International Journal of Evaluation and Research in Education (IJERE)
Vol. 15, No. 1, February 2026, pp. 544~554
ISSN: 2252-8822, DOI: 10.11591/ijere.v15i1.36429

Motivation and generative artificial intelligence: perceived benefits among advertising and multimedia students

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Article Info

Article history:

Received Aug 1, 2025
Revised Jan 1, 2026
Accepted Jan 16, 2026

Keywords:

Advertising multimedia
Artificial intelligence
Extrinsic motivation
Intrinsic motivation
Perceived benefits

ABSTRACT

This study aimed to examine how intrinsic and extrinsic motivation, along with the use of and exposure to generative artificial intelligence (GenAI), influence the educational benefits perceived by students in disciplines linked to digital creativity and visual communication, namely graphic design, advertising, and multimedia. A quantitative, correlational and non-experimental design was used. The data was collected online during the 2024 academic year through a validated survey administered to 203 college students selected by convenience sampling. An instrument based on and adapted from previous studies was used to measure intrinsic and extrinsic motivation, perceived benefits, and creative use of GenAI tools. The answers were collected with a five-item Likert scale. The relationships between the variables were analyzed with the partial least squares structural equation modeling (PLS-SEM) procedure using the SmartPLS 4. The results indicate that both intrinsic and extrinsic motivation positively influence perceived benefits. These findings highlight the educational impact of GenAI on creative disciplines and highlight the need for academic programs and education policy directors to promote its responsible adoption, ensuring that students gain the skills and confidence to use these technologies effectively.

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1. INTRODUCTION

Within recent years, the position of artificial intelligence (AI) is elevating in the education sector. The emergence and acceptance of AI is fostering changes to dynamics of teaching and learning in the practices of knowledge production [1]. The factors associated with the adoption and acceptance of AI are being studied through the lens of several additional factors [2]. These studies have encompassed consistent use, motivation, and perceived usefulness and in this investigation, we regard AI usage (i.e., usage of AI by students), intrinsic motivation (IM) (i.e., personal motivations), and extrinsic motivation (EM) with respect to perceived usefulness of AI from the perspective of university students, who are participating in university academic practice and developing design and multimedia projects. Recent evidence shows that the acceptance of AI in education is strongly shaped by attitude, trust, ease of use, and perceived value [3].

The adoption and use of AI (USE)-based systems is associated with perceived usefulness and perceived ease of use of students [4]. Generative artificial intelligence (GenAI) refers to advanced AI models capable of producing original outputs such as images, videos, texts, and designs by learning patterns from large datasets, thereby expanding creative and educational possibilities. Recent evidence shows that GenAI not only enhances efficiency but also fosters motivation and creativity in higher education contexts [5].

With respect to education, generative visual AI tools such as Leonardo AI, Stable Diffusion, Midjourney, and DALL·E 2 produce originality and inspiration through the creation of images from text-based instructions (or prompts). In parallel, text-based GenAI systems like ChatGPT enhance this process by providing refined prompts, conceptual frameworks, or narrative contexts that can guide and enrich visual outputs, making the integration of both text and image generation highly valuable in creative learning environments. This is a new form of visual creation available for students. For example, a study on GenAI describes how architecture and interior design students perceive AI-generated imagery tools as very useful tools in early stages of design, and ideas for creativity [6]. Having previous technological experiences has been positively associated with student acceptance of GenAI tools relevant to creative products and learning environments. Studies on design-based learning in art and design education show how the use of design-centered learning technologies enhances students' motivation, creativity, and skills [7].

GenAI in visual education has implications for student motivation. Making complex visual compositions, or videos, rapidly with tools such as HeyGen AI, or Runway ML (AI video generator), increases efficacy perceptions, self-direction, and IM. Research by Wei *et al*. [8] complex problem-solving, and advanced visual skill acquisition, while also considering important ethical challenges such as authorship, technology dependence, and training data quality, particularly in a domain where the visual is so central to meaning-making backed by recent findings showing that GenAI enhances creativity, productivity, and student motivation, especially when integrated into visual design processes [9]. In education, GenAI not only personalizes learning and provides adaptive feedback, but also enhances students' motivation, creativity, and productivity by enabling rapid visual experimentation and problem-solving in design contexts [10].

Using tools like Stable Diffusion or Kaiber AI lets students try out different visual styles and turn their sketches or written ideas into animations. This helps them make school projects more engaging and feel more involved and confident in the creative process. Motivation and the sense of benefit are two key factors that influence whether someone decides to try out new tech tools. According to self-determination theory [11], IM associated with the intrinsic desire to learn, and EM associated with external rewards or demands, are both determinants in the adoption of tools such as visual GenAI. Li *et al*. [12] analyzed the network structure of students' motivation to learn AI, showing that some forms of regulation are more central than others in sustaining learning and adoption. Recent studies further confirm that motivational factors significantly influence the uptake of GenAI services, where trust and acceptance attitudes mediate the influence of social, technical, and personal motivators on continuous use intention [13]. In visual design, one thing that really seems to drive student motivation is how quickly and impressively these AI tools can generate results, especially when students are personally invested in their projects. Some recent studies suggest that when students genuinely enjoy what they are working on, their IM increases. On the other side, when they feel pushed to pick up new digital skills, that's more connected to external pressure.

The role of AI in creating visuals can fulfill both dimensions: it provides freedom for artistic experimentation and contributes to the demands of today's creative economy. However, also noted were challenges such as technological anxiety or concern about being made redundant by algorithms, which could negatively impact perceptions of the benefits [14]. Research with graphic design and visual communication students found that students with higher levels of IM reported more benefits from AI, especially if they could generate a concrete, original visual product. They tended to see AI as useful tools to inspire and generate creativity, inform their style, and address complex visual problems, which improved their emerging professional identity. Similarly, Kadyirov *et al.* [7] noted that in art and design education, IM significantly boosts creative performance, reinforcing our finding about motivation's central role. In conclusion, GenAI is changing the character of design tools and the subjective dispositions of the users of these tools. The role of motivation and benefits for university students indicates that there is a reconfiguration of creative and educational processes in which the visual and technological were in dialogue for the first time in this way.

This study explores how EM, IM, and the use of GenAI (AI usage) influence students' perceived benefits (BEN) in advertising and multimedia programs. Grounded in self-determination theory, the research examines both direct and indirect relationships among these variables within a creative, technology-focused educational context. It offers a novel contribution by analyzing the dynamics of motivation and GenAI adoption specifically within visual disciplines such as graphic design, illustration, and multimedia production. Thus, the direct hypotheses are:

- H1: EM has a direct impact on the BEN perceived by students.
- H2: EM has a positive and significant influence on IM.
- H3: EM has a direct, positive and significant relationship with the use of GenAI.
- H4: IM has a direct and significant relationship with perceived BEN.
- H5: IM has a direct and significant relationship with the use of GenAI.
- H6: The use of GenAI has a direct and significant relationship with the perceived BEN.

In addition, the indirect hypotheses are:
- H7: EM has a positive and significant influence on perceived BEN, mediated by the use of GenAI.
- H8: IM has a positive and significant influence on perceived BEN, mediated by the use of GenAI.

2. METHOD

2.1. Research design

This research was quantitative and correlational and used a cross-sectional design. The aim was to explore EM, IM, and AI based technology use, which affects perceived BEN to students. The research is in the visual arts and graphic design domain and focuses on investigating how these technological tools have begun to affect the creative practices of design, illustration and multimedia students.

2.2. Participants and study group

The research included 203 students, with 66% reporting to be male, and 34% being female. The modal age was 20 (33% of participants), and it declined from that point, with the next common ages being 21 (17.7%) and 18 (17.2%), suggesting that students were quite young, and between the ages of 18-21 years. With regards to the advancement in their career, the most common progression was in terms of semester enrolled, most students were in the 7th semester (41.9%), 3rd semester 21.7%, and 9th semester 16.7% under that assumption. Most participants had adequate university experience, meaning that they had seen some digital use and were on creative projects related to the study theme.

2.3. Data collection and respondents

A questionnaire was developed by adapting items from two previous studies: [15], [16]. The final instrument comprised 50 items distributed across seven constructs: EM (7), IM (7), use of GenAI (7), AI skills (4), AI limitations (3), AI-related anxiety (10), and perceived BEN (12). The questionnaire was specifically adapted to the context of students in visual disciplines, particularly graphic design, illustration, and multimedia production, in order to capture motivation and perceptions regarding the use of GenAI in their creative processes. Responses were obtained using a four-level Likert scale, where 1 indicated total disagreement and 4 represented full agreement.

Data collection took place over two weeks, coordinating dates with the instructors of the involved programs. Each questionnaire took approximately 15 to 20 minutes per participant. The instrument was administered online through Microsoft Forms, and the link along with a QR code was sent to instructors from different semesters, who then shared it with their students via the QR code. The questionnaire included clear instructions and the study's objectives to reduce the likelihood of random or rushed responses. In total, 238 completed questionnaires were received. However, during the preliminary analysis, 33 responses were excluded due to lack of variance or excessive variance in responses, and 2 were removed for being incomplete. As a result, 203 valid responses were retained for analysis. Subsequently, the results were downloaded from Microsoft Forms into a Microsoft Excel template. Subsequently, the data matrix was processed in the SPSS 25.0 software and then, the .sav file was transferred to the analysis environment to apply the structural equation model using partial least squares structural equation modeling (PLS-SEM). Respondents have been informed about the purpose of the study in which they will participate, indicating that the privacy of their data and the confidentiality of the information collected will be respected.

2.4. Descriptive overview of the sample

Students demonstrated a certain level of knowledge and usage of GenAI tools in both their academic practices, as well as for their more creative endeavors with writing, image creation, and video creation. Table 1 illustrates the knowledge levels and usage of various GenAI tools among the students. There is a high frequency of active usage for tools such as ChatGPT and Canva-89% or more students indicate that they are both familiar with and actively using the tools. This suggests a strong present uptake of these tools in student academic work. Between students ChatGPT is commonly used to generate text, doing creative writing, generate brainstorm ideas, and suggest ways to improve written assignments. Conversely, Canva appears to be an indispensable tool for generating images and media in graphic design for students engaged in visual and multimedia contexts.

Most of the other AI tools included are more specialized platforms for visual and audiovisual creation, for example, Stable Diffusion, Midjourney, HeyGen AI, and Leonardo AI. While students used these platforms less on the whole (8.4% to 14.8% of students using these), a moderate number of students know of these tools (15% to 28.6% of students). This hint's that usage of these tools will likely increase in terms of creating visuals and audiovisuals, which is important for creating creative and academic work in graphical and multimedia education. Of the tools considered, of the tools Copilot shows the third-highest rate

of usage (26.1%) and is known to only 40.4% of students. This suggests that there was a fair amount of prior use and usage is growing steadily. Perplexity has much less awareness and use (only 27.6% know the tool and 19.7% use the tool), suggests it is at a much earlier level of diffusion, You.com also shows limited adoption with only 8.3% of students self-reporting active use and 9.4% aware of without having use.

The overall pattern of limited use but awareness that is moderate and growing for some tools represents an early stage in the adoption process, where students are aware of the value of the object but are still exploring how to use it effectively. Encouraging the distribution and training of these technologies could create a significant boost in creativity, innovation, and quality of academic work and multimedia projects. Finally, knowledge and use of GenAI when students create not only improves efficiency and quality for students to pursue creative writing processes, but also changes the way and what can be produced when students generate visual and audiovisual representation in academic contexts, reinforcing important interdisciplinary skills needed in contemporary higher education.

Table 1. Knowledge and USE tools for academic work

AI tool	I do not know		I know but I have not used		I know and I have used	
	n	Percentage (%)	n	Percentage (%)	n	Percentage (%)
ChatGPT	1	0.5	17	8.4	185	91.1
Copilot	121	59.6	29	14.3	53	26.1
Gemini	93	45.8	58	28.6	52	25.6
Canva	9	4.4	12	5.9	182	89.7
Perplexity	147	72.4	16	7.9	40	19.7
Stable Diffusion	116	57.1	58	28.6	29	14.3
HeyGen AI	170	83.7	15	7.4	18	8.9
Midjourney	130	64.0	43	21.2	30	14.8
You.com	167	82.3	19	9.4	17	8.3
Leonardo AI	145	71.4	31	15.3	27	13.3

3. FIELDWORK AND DATA ANALYSIS

The researchers conducted an analysis using the PLS-SEM approach using SmartPLS software. Before evaluating the structural relationships, the researcher needed to evaluate the measurement model for quality and dependability of the constructs. These evaluations confirm that the items used in the questionnaire were reliable and measured what they were intended to measure theoretically [17]. To attain internal consistency or dependability for a construct, both the Cronbach's alpha and composite reliability values must be greater than 0.70 [18]. In the original analysis of the data, there were 50 indicators for 7 latent variables. After running a confirmatory factor analysis, 19 indicators were removed for not reaching the minimum required value.

As a result, variables "AI skills", "AI limitations", and "AI anxiety", were removed from the final model for methodological reasons and verified with statistical analysis indicating these constructs do not meet the necessary factor loading criteria, this study was able to present a more parsimonious model while strengthening reliability, and added confidence that the other constructs were closely related. Finally, all other constructs showed a Cronbach's alpha and composite reliability greater than 0.70, suggesting an acceptable level of internal consistency of the tools used, as shown in Table 2. The literature describes that an average variance extracted (AVE) value over 0.50 indicates more than 50% of variance of the items is accounted for by the separate latent construct, indicating good convergent validity [19]. In our case, all constructs had an AVE value above 0.610. The indicator reliability refers to each item's ability to account for the variance of the constructs to which they belong. Factor loadings are routinely used as an indicator of this reliability. Hair *et al.* [20] shows factor loadings of a value of 0.70 indicates an item is reliable.

Discriminant validity was evaluated based on guidelines from the literature, which state that for each construct to achieve discriminant validity. The purpose of this evaluation is to confirm that a reflective construct maintains stronger links to its own indicators than to the indicators of any other construct within the PLS route model [20]. The heterotrait-monotrait ratio (HTMT) value must be below the threshold of 0.9 [21]. In our study, as shown in Table 3, all HTMT values are below 0.71, indicating adequate discrimination between the different latent constructs.

The Fornell-Larcker criterion indicates that, for there to be discriminant validity, the square root of the AVE of each construct must overcome the correlations that this construct maintains with the others, thus showing that it is adequately differentiated from them [22]. The square root of the AVEs, which are the diagonal elements of the table (the bold values), indicate that each construct is larger than the correlation with the other constructs; thus, we can conclude that all constructs (BEN, EM, IM, and USE) achieved discriminant validity. This means that all constructs each measure their own concept, and do not overlap with the other constructs in the model. Another criterion is to review multicollinearity, which occurs when two or

more independent variables within a multiple regression model show high correlations with each other [23]. Something that indicates the multicollinearity of the variables is the variance inflation factor (VIF). By the way, a VIF that is greater than 10 indicates a high level of multicollinearity, while a VIF that is closer to 1 indicates that there is no multicollinearity. In this study, no item had a VIF that was higher than 2.7 according to Table 2; therefore, we can say that the multicollinearity was not a concern in the model.

Table 2. External loads and indicator reliability

Construct	Items	Factor loading	VIF	AVE	Cronbach alpha
BEN	BEN1	0.769	1.871	0.610	0.892
	BEN2	0.723	1.741		
	BEN3	0.827	2.442		
	BEN6	0.850	2.778		
	BEN7	0.829	2.478		
	BEN8	0.733	1.903		
	BEN9	0.724	1.682		
EM	EM31	0.826	2.309	0.666	0.902
	EM32	0.785	2.198		
	EM33	0.866	2.832		
	EM34	0.814	2.640		
	EM35	0.815	2.622		
	EM36	0.787	1.621		
IM	IM24	0.725	1.635	0.612	0.841
	IM25	0.732	1.676		
	IM27	0.811	1.853		
	IM28	0.827	2.045		
USE	USE1	0.814	2.023	0.654	0.739
	USE2	0.849	1.430		
	USE4	0.762	1.516		

Table 3. HTMT matrix and Fornell-Larcker criterion

Construct		BEN	EM	IM	USE
HTMT matrix	BEN				
	EM	0.388			
	IM	0.586	0.421		
	USE	0.717	0.430	0.454	
Fornell-Larcker criterion	BEN	0.781			
	EM	0.382	0.816		
	IM	0.510	0.403	0.782	
	USE	0.599	0.376	0.372	0.809

3.1. Model fit evaluation

The standardized root mean square residual (SRMR) is used to compare the adjusted model with a saturated model, showing how different they are. Generally, the lower the SRMR value the better the fit. Values below 0.08 are regarded as generally acceptable [24]. For our study, the SRMR value for the estimated model (0.07) is actually very close to that of the saturated model. The proposed model as shown in Figure 1 was built to examine the relationships among IM, EM, GenAI use, and perceived BEN among students enrolled in the publicity and multimedia program at a higher education institution. The proposed model entails four latent constructs, each of which is expressed through different items or indicators representing different dimensions of the variables under study: IM, EM, GenAI use (USE), and perceived BEN of AI use. GenAI use is considered to be the many tools such as ChatGPT, Stable Diffusion, and HeyGen AI that students use to generate creative writing, images, videos, and multimedia content.

The analysis was completed using bootstrapping (5,000 samples) to ensure results would hold up to the statistical rigor of bootstrapping. To assess the predictive capabilities of the research model we use the coefficient of determination (R^2). With regard to R^2 and adjusted R^2, the research model demonstrates predictive relevance, as discussed:

- IM: this construct is characterized as students' IM to use AI in an academic context which translates into students' interest, satisfaction and accomplishment with the technology.
- EM: this construct refers to students' motivations to use AI which emanate from extrinsic sources such as academic rewards, social recognition, and environmental pressures.

- USE: this construct measured students continued habitual and effective USE for academic practice. As noted, use primarily refers to using GenAI tools (e.g., ChatGPT, Stable Diffusion, Midjourney, HeyGen AI) used for performing tasks including creative writing, visual design, image generation, and video production in academic and multimedia contexts.
- BEN: this construct refers to the positive results one could expect from the USE when viewed through the lens of students' academic performance, efficiency of task completion and enhanced learning.

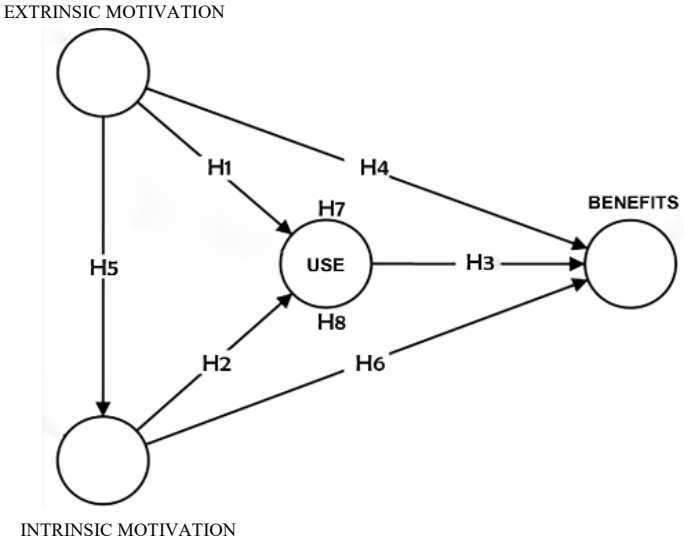

Figure 1. Proposed model

The model proposes that EM has a positive effect on IM; this suggests that external stimulus may promote personal agency regarding AI use. Both IM and EM are predictors of USE, which connects motivations and students' willingness to utilize AI for their work. USE also predicts BEN, which suggests that increased AI use leads to BEN. IM also has a direct effect on BEN. From this model it is also suggested that students with stronger personal motivation consider the BEN that come from AI having more positive experiences.

USE also mediates the effects in this model providing further understanding of how motivations can lead to positive experiences with AI. The use of GenAI technology tools as central to our model's concept of USE, not just technology tools, emphasizes their distinctive role as facilitators of creativity and expression in study and as expressions of creativity in academic and artistic production. It is chosen to explore these relationships and to understand them more deeply with structural equation modelling (SEM) with SmartPLS provided the most relevant way to get insights into how to build pedagogically sound strategies in educational design to facilitate effective USE.

3.2. Direct effects

The analysis was carried out with bootstrapping, 5,000 samples, to ensure the validity of results, as seen in Figure 2. The coefficient of determination (R^2) was used to assess the structural model's predictive power. The model exhibits predictive validity, and the interpretation of the R^2 values, as well as the adjusted R^2 values, is shown. The value of R^2 shows how much of the variation in the dependent variables (USE, BEN, and IM) is explained by the model as a whole:

- USE: the model captured 19.9% of the variance in the behavioral outcome-particularly that of GenAI tools for academic writing, design, and multimedia content creation.
- BEN: the model picked up on 46% of the variance in perceived BEN to adoption for GenAI technologies, such as increase productivity and creativity to name a few.
- IM: the model captured 16.2% of the variance in IM. Following with the adjusted R^2 values, because these numbers are adjusted for the number of predictors in the model, they provide a more reliable measure than R^2: USE (19.1%); BEN (45.2%); IM (15.8%).

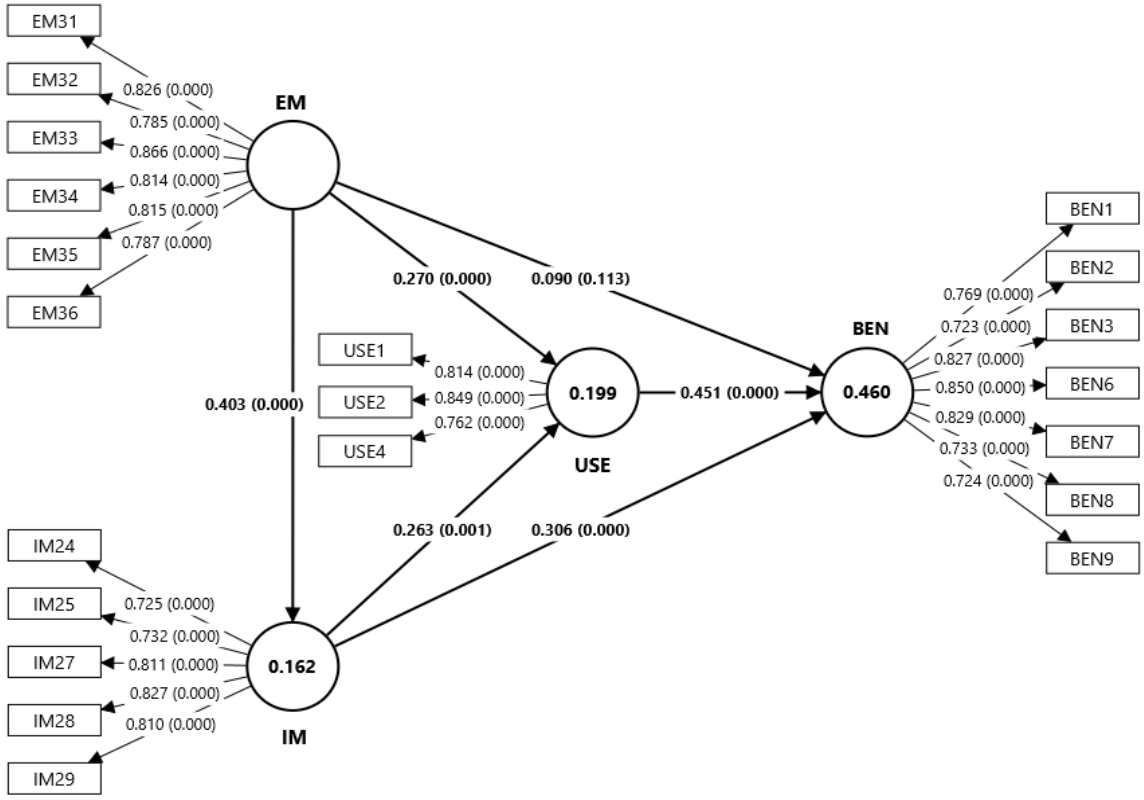

Figure 2. Path coefficients

The results from path analysis, as shown in Table 4, determine students using AI more often report greater BEN. Engagement frequency (USE) shows strong positive influence on perceived benefit (β=0.451, t=6.841, p<0.001). Students driven by personal interest (IM) also perceive more BEN. IM directly increases perceived benefit (β=0.306, t=3.906, p<0.001). EM does not affect perceived benefit. The relationship between EM and benefit is not significant (β=0.090, t=1.583, p=0.113).

Table 4. Hypothesis testing results (PLS-SEM)

H		Paths	Coefficients (β)	Standard deviation (STDEV)	T values	P values	Result
Direct	H1	EM->BEN	0.090	0.057	1.583	0.113	Not supported
	H2	EM->IM	0.403	0.073	5.495	0.000	Supported
	H3	EM->USE	0.270	0.061	4.426	0.000	Supported
	H4	IM->BEN	0.306	0.078	3.906	0.000	Supported
	H5	IM->USE	0.263	0.077	3.406	0.001	Supported
	H6	USE->BEN	0.451	0.069	6.569	0.000	Supported
Indirect	H7	EM->USE->BEN	0.122	0.035	3.528	0.000	Supported
	H8	IM->USE->BEN	0.119	0.037	3.235	0.001	Supported

3.3. Indirect effects

The findings provide evidence of significant indirect effects that further illuminate the link between motivations and perceived BEN of using AI in the domain of visual and multimedia design. EM has a positive and significant indirect effect on perceived BEN (β=0.122) through the use of GenAI tools (USE) as an outcome of EM. This means higher EM, not only enhances the level of engagement and USE but it also reflects in increased perceived benefit in this area, which is demonstrated by students using GenAI technologies in their academic writing, visual presentation creation, and multimedia production. Findings such as these support the view of EM in the effective adoption of GenAI allowing students to enhance their personal learning and perception of usefulness of GenAI within the creative and academic context. In addition, IM has a positive and significant indirect effect on BEN (β=0.119) through USE AI. Students with high IM, are likely to use GenAI as intended, more frequently and with more meaning, producing greater perceived BEN in terms of academic and creative usage.

This supports the perspective of IM and EM as both indispensable for obtaining more educational and creative BEN from GenAI tools used in educational and professional contexts. This interpretation reinforces that IM and EM are both critically important indirect antecedents of BEN, and both forms of motivation are important to ensure the maximum educational and professional benefit is obtained from the use of GenAI. Finally, the f-squared effect sizes [25] were reported, as: USE→BEN: f^2=0.302 (moderate effect), EM→USE: f^2=0.076 (small effect), EM→BEN: f^2=0.012 (very small/not significant), EM→IM: f^2=0.194 (moderate effect), IM→USE: f^2=0.072 (small/not significant), and IM→BEN: f^2=0.135 (small/not significant).

4. RESULTS AND DISCUSSION

After the SEM analysis, we appreciate that there are some theoretical and practical implications on motivation, the USE and the perceived benefits among students in advertising and multimedia programs.

4.1. Theoretical implications

The results highlight the central role of IM in explaining both the adoption of GenAI tools and the perception of benefits. Students with genuine interest reported greater engagement and higher perceived educational value, which is consistent with Zhou and Li [1], who found that motivation rooted in self-determination significantly drives learning outcomes when mediated by AI. Similarly, our findings reinforce observations by Kadyirov *et al*. [7], where students perceived AI as useful when they could link it to meaningful and complex tasks. In contrast, EM showed no significant direct effect on perceived benefits, although it positively influenced AI usage and supported IM. This apparent contradiction is reconciled by the mediation analysis, which revealed that EM indirectly contributed to perceived benefits through its influence on AI usage and, to a lesser extent, AI-related anxiety. In other words, external motives did not translate into benefits on their own but became effective once transformed into active engagement with AI tools or moderated by psychological factors. This partially differs from Sova *et al*. [2] who found that factors like perceived usefulness, positive attitude, and training significantly influence AI adoption among economics students in higher education. Our results suggest that external pressures alone are insufficient unless transformed into intrinsic interest, which aligns with the balanced view presented by Bai and Wang [5], whose showed that both interaction quality and output quality of GenAI tools significantly boost learning motivation and creative self-efficacy, which in turn mediate learning outcomes.

Students reported that supportive environments increased their willingness to adopt AI, echoing the findings of Kang *et al*. [13], which emphasized the mediating role of trust in maintaining the continuous USE. Furthermore, our observation that IM reduces technology-related anxiety is consistent with Wang [26], who demonstrated that motivation can reduce emotional barriers in digital learning. Overall, these results support the self-determination theory framework [10], reinforcing that the most sustainable learning benefits arise from a dynamic between extrinsic triggers and intrinsic engagement [27].

4.2. Practical implications

The practical implications of these findings point to the need for academic programs to foster IM while strategically using extrinsic incentives. For example, while external recognition (e.g., certificates, performance awards) can generate engagement, the long-term benefits depend on the development of students' genuine interest in creative experimentation with AI, in line with Wei *et al*. [8] in the context of design education. Therefore, universities should not only provide access to tools, but also create supportive pedagogical ecosystems, as suggested by Guo and Wang [14], where the adoption of AI is framed by trust, ethics, and professional development. Teacher training is equally essential, as educators play a central role in guiding the use of AI towards responsible and creative practices, as confirmed by Fang and Jiang [9] on the challenges of AI in arts education.

Among the limitations found, the sample (203 students) lacks diversity, limiting generalizations. Future research should employ multi-contextual samples and longitudinal designs. Our self-reported data could contain biases (social desirability). In addition, the study did not analyze the moderating variables, which could have enriched its effects in new study contexts.

5. CONCLUSION

Among higher education students, the study findings show that both EM and personal motivation greatly influence the seen advantages of using GenAI. External inspiration, such as accolades, certificates, or academic rewards, raises students' valuation of the advantages of AI, therefore implying that contextual influences can increase interest and openness to these new technologies. Driven by internal interests and professional development objectives, personal motivation also greatly enhances one's view of benefits.

External motivators can shape students' perceptions of the value of AI, but they do not necessarily shape how students can use them. While a reward or recognition may motivate students to experiment with or try these tools, that alone could not transform how they perceive the true value of what GenAI has in terms of its contribution to their learning and growth in creative skills. In fields that rely on creative endeavors, such as graphic design, advertising, or multimedia, technology like GenAI is inherently valuable because it requires adaptability, innovation, and a core skill set. These new technologies amplify the space available to experiment with new creative thinking and even provide new means of expression in visual, textual, and audiovisual forms.

From this lens, university institutions must provide students with access to generative forms of AI. They should also help students learn how to use GenAI responsibly. In the university classroom, teaching and learning experiences could be designed to motivate students to be creative and self-expressive, while also acquiring awards or certificates of recognition.

In addition, educational institutions should promote students' reflections on students' ethical use of GenAI so that they can continue to develop their own creative identity. Institutions should establish policies that ensure equitable access to GenAI for use. Future research should expand on these findings by comparing creative disciplines with non-creative programs, conducting longitudinal studies to observe changes in motivation over time, and analyzing how specific AI tools (e.g., ChatGPT, Midjourney, or Runway ML) influence different dimensions of student learning. Such directions would deepen our understanding of how GenAI transforms both educational practice and creative development.

FUNDING INFORMATION

This research was supported by institutional resources from Universidad Nacional de San Agustín de Arequipa (UNSA) and Universidad Católica de Santa María (UCSM).

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Fanny Paredes-Quispe	✓	✓			✓	✓	✓	✓	✓	✓		✓		
María del Pilar Ponce		✓				✓	✓	✓		✓		✓	✓	
Luis Melgar-Amado		✓	✓	✓	✓		✓			✓	✓		✓	

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

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

INFORMED CONSENT

Written informed consent was obtained from all adult participants prior to data collection. Participation was voluntary and anonymous, and no personally identifiable information was collected.

DATA AVAILABILITY

Anonymized data supporting the results can be obtained from the corresponding author, [YT-Q], upon reasonable request.

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