonal values (bold) are the square roots of each construct's AVE. *** $p < 0.001$; * $p < 0.05$.

5.5. Structural Model Assessment

We used structural equation modeling (SEM) to test the hypotheses derived from the proposed framework; the model structure appears in Figure 4.

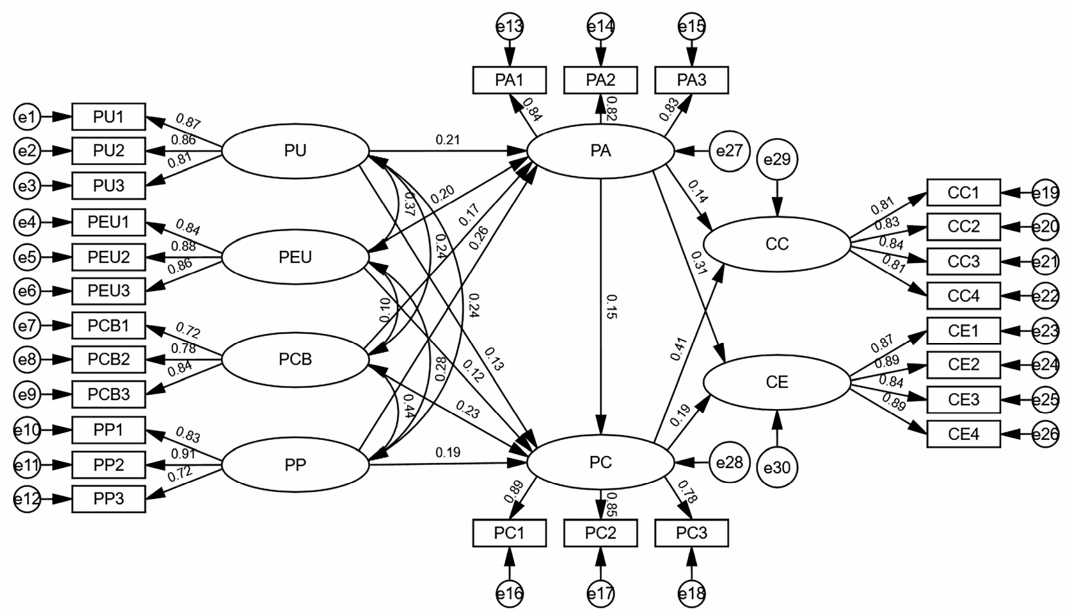

Figure 4. Structural Equation Model.

The global fit of the model is within acceptable ranges. Absolute-fit indices—CMIN/DF = 2.231, GFI = 0.920, AGFI = 0.900, RMSEA = 0.048—meet recommended standards. Incremental-fit indices—NFI = 0.932, IFI = 0.961, TLI = 0.955, CFI = 0.961—exceed commonly accepted thresholds. Parsimony indices (PNFI = 0.803, PCFI = 0.828) surpass conventional benchmarks; Table 7 reports the full set of fit indices. Altogether, the evidence indicates acceptable fit and that the model captures the hypothesized relations among latent variables.

Table 7. Model Fit Indices for the Structural Equation Model.

Fit Index	Recommended Threshold	Actual Value	Fit Evaluation
Absolute Fit Indices			
CMIN/DF	<3	2.231	Good
GFI	>0.80	0.920	Good
AGFI	>0.80	0.900	Good
RMSEA	<0.08	0.048	Good
Incremental Fit Indices			
NFI	>0.9	0.932	Good
IFI	>0.9	0.961	Good
TLI	>0.9	0.955	Good
CFI	>0.9	0.961	Good
Parsimonious Fit Indices			
PNFI	>0.5	0.803	Good
PCFI	>0.5	0.828	Good

5.6. Path Analysis

We estimated path coefficients using ML. As Table 8 shows, all paths had positive, well-behaved standard errors (S.E.) with no abnormal deviation. All critical ratios (C.R.) exceeded |1.96|, indicating $p < 0.05$. Specifically, C.R. > 1.96/2.58/3.29 correspond to $p < 0.05/0.01/0.001$, respectively.

Table 8. Path Coefficients and Hypothesis Testing Results.

Path			Estimate	S.E.	C.R.	*p*
PA	←	PU	0.212	0.045	4.409	***
PA	←	PEU	0.199	0.047	4.171	***
PA	←	PCB	0.172	0.057	3.350	***
PA	←	PP	0.262	0.046	5.123	***
PC	←	PU	0.128	0.046	2.610	0.009
PC	←	PEU	0.118	0.048	2.434	0.015
PC	←	PCB	0.229	0.059	4.356	***
PC	←	PP	0.193	0.047	3.670	***
PC	←	PA	0.148	0.054	2.718	0.007
CC	←	PA	0.145	0.049	2.917	0.004
CE	←	PA	0.312	0.051	6.162	***
CC	←	PC	0.408	0.051	7.954	***
CE	←	PC	0.194	0.049	3.927	***

Note: *** indicates significance at the $p < 0.001$ level.

The path analysis results confirm that the structural model fits well, and all hypothesized paths are statistically significant. Specifically, PU significantly predicted PA ($\beta = 0.212$, $p < 0.001$), as did PEU ($\beta = 0.199$, $p < 0.001$), PCB ($\beta = 0.172$, $p < 0.001$), and PP ($\beta = 0.262$, $p < 0.001$).

In predicting PC, PU ($\beta = 0.128$, $p = 0.009$), PEU ($\beta = 0.118$, $p = 0.015$), PCB ($\beta = 0.229$, $p < 0.001$), and PP ($\beta = 0.193$, $p < 0.001$) all had significant positive effects. PA also significantly influenced PC ($\beta = 0.148$, $p = 0.007$).

At the behavioral outcome level, PA exerted significant positive effects on both CC ($\beta = 0.145$, $p = 0.004$) and CE ($\beta = 0.312$, $p < 0.001$). Similarly, PC was a significant predictor of CC ($\beta = 0.408$, $p < 0.001$) and CE ($\beta = 0.194$, $p < 0.001$).

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All path coefficients meet the criteria for significance (C.R. > 1.96), providing robust statistical support for the proposed hypotheses.

5.7. Mediation Analysis

We examined parallel mediation through PA and PC using a nonparametric bias-corrected bootstrap (5000 resamples); standardized specific indirect effects and 95% CIs are reported in Table 9. For both CC and CE, all PA- and PC-based indirect effects of PU, PEU, PCB, and PP were significant (CIs excluded zero). The pattern aligns with SDT: PA-driven paths map more closely to CE, whereas PC-driven paths map more closely to CC.

Table 9. Mediation test results (bootstrap, standardized effects).

Parameter	Coeff	SE	Bias-Corrected 95% CI		
			Lower	Upper	p
PU-PA-CC	0.031	0.015	0.008	0.066	0.003
PU-PC-CC	0.052	0.024	0.009	0.104	0.018
PU-PA-CE	0.066	0.023	0.027	0.119	0.000
PU-PC-CE	0.025	0.014	0.004	0.062	0.014
PEU-PA-CC	0.029	0.013	0.010	0.061	0.002
PEU-PC-CC	0.048	0.025	0.003	0.102	0.039
PEU-PA-CE	0.062	0.021	0.025	0.111	0.001
PEU-PC-CE	0.023	0.015	0.002	0.061	0.029
PCB-PA-CC	0.025	0.013	0.006	0.058	0.006
PCB-PC-CC	0.094	0.030	0.043	0.159	0.000
PCB-PA-CE	0.054	0.021	0.018	0.102	0.003
PCB-PC-CE	0.044	0.019	0.014	0.093	0.003
PP-PA-CC	0.038	0.017	0.012	0.081	0.003
PP-PC-CC	0.079	0.028	0.029	0.141	0.004
PP-PA-CE	0.082	0.030	0.034	0.155	0.000
PP-PC-CE	0.037	0.021	0.006	0.091	0.006

For PU, the indirect effect on CC through PA was 0.031 (SE = 0.015, BC 95% CI [0.008, 0.066], $p = 0.003$), and the indirect effect through PC was 0.052 (SE = 0.024, BC 95% CI [0.009, 0.104], $p = 0.018$). For CE, PU showed a significant indirect effect via PA of 0.066 (SE = 0.023, BC 95% CI [0.027, 0.119], $p < 0.001$) and via PC of 0.025 (SE = 0.014, BC 95% CI [0.004, 0.062], $p = 0.014$).

For PEU, the indirect effect on CC through PA was 0.029 (SE = 0.013, BC 95% CI [0.010, 0.061], $p = 0.002$), and through PC was 0.048 (SE = 0.025, BC 95% CI [0.003, 0.102], $p = 0.039$). For CE, PEU exhibited a significant indirect effect via PA of 0.062 (SE = 0.021, BC 95% CI [0.025, 0.111], $p = 0.001$) and via PC of 0.023 (SE = 0.015, BC 95% CI [0.002, 0.061], $p = 0.029$).

For PCB, the indirect effect on CC via PA was 0.025 (SE = 0.013, BC 95% CI [0.006, 0.058], $p = 0.006$), and via PC was 0.094 (SE = 0.030, BC 95% CI [0.043, 0.159], $p < 0.001$). For CE, PCB produced a significant indirect effect via PA of 0.054 (SE = 0.021, BC 95% CI [0.018, 0.102], $p = 0.003$) and via PC of 0.044 (SE = 0.019, BC 95% CI [0.014, 0.093], $p = 0.003$).

For PP, the indirect effect on CC through PA was 0.038 (SE = 0.017, BC 95% CI [0.012, 0.081], $p = 0.003$), and through PC was 0.079 (SE = 0.028, BC 95% CI [0.029, 0.141], $p = 0.004$). For CE, PP showed a significant indirect effect via PA of 0.082 (SE = 0.030, BC 95% CI [0.034, 0.155], $p < 0.001$) and via PC of 0.037 (SE = 0.021, BC 95% CI [0.006, 0.091], $p = 0.006$).

Taken together, PA and PC significantly mediate the effects of PU, PEU, PCB, and PP on both CC and CE.

6. Discussion

6.1. Major Findings

After establishing satisfactory reliability and validity for all constructs (Table 3), we estimated a structural path model that combines SOR and SDT to examine how students' perceptions of generative tools relate to CC and CE. All thirteen hypotheses (H1–H13) were supported, mapping links among perceptual features, motivational states, and creative behavior. These findings inform how generative AI can be embedded in smart learning.

Across the four perceptual variables (PU, PEU, PCB, PP), each showed a positive, significant association with PA and PC, supporting H1–H8. PP displayed the largest association with PA, suggesting greater agency when tool behavior aligns with style and mode of expression. This pattern is consistent with prior work on person–tool alignment [51] and on system responsiveness in creative learning [70].

PP also related positively to PC, consistent with effects of personalized feedback and adaptive interaction [61]. A sense of being understood and supported reduces distance from the tool and builds task-management confidence. PCB likewise related positively to PA and PC; reading AI as enhancing (rather than replacing) creativity aligns with agency and self-affirmation [68]. This aligns with discussions of creative empowerment [66], pointing to the role of generative tools in activating internal motivation, especially in open-ended tasks. Conceptually, affective affordances (PP, PCB) primarily address SDT needs: PP supports autonomy/authorship (PA), and PCB supports capability beliefs (PC); by contrast, PU/PEU mainly lower entry costs and improve fluency, which are necessary but not sufficient for sustained intrinsic motivation.

By contrast, PU/PEU index performance and fluency. PU related positively to PA and PC [100]. PEU also showed positive effects, consistent with the role of intuitive interfaces and low operational barriers [64,65]. Although we do not adopt TAM as a full model, these results align with TAM-related evidence on usability and motivational activation [46,47].

Within the organism layer, PA $\rightarrow$ PC was positive and significant (H9), consistent with SDT claims that autonomy supports the growth of competence [72]. Freedom to choose how to engage with tools increases agency, which raises confidence in managing creative tasks. Pedagogically, supporting autonomy alongside capability-building helps sustain intrinsic motivation and long-run engagement.

In the response layer, PA and PC predicted CC and CE (H10–H13). PC showed the strongest link to CC, consistent with SDT's emphasis on competence [29] and with findings on competence beliefs in artistic tasks [77]. Clear interfaces and prompt feedback appear to consolidate ability beliefs and leave students better prepared for creative challenges. In line with this account, pathways through autonomy (PA) map more closely onto process participation (CE), whereas pathways through competence (PC) map more closely onto capability beliefs (CC); this pattern appears in the mediation results (Table 9).

PA was positively associated with CE, suggesting that expressive autonomy supports immersion and sustained participation [75,76]. The PC $\rightarrow$ CE link highlights the role of competence in sustaining action; in AI-assisted creation, repeated successes and timely feedback help build resilience and commitment [48]. Although the PA $\rightarrow$ CC path is smaller in magnitude, PA remains a key driver of motivational activation, especially early in creative work.

On balance, perceptions of the tools (PU, PEU, PCB, PP) affect creative behavior mainly through motivational states (PA, PC), showing that generative tools can help cultivate both confidence and engagement. The estimates also motivate comparative follow-ups and suggest a model that travels across diverse educational settings.

6.2. Theoretical and Practical Implications

Positioning relative to TAM. While TAM remains central for explaining intention via PU and PEU, this study complements that perspective by locating PU/PEU together with PP/PCB at the Stimulus layer of SOR and specifying the Organism with SDT (PA, PC). In many SOR applications, the "organism" is described in broad terms as internal states (e.g., psychological, emotional, or cognitive responses); here, we make this layer explicit by modeling autonomy and competence needs as the core organismic states through which tool perceptions are internalized. Compared with TAM-style pathways from beliefs to attitude and intention, the SOR–SDT integration shifts the focus from usage intention to the motivational quality of participation and from a single evaluative node to differentiated basic needs that mediate the effects of PU/PEU/PP/PCB on CC and CE in creative learning. The contribution is therefore mechanistic rather than competitive, clarifying how tool perceptions are translated into PA and PC and how these motivational states, in turn, align with CC and CE.

Theoretical implications. Integrating SOR with SDT, the structural model indicates that PU, PEU, PP, and PCB are associated with CC and CE primarily through indirect paths via PA and PC, with PA aligning more strongly with CE than with CC. The results also differentiate technology-oriented perceptions (PU, PEU) from personal value-oriented perceptions (PP, PCB), refining how distinct perceptions correspond to the needs for autonomy and competence and, in turn, to participation outcomes.

Practical implications. For course integration in higher education, instructors can enable choice-rich prompt menus and basic parameter control so that students direct outputs toward individual goals; organize short creative sprints with quick formative feedback (e.g., before–after galleries, brief rubric notes) to make progress visible; and assess not only final artifacts but also process artifacts (iteration logs, rationale notes, peer comments) to sustain participation over multiple weeks. At the program level, departments may curate a starter prompt library, schedule TA office hours dedicated to iteration support, and publish lightweight guidelines on attribution, dataset use, and documentation. In practice, these resources can be introduced as scaffolds in early assignments—where students work from curated prompts, experiment with different parameter settings, and document how AI was used—and then gradually shifted toward student-authored prompts and self-directed projects that are evaluated with rubrics rewarding transparent reporting, critical reflection, and the originality of students' own contributions. However, integrating generative AI as a creative enabler also raises concerns about academic integrity, overreliance on automation, creative displacement, and potential de-skilling, which may affect how sustainable gains in CC and CE are over time. Recent work on "creative displacement anxiety" cautions that the perceived overshadowing of human creativity by AI tools can undermine learners' confidence and agency in the longer term [4].

6.3. Limitations and Future Research

This study is based on cross-sectional survey evidence. Although the estimated structural paths are statistically robust, a single time point cannot reveal how students' perceptions and motivational states evolve as they continue to work with generative AI tools. Designs that follow learners across multiple tasks or introduce course-level interventions (e.g., staggered access to specific AI features) would be better suited to illuminating temporal dynamics and establishing temporal precedence among perceptions, motivational states, and behavioral engagement.

The sample is drawn from students in mainland China enrolled in upper-secondary (high school/vocational) and post-secondary (associate, bachelor's, and master's) programs, which narrows external validity. Broader coverage of learner groups—such as adult learners, in-service professionals, and participants in community or workplace training programs—would indicate whether the model travels across non-tertiary and lifelong-learning settings. Because all data were collected within the Chinese education system, which is often characterized by exam-oriented assessment and relatively hierarchical teacher–student relationships, generalizability is further constrained; cross-cultural or multi-country studies are needed to examine whether cultural context conditions the associations among perceptions, organismic states, and creative outcomes, especially in more individualistic or less exam-driven academic environments. Parallel replications in other institutional contexts, including secondary and non-formal education, would also help to determine whether the model extends beyond conventional higher education.

Measurement choices also set boundaries. The analysis relies entirely on a single self-report survey of perceived tool attributes and motivational states (e.g., PU, PEU, PA, PC), which raises the possibility of common method bias and social desirability effects, and does not include behavioral or performance-based indicators such as objective evaluations of AI-assisted output quality. Future work could add product-level evidence—such as expert ratings of originality and coherence, rubric-based scores for stylistic diversity, or automated indicators of semantic precision—as controls or moderators to strengthen explanatory power and ecological validity. In addition, the study treats generative AI tools as a single category without differentiating between text-, image-, and video-based systems, which may obscure modality-specific patterns of perception and engagement. Subsequent studies could distinguish between text-, image-, and video-based applications in both measurement and analysis, for example by including tool type as a control variable or by comparing modality-specific subgroups. Students' pre-existing creative self-efficacy and disciplinary training in creative fields were not measured either, even though these baseline characteristics are likely to influence perceived autonomy, competence, and creative confidence. As a result, the present model cannot fully isolate the incremental contribution of perceptions of generative AI tools beyond these pre-existing dispositions. Moreover, although Table 2 reports students' demographic characteristics and their self-reported familiarity with generative AI tools, we did not conduct formal subgroup or multi-group analyses based on these variables in order to keep the structural model parsimonious. It is plausible that students with different levels of AI familiarity, disciplinary backgrounds, ages, or educational levels exhibit distinct patterns of autonomy, competence, creative confidence, and engagement. Future research could therefore incorporate demographic and familiarity variables as controls or grouping factors, and apply multi-group SEM or moderated analyses, to examine whether the SOR–SDT relationships observed here vary across student subpopulations. Future work could also refine the CC scale by separating purely self-referential items from those that tap anticipated social recognition, in order to more clearly isolate intrinsic creative self-efficacy from perceptions of external evaluation.

The present study estimated specific indirect effects via PA and via PC using bias-corrected bootstrapping. Future work should additionally test the serial pathway (Stimulus $\rightarrow$ PA $\rightarrow$ PC $\rightarrow$ Response) and conduct formal contrasts among specific indirect effects (e.g., PP/PCB vs. PU/PEU) to delineate which motivational routes contribute most to confidence and engagement in different learning contexts.

7. Conclusions

A structural model was proposed and empirically confirmed, incorporating the Stimulus–Organism–Response (SOR) framework alongside Self-Determination Theory (SDT), to examine how students' perceptions of generative AI tools influence their creative confidence (CC) and creative engagement (CE) through underlying motivational processes.

Using survey data from 540 university students, we identified psychological routes that link students' perceptions of AI tools to creative behavioral outcomes.

The results indicate that Perceived Autonomy (PA) and Perceived Competence (PC) serve as the organismic states through which technology-based perceptions (PU, PEU) and value-oriented perceptions (PCB, PP) relate to subsequent outcomes. Perceived personalization (PP) has the stromgest link to autonomy; tailored feedback appears to support students' sense of agency. Taken together, the patterns point to a role for responsive AI systems in user-centered motivation and make explicit the perception → motivation → behavior sequence in AI-enhanced settings. The study extends prior work by looking beyond purely utilitarian views of functionality and usability to document motivational pathways.

In sum, these results clarify how perceived features of generative AI tools relate to autonomy- and competence-driven creative outcomes, offering practical guidance for motivating student participation in smart learning in higher education.

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