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Understanding Differences in Student Engagement with AI in Art Education through a Cluster Analysis Approach

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ABSTRACT

This study explores how university students in Kazakhstan experience and engage with artificial intelligence (AI) tools in their art education. Focusing on students' creative thinking, digital self-confidence, and attitudes toward AI, we gathered responses from 248 participants studying in design and art-related programs across four universities. Using a self-developed survey, we analysed the data with clustering techniques to identify four different student profiles, each reflecting different levels of creativity and comfort with AI: Practical Technophiles, Creative Traditionalists, Disengaged Learners, and Balanced Creatives. The findings reveal that students vary widely in how they perceive and use AI in their creative processes. While some embrace AI as a helpful and inspiring tool, others remain cautious, preferring traditional artistic approaches. These differences indicate the importance of flexible teaching strategies that respect students' diverse perspectives. By taking these findings into account, educators can create more inclusive and effective art education practices that integrate digital tools without losing sight of artistic identity and student agency.

Keywords: Art Education, Artificial Intelligence, Cluster Analysis, Student Engagement.

INTRODUCTION

Artificial Intelligence (AI) is reshaping education by introducing new opportunities for personalization, feedback, and content generation across disciplines. While most research on AI integration has focused on science, technology, engineering, and mathematics (STEM) education (El Bedewy et al., 2024; Károly, 2025; Okwara & Henrik Pretorius, 2023), creative fields such as visual arts are increasingly incorporating AI tools that allow for new forms of artistic expression and creative exploration (Zawacki-Richter et al., 2019). In particular, generative AI applications such as DALL·E, Midjourney, and Adobe Firefly are enabling students to visualize and produce complex visual outputs based on text prompts or stylistic inputs. These tools improve the creative process and raise important pedagogical, philosophical, and ethical questions about the nature of creativity, authorship, and artistic identity.

In art education, the development of creative thinking is essential. Creative thinking includes cognitive and dispositional abilities such as fluency (the generation of multiple ideas), flexibility (the ability to shift perspectives), originality (the production of novel ideas), and elaboration (the expansion and refinement of concepts) (Kim, 2006; Torrance, 1974). These abilities are considered critical for students to express themselves, solve problems, and engage with complex visual and social phenomena (Runco & Jaeger, 2012). With the integration of AI into studio classrooms, students are both creators and co-designers in collaboration with machine-generated outputs. This transformation demands a rethinking of how creative thinking is improved, measured, and supported in higher education.

The integration of AI tools into creative disciplines compels a reconceptualization of creativity in design education, particularly as students increasingly act not as sole authors but as collaborators in algorithmically mediated processes. This shift challenges traditional assumptions of design authorship, originality, and ideation (McCormack et al., 2019; Verganti et al., 2020). In AI-supported creative learning environments, creativity is no longer an entirely human-centered process but a distributed, hybrid activity that is partially shaped by data-driven systems and generative models (Bertrand et al., 2023; Garcia, 2024).

Despite the increasing adoption of AI in creative practice, limited empirical research has explored how students experience AI in art education, particularly in non-Western contexts. Studies tend to focus on the affordances of AI or its role in enhancing learning outcomes in general, but they often overlook students' perceptions, attitudes, and confidence in using AI tools for artistic creation (Mikrouli et al., 2024; Wang et al., 2023). Moreover, traditional creativity assessments are not fully equipped to evaluate hybrid human-machine creativity, especially in environments where students use AI tools during ideation, prototyping, and composition stages.

This gap is particularly evident in Kazakhstan, where higher education institutions are beginning to adopt digital and AI-supported educational technologies. Although the country has made significant investments in digitalization and innovation, little research has been conducted on how these technologies are shaping pedagogical practices in creative disciplines such as visual arts. Understanding how Kazakhstani students perceive, adapt to, and benefit from AI in art education is vital for developing relevant curricular frameworks that promote creativity while also addressing cultural and ethical considerations.

Significance of the Study

This study contributes to a growing body of interdisciplinary research at the intersection of art education and AI by providing empirical data on university students' creative thinking, self-efficacy, and attitudes toward AI-supported artmaking. By focusing on students in Kazakhstan, the study provides region-specific perspectives that are underrepresented in the international literature, supporting the broader inclusion of Central Asian perspectives in discussions about digital innovation in education. The findings will help educators, policymakers, and curriculum developers design more responsive, equitable, and creativity-focused educational environments that make meaningful use of AI technologies while honoring artistic intent and student voice.

This research contributes to the evolving discourse on design creativity by introducing a nuanced framework for understanding how students position themselves within hybrid creative environments. While recent theoretical works have called for a redefinition of creativity in the age of AI (Park, 2023; Carceller, 2024), there remains limited empirical evidence of how learners actually perceive, experience, and adapt to these changes in studio-based design education. By identifying distinct student profiles through cluster analysis, the study bridges a critical gap in the literature between conceptual discourse and pedagogical application.

LITERATURE REVIEW

Conceptualizing Creative Thinking in Art Education

Creative thinking is a central objective in art education, often regarded as a cornerstone of artistic development and self-expression. It is commonly defined as the ability to generate novel and valuable ideas (Runco & Jaeger, 2012). In the context of visual arts, creative thinking extends beyond cognitive ideation to encompass aesthetic, emotional, and symbolic dimensions. Scholars and educators generally conceptualize creative thinking through four core dimensions: fluency, flexibility, originality, and elaboration (Torrance, 1974; Kim, 2006).

In visual arts education, creativity is about generating artistic products and about engaging in reflective, exploratory, and interpretive processes (de Gastyne, 2020; Gil-Glazer, 2020). These processes empower students to develop personal voice and meaning-making abilities, reinforcing their identity and engagement with the world. The development of creative thinking through art encourages interdisciplinary linkages, problem-solving capacities, and critical interpretation of societal issues (Nathan, 2017).

To assess creative thinking in art education, researchers have traditionally employed psychometric tools like the Torrance Tests of Creative Thinking, which remain one of the most cited instruments for measuring divergent thinking skills (Fan & Zhong, 2022; Kim, 2006). These tests have been adapted and criticized over time, particularly for their reliance on linguistic or abstract tasks not always aligned with visual arts education. Consequently, many educators also rely on self-perception scales that measure students’ confidence in their creative abilities and frequency of engaging in divergent thinking strategies (Karwowski et al., 2013). These self-report measures are particularly relevant when examining students' beliefs in environments that incorporate new technologies, such as AI, where traditional performance assessments may not fully capture students' experiences of creativity.

The Role of Artificial Intelligence in Education

AI has emerged as a transformative force in education, offering new opportunities for personalized learning, formative assessment, and content generation. AI technologies have increasingly been integrated into educational platforms to support instruction, analyze learner behavior, and optimize the delivery of content based on students' needs and preferences (Bekdemir, 2024; Ogurlu et al., 2023; Zawacki-Richter et al., 2019). These systems include intelligent tutoring systems, adaptive learning environments, recommendation engines, and generative tools that produce educational content, including images, texts, and interactive experiences (Aldazharova et al., 2024).

A significant application of AI in education lies in its ability to personalize learning pathways. AI-driven platforms can adapt instructional content and pace based on real-time assessment of student performance, thus supporting differentiated instruction at scale (Bacolod, 2023; de los Ángeles Domínguez-González et al., 2023; Holmes et al., 2019). Furthermore, AI supports automated feedback, which has proven particularly beneficial in large or asynchronous learning environments. Feedback mechanisms can be immediate, tailored, and iterative that help learners identify mistakes, revise work, and track progress (Barbu & Sbughea, 2024; Luckin et al., 2016). In creative fields like art and design, AI also acts as a co-creator, enabling students to explore novel visual outputs, remix styles, or simulate creative processes, which extends the boundaries of individual ideation (Bertrand et al., 2023; Verganti et al., 2020).

The integration of AI into education has shown promising results in enhancing student engagement, creative performance, and self-efficacy (Medina-Gual & Parejo, 2026). For example, a study by Lee et al. (2023) found that peer-feedback strategies supported by mobile-based AI tools led to increased creativity and metacognitive awareness among learners. Moreover, AI tools can facilitate experimentation and iteration, thus helping students build confidence in their learning processes, especially in subjects requiring visual or creative exploration (Hare et al., 2025).

Despite the potential benefits, concerns remain regarding equity, ethics, and authenticity. Critics argue that overreliance on AI may diminish human creativity or promote superficial engagement with content (Selwyn, 2019). Therefore, educators must approach AI integration thoughtfully, ensuring that it complements, rather than replaces, core pedagogical goals such as critical thinking and creativity development (Togabayeva et al., 2026).

AI Tools and Creative Practices in Art Education

The integration of AI tools into art education is transforming how students conceptualize, produce, and reflect on creative work. Generative AI applications such as DALL·E, Midjourney, and Adobe Firefly allow users to create original visual content based on textual input or existing image prompts. These tools enable students to experiment with new forms of visual expression, explore stylistic variations, and iterate on ideas rapidly, capabilities that have traditionally required significant technical skill and time investment (McCormack et al., 2019; Yu et al., 2024).

In educational contexts, these tools are increasingly being leveraged both for final product creation and as part of ideation and exploration stages. For instance, students might use generative AI to brainstorm visual compositions, simulate the application of design principles, or remix cultural symbols. Such interactions expand the boundaries of visual literacy and align well with postmodern pedagogies that emphasize hybridity, process, and interactivity (Evangelidis et al., 2024; Gil-Glazer, 2020). As AI becomes a co-creative agent, students shift from being sole authors to collaborators with technology, a shift that invites both pedagogical innovation and philosophical reflection.

While many educators and artists celebrate the affordances of AI in expanding creativity, others raise critical concerns. One concern is the risk of aesthetic homogenization, where models trained on large existing datasets may reproduce dominant styles, thereby narrowing the range of creative diversity (Irbite & Strode, 2021). Another issue is the potential loss of craft-based engagement in favor of rapid digital production, which may undermine deep skill development and material sensitivity (Garcia, 2024). Furthermore, questions around authorship, originality, and ethical use remain contentious, particularly in academic environments where students are graded based on creative merit.

Despite these challenges, emerging pedagogical models show promise in integrating AI tools with traditional studio-based learning. Hybrid approaches that combine manual and digital exploration, such as using AI to prototype and then hand-render final works, help preserve artistic intentionality while embracing technological innovation (Leonard, 2023). Other models encourage students to critically analyze the datasets and biases behind generative tools, thus embedding digital literacy and ethical reasoning into the creative process.

There is growing theoretical interest in how AI reshapes creative processes in design education (McCormack et al., 2019; Garcia, 2024), however, there is the absence of empirical studies examining how students themselves interpret, adapt to, and engage with AI as a co-creative agent. Much of the current literature focuses on either technological affordances or philosophical implications, often neglecting the learner perspective in authentic educational contexts (Irbite & Strode, 2021; Leonard, 2023). As design education shifts from isolated authorship to distributed creativity involving algorithmic systems, understanding how students conceptualize creativity and authorship within these hybrid environments is essential (Park, 2023).

Students’ Attitudes and Self-Efficacy in Digital and AI Contexts

As artificial intelligence and digital technologies increasingly permeate educational settings, understanding students’ attitudes and self-efficacy (Shukla, 2024) becomes essential for effective technology integration. Two prominent theoretical frameworks used to assess user acceptance of technology are the Technology Acceptance Model (Davis, 1989; Yilmaz et al., 2023) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). These models suggest that students’ perceived usefulness and ease of use of AI-based tools strongly influence their willingness to adopt them in academic contexts. In art education, this translates to how students view AI as a facilitator of creativity, problem-solving, and innovation.

Closely tied to acceptance is the concept of digital art self-efficacy, that is, students' confidence in their ability to effectively use digital tools for creative expression. Research shows that higher self-efficacy correlates with greater engagement in digital artistic tasks, higher persistence when facing challenges, and more openness to experimenting with AI-assisted tools (Falebita & Kok, 2025; Karwowski et al., 2013). For example, Wang et al. (2023) found that students' perceived AI capability of their institutions significantly predicted their self-efficacy and creativity in learning environments that incorporate intelligent systems. This is particularly relevant in creative fields, where the ability to navigate and manipulate technology is becoming as critical as traditional techniques.

However, students’ attitudes toward AI in education are not only shaped by functional considerations. Psychological and ethical concerns also influence acceptance and use. In creative domains, where authorship and originality are core values, students may question the legitimacy of using AI-generated content in their work. Some students may perceive AI as diminishing their role as artists or compromising the authenticity of their creative process (Carceller, 2024). Others may worry about over-reliance on algorithms that are trained on biased or commercially curated datasets, leading to aesthetic uniformity and ethical dilemmas in ownership (McCormack et al., 2019).

Furthermore, there is a growing need to prepare students to use AI tools and critically interrogate them. Encouraging students to ask questions about who designs AI systems, what data is used, and how decisions are made promotes critical digital literacy and empowers learners to use technology responsibly and creatively (Dong & Gan, 2026; Park, 2023).

Gaps in the Literature and Research Needs

A significant gap in the *design creativity* literature lies in the absence of typological models that capture the diversity of student experiences in AIaugmented creative education. While scholars have called for a rethinking of creativity as a distributed and co-constructed phenomenon (Verganti et al., 2020; Carceller, 2024), few empirical studies have explored how students' self-efficacy, attitudes, and tool usage patterns align with this transformation. Traditional design education research has often treated learners as a homogeneous group, overlooking the distinct ways in which different students respond to AI integration. There is also limited data from emerging educational contexts, particularly in Central Asia, where digital transformation is occurring rapidly but is underrepresented in global design discourse.

Although recent scholarship has indicated the growing role of AI in education and the creative industries, there remains a significant lack of empirical data specifically addressing university students' experiences with AI in the context of art education. Most existing studies focus on either the technological affordances of AI (Chadha, 2024; Zawacki-Richter et al., 2019) or its general impact on cognitive and academic outcomes (Wang et al., 2023), with limited attention to how students in creative disciplines engage with, adapt to, and make meaning from these technologies. This presents a research gap in understanding how AI integration influences creative thinking formation and artistic self-concept among higher education learners.

Another pressing concern is the absence of validated instruments designed to assess creativity within AI-supported learning environments. While tools like the Torrance Tests of Creative Thinking (Kim, 2006) and various creative self-efficacy scales (Karwowski et al., 2013) provide a foundation, they may not fully capture the complexity of creative processes mediated by AI tools such as DALL·E or Midjourney. These platforms introduce a new layer of algorithmic mediation and co-creation, complicating traditional definitions of fluency, originality, and elaboration. Therefore, there is a need for updated assessment frameworks that account for hybrid human-machine creativity and reflect both technical proficiency and conceptual depth.

Equally important is the understanding of student perceptions regarding AI in art education. Much of the current discourse centers on learning outcomes, yet students' attitudes, emotional responses, ethical concerns, and sense of authorship are essential for a holistic understanding of technology integration (Lazkani, 2024; Pente, 2022). Perceptions shape engagement, willingness to experiment, and openness to interdisciplinary practices, factors that are especially critical in improving creativity. Without considering students' subjective experiences, educators risk implementing AI in ways that alienate learners or undermine creative confidence.

This study responds to these gaps by empirically investigating university students' self-reported creative thinking, digital art self-efficacy, attitudes toward AI, and actual AI tool usage in art creation. In doing so, it contributes to both theoretical development and practical understanding of how to cultivate meaningful, student-centered innovation in art education

RESEARCH METHOD

This study used a quantitative, cross-sectional survey design to look into university students' perceptions and students' own experiences about creative thinking, AI tool usage in art creation, attitudes toward AI in art education, and digital art self-efficacy.

Sample and Context

This study involved a total of 248 undergraduate students from four universities in Kazakhstan, all of whom were enrolled in art-related programs. Participants represented a linguistically diverse and predominantly female cohort, with 91.9% identifying as female, 7.7% as male, and one student not reporting their gender. In terms of language, 132 students (53.2%) reported Kazakh as their primary language of instruction, and 116 (46.8%) reported Russian. Students were distributed across academic years, with 67 in their 1st year, 51 in 2nd year, 69 in 3rd year, and 46 in 4th year of study. The sample was drawn from the following institutions.

Abai Kazakh National Pedagogical University (AKNPU): Students from the Departments of *Art Education* and *Design* participated in the study. A total of 122 students, ranging from the 1st to 5th year, voluntarily completed the survey. These departments offer programs in painting, graphics, and vocational education across all degree levels (bachelor's, master's, and PhD). The programs aim to prepare professionals in art pedagogy and design with a focus on creative development and educational sciences.

Almaty Technological University (ATU): This university's Faculty of Design, Textile, and Clothing Technology contributed 76 students from the Department of *Design*. Students were enrolled in a 5-year bachelor's program specializing in either Fashion Design or Graphic Design. The curriculum integrates traditional studio practices with contemporary digital subjects, including computer graphics, packaging, web design, and introductory courses in artificial intelligence for design applications. Instruction is delivered in both Kazakh and Russian.

Kazakh National Women's Pedagogical University (KNWPU): From the Department of *Vocational Education*, 28 students (1st to 4th year) studying in the Visual Arts, Art Work, Graphics, and Design program participated. Their coursework emphasizes pedagogical approaches to teaching visual art, including modules on creative drawing, painting, and design methodology. These students are trained as future educators in creative disciplines.

Kazakh Leading Academy of Architecture and Civil Engineering (KazGASA) – A total of 20 students, primarily from the 4th and 5th years, were surveyed from the *Graphic and Media Design Department*. These students follow a curriculum focused on applied aspects of design, including UX/UI, multimedia, advertising, and branding. The program prepares students for diverse roles in the creative industries, from illustrators and junior designers to art directors, with a strong emphasis on digital fluency and project-based learning.

Instrument

The instrument used in this study was a self-report questionnaire developed by the authors. Because no existing validated instrument simultaneously measures creative thinking, AI tool usage in art creation, attitudes toward AI in art education, and digital art self-efficacy within a single framework, a new survey instrument was developed for this study. Its development followed a rigorous multi-phase process to have content validity, clarity, and psychometric robustness. The initial version of the survey was generated through extensive discussion among the authors, grounded in theoretical frameworks related to creativity, technology use, and digital self-efficacy. Items were designed to reflect both behavioral engagement with AI tools and underlying perceptions and confidence related to their use in artistic processes. Following item construction, the draft was reviewed by three independent experts in art education and educational technology. They evaluated each item for clarity, relevance, and alignment with the aim of the survey. Revisions were made based on their feedback to improve language precision and conceptual accuracy. Subsequently, three university students participated in a think-aloud session, reading each item aloud and commenting on their understanding. Minor revisions were done after this process as well.

To validate the structure of the instrument, an Exploratory Factor Analysis (EFA) was conducted by using Jamovi program. The minimum residual extraction method and oblimin rotation were applied for the EFA. Bartlett's Test of Sphericity indicated suitability for factor analysis ($\chi^2(253) = 3997.23$, $p < .001$), and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was excellent (overall KMO = 0.92). Factor loadings of each item are presented in Table 1.

The EFA resulted in a four-factor solution consistent with the hypothesized model in the survey. Items measuring Creative Thinking Skills (CTS1–CTS5) loaded strongly on one factor, with factor loadings ranging from 0.79 to 0.83. Items related to AI Tool Usage in Art Creation (TUAC1–TUAC6) loaded on another factor, with loadings between 0.62 and 0.85. The Digital Art Self-Efficacy items (DASE1–DASE6) loaded on a third factor (loadings from 0.51 to 0.83), and Attitudes Toward AI in Art Education (ATAE1–ATAE6) made the fourth factor, with loadings ranging from 0.48 to 0.71. These results indicate the construct validity of the used instrument and the uniqueness of each dimension of the instrument.

Table 1: Exploratory Factor Analysis- Factor Loadings

	Factor				
	1	2	3	4	Uniqueness
CTS1			0.79		0.37
CTS2			0.83		0.28
CTS3			0.79		0.28
CTS4			0.79		0.32
CTS5			0.81		0.32
TUAC1	0.62				0.5
TUAC2	0.85				0.29
TUAC3	0.79				0.33
TUAC4	0.77				0.29
TUAC5	0.66				0.33
TUAC6	0.68				0.44
ATAE1				0.48	0.44
ATAE2				0.61	0.49
ATAE3				0.62	0.34
ATAE4				0.71	0.31
ATAE5				0.58	0.6
ATAE6				0.7	0.53
DASE1		0.51			0.49
DASE2		0.82			0.3
DASE3		0.83			0.25
DASE4		0.83			0.26
DASE5		0.83			0.28
DASE6		0.62			0.42

Note. 'Minimum residual' extraction method was used in combination with a 'oblimin' rotation

Internal consistency reliability was assessed using Cronbach's alpha. The results demonstrated excellent reliability across all scales: Creative Thinking Skills ($\alpha = 0.91$), AI Tool Usage in Art Creation ($\alpha = 0.91$), Digital Art Self-Efficacy ($\alpha = 0.91$), and Attitudes Toward AI in Art Education ($\alpha = 0.85$). The total reliability for the full instrument was also high ($\alpha = 0.94$).

Data Collection

The survey instrument, including the demographic section and all validated scale items, was transferred to a Google Form for digital distribution. Prior to dissemination, the form was thoroughly reviewed by all authors to ensure that item formatting, skip logic, and question flow were consistent with the intended structure of the instrument. The link to the survey was distributed via universities email lists and WhatsApp groups associated with art-related academic programs. To increase response rates, three reminders were sent at regular intervals to students who had not yet completed the survey. In total, the survey was sent to 287 students, and responses were collected over a two-week period. Participation was voluntary and anonymous. Students were informed of the study's purpose and provided digital consent before proceeding with the questionnaire.

Data Analysis

The data were first cleaned. Of the 287 participants, 17 did not respond and 22 were removed due to selecting the same response for all items. Data were analyzed using Jamovi (2.6.13), an open-source statistical software designed to provide a user-friendly interface for statistical analysis. A K-means cluster analysis was conducted to identify natural groupings among students based on their composite scores in the four dimensions of the survey. This technique segments individuals into distinct clusters that minimize within-group variance and maximize between-group separation. The best number of clusters (k = 4) was determined using the Gap Statistic method. The results, indicated in Figure 1, supported the selection of a four-cluster model. Then, cluster centroids were tabulated to interpret the defining characteristics of each profile (Table 3) and mean scores of individual survey items were plotted across clusters (Figure 2) to show detailed differences. Dimensionality reduction was performed using Principal Component Analysis (PCA), and the results were shown in cluster plots (Figure 3) and a biplot of item contributions (Figure 4) to improve interpretation. Finally, demographic variables such as gender, grade level, language background, prior art course experience, and AI usage frequency were explored across clusters using cross-tabulations and mean comparisons.

RESULTS

Figure 1 shows the application of the Gap Statistic method to identify the most appropriate number of clusters (k) for the dataset. The horizontal axis represents the number of clusters and the vertical axis displays the gap statistic values, that measure the improvement in clustering performance compared to a null reference distribution.

The curve in the Figure 1 shows a marked increase in the gap value from $k = 1$ to $k = 4$, indicating that each additional cluster up to this point leads to a substantial gain in clustering quality. Beyond $k = 4$, the improvements become marginal, and the gap values begin to stabilize. The error bars reflect the standard deviation of the gap statistic. The vertical dashed line at $k = 4$ shows the optimal number of clusters, as it represents the point where the gap statistic first reaches its maximum before leveling off.

Figure 1: *The Optimal Number of Clusters identified*

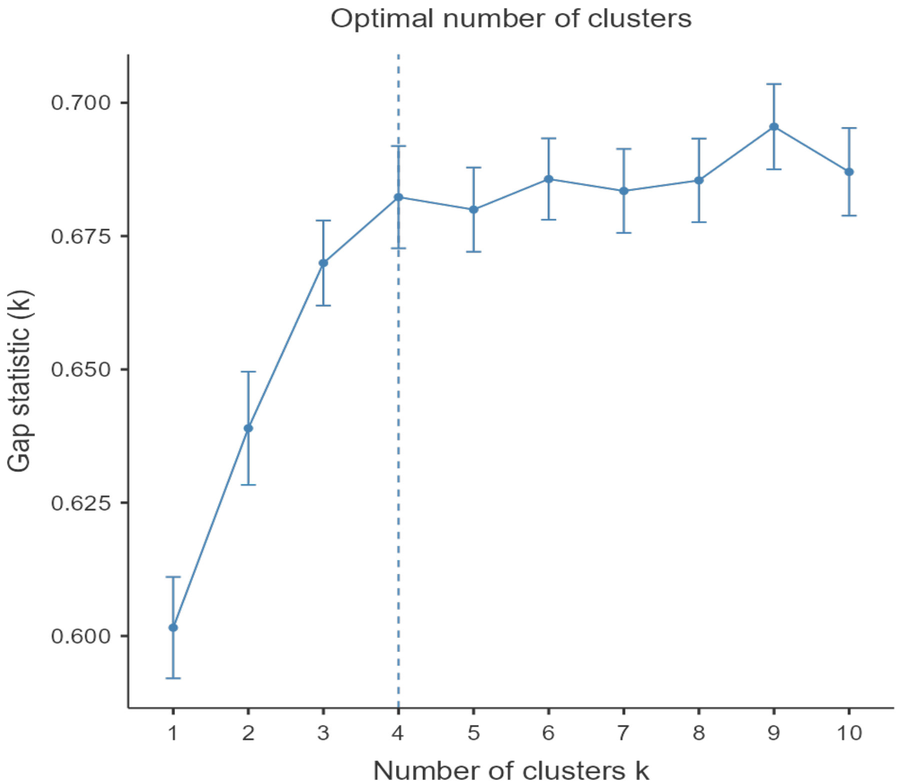


Table 2 displays the sum of squares (SS) values obtained through the K-means clustering analysis.

Table 2: Sum of Squares Analysis and Cluster Distribution

	Value	Count
Cluster 1	527.23	32
Cluster 2	993.44	68
Cluster 3	1721.71	98
Cluster 4	1123.32	50
Between clusters	3206.44	
Total	7572.15	

As seen in Table 2, the total variance in the data was 7572.15. Of this, 3206.44 was attributed to variance *between* clusters, indicating a meaningful separation among the four clusters. The remaining variance, distributed *within* clusters, shows that Cluster 3 had the highest internal variability (1721.71), followed by Cluster 4 (1123.32), Cluster 2 (993.44), and Cluster 1 (527.23). This shows that students in Cluster 3 exhibited more diverse responses. The clustering Table 2 further indicates the number of students assigned to each group: Cluster 3 was the largest with 98 students and Cluster 1 was the smallest with 32 students.

Table 3 presents the centroids of the four clusters across all survey dimensions. Each cluster represents a group of students who responded similarly in terms of their creative thinking skills, AI tool usage in art creation, attitudes toward AI in art education, and digital art self-efficacy.

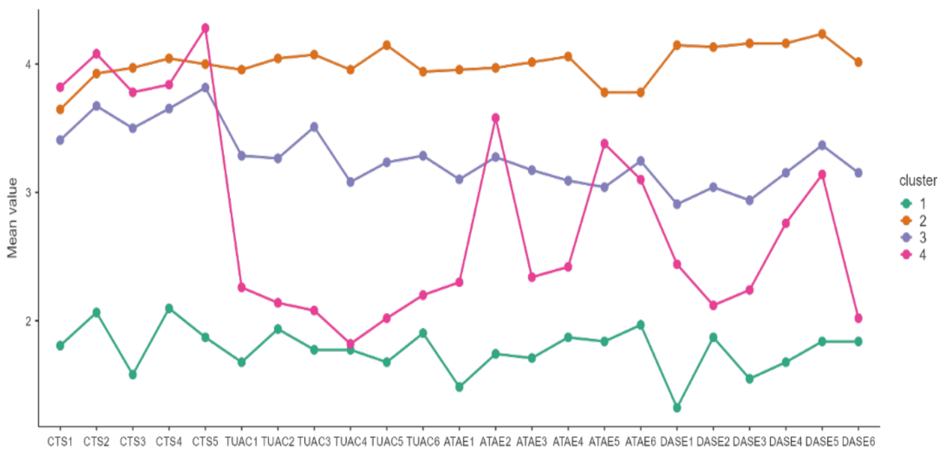
Table 3: Cluster Centroids and Student Profiles

	1	2	3	4
CTS1	1.81	3.65	3.41	3.82
CTS2	2.06	3.93	3.67	4.08
CTS3	1.58	3.97	3.5	3.78
CTS4	2.10	4.04	3.65	3.84
CTS5	1.87	4.00	3.82	4.28
TUAC1	1.68	3.96	3.29	2.26
TUAC2	1.94	4.04	3.27	2.14
TUAC3	1.77	4.07	3.51	2.08
TUAC4	1.77	3.96	3.08	1.82
TUAC5	1.68	4.15	3.23	2.02
TUAC6	1.9	3.94	3.29	2.20
ATAE1	1.48	3.96	3.10	2.30
ATAE2	1.74	3.97	3.28	3.58
ATAE3	1.71	4.01	3.17	2.34
ATAE4	1.87	4.06	3.09	2.42
ATAE5	1.84	3.78	3.04	3.38
ATAE6	1.97	3.78	3.24	3.1
DASE1	1.32	4.15	2.91	2.44
DASE2	1.87	4.13	3.04	2.12
DASE3	1.55	4.16	2.94	2.24
DASE4	1.68	4.16	3.15	2.76
DASE5	1.84	4.24	3.37	3.14
DASE6	1.84	4.01	3.15	2.02

Cluster 1 shows consistently low scores across all dimensions, indicating these students are disengaged or less confident in both creative and digital domains. In contrast, Cluster 2 emerges as the most enthusiastic and digitally competent group, scoring highest in every section, indicating a strong embrace of AI tools, high creative confidence, and positive attitudes toward AI-supported learning. Cluster 3 reflects moderate engagement, with average scores that suggest a balanced but not particularly strong orientation toward AI-enhanced creativity. Cluster 4 reveals an interesting profile, such that, while their creative thinking scores are relatively high, their digital confidence and attitudes toward AI are more reserved, pointing to students who may value traditional creative processes over digital innovation.

Figure 2 provides a visual comparison of how students in each of the four clusters responded to individual survey items across the dimensions of the survey. Each line represents the mean scores of one clusters across all 27 items.

Figure 2: *Mean Scores of Survey Items by Cluster*



Cluster 2 (orange) clearly stands out with consistently high scores across all survey items, reaffirming its profile as the most digitally confident, AI-positive, and creatively engaged group. Cluster 1 (green), in contrast, shows the lowest scores throughout, particularly in DASE and ATAE items, indicating a group with limited confidence and engagement in AI-supported creative learning.

Cluster 3 (purple) demonstrates moderate and stable engagement across most areas, although slightly lower in TUAC and DASE. Cluster 4 (pink) exhibits a distinct pattern: high scores in creative thinking items (CTS), but sharply lower values in TUAC, ATAE, and DASE.

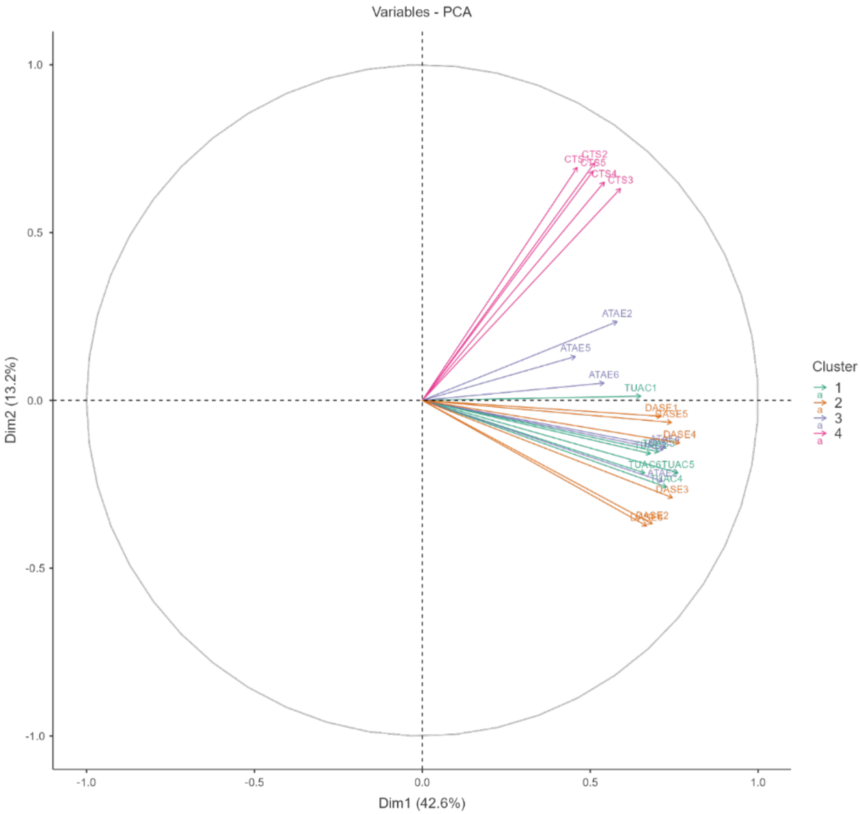
Figure 3 visualizes the distribution of student responses in a reduced two-dimensional space, derived through PCA. Each point represents an individual student, colored according to their assigned cluster (1 to 4). The polygonal boundaries illustrate the separation between clusters.

Figure 3: *Cluster Plot Using Dimensionality Reduction*

Cluster 1 (green in Figure 3) occupies a distinct space on the left side, with a compact structure indicating high internal consistency. Cluster 2 (orange) and Cluster 3 (purple) slightly overlap, but still show reasonable separation, indicating nuanced but distinguishable patterns in their survey responses. Cluster 4 (pink), the largest and most dispersed, spans the right side of the plot, reflecting a wide variety of student perspectives within this group.

Figure 4 displays a PCA biplot that projects survey variables onto a two-dimensional space defined by the first two principal components, Dim1 (42.6%) and Dim2 (13.2%), which together explain over half of the total variance in the dataset. Each arrow represents a variable from the survey, categorized by dimension.

Figure 4: *Principal Component Analysis Biplot of Variables by Cluster*



The direction and length of the arrows in the Figure 4 indicate how strongly each variable contributes to the principal components. Notably, CTS items cluster toward the top-right quadrant, showing they are strongly associated with higher scores along Dim1. In contrast, many DASE and TUAC variables align more horizontally, contributing significantly to Dim1 but less so to Dim2. Each variable is also color-coded by cluster association, revealing how different clusters emphasize distinct aspects of the student profile. For example, Cluster 4 (pink) aligns most with creative thinking variables, while Cluster 2 (orange) is strongly associated with DASE and TUAC items, consistent with earlier findings showing their technological fluency.

Based on the above analyses and demographics from the survey, the details for each cluster are as follows:

Cluster 1: Disengaged Learners (N = 32)

Cluster 1 represents students who demonstrate consistently low scores (see Table 3) across all four dimensions measured in the study, indicating limited engagement with both creative and AI-supported learning processes. The centroid values show particularly low levels of creative thinking skills. Similarly, their engagement with AI tool usage in art creation is minimal, reflected in low centroid values. Students in this cluster also exhibit very low attitudes toward AI in art education. In addition, their digital art self-efficacy scores are the lowest among all clusters.

Cluster 2: Practical Technophiles (N = 68)

Cluster 2 represents students who show the highest levels of engagement with artificial intelligence tools and digital creative practices (See Table 3). The centroid values indicate very strong creative thinking skills. In addition, this group demonstrates the most intensive AI tool usage in art creation, with high centroid values across all related items. Students in Cluster 2 also report very positive attitudes toward AI in art education, reflecting a strong acceptance of AI technologies as valuable resources for artistic learning and innovation. Similarly, their digital art self-efficacy is the highest among all clusters, suggesting high confidence in their ability to effectively use digital tools for creative production.

Cluster 3: Balanced Creatives (N = 98)

Cluster 3 represents students who display moderate and relatively balanced scores across all four dimensions measured in the study. The centroid values for creative thinking skills indicate a solid but not exceptional level of creativity. Regarding AI tool usage in art creation, the centroid values are also moderate. Students in this cluster show moderately positive attitudes toward AI in art education, reflecting a generally open but cautious perspective toward AI-supported learning. Their digital art self-efficacy is also at a moderate level suggesting that while they possess some confidence in using digital tools, they may still be developing their technical skills.

Cluster 4: Creative Traditionalists (N = 50)

Cluster 4 represents students who demonstrate relatively strong creative thinking skills but lower engagement with artificial intelligence tools and digital creative technologies (see Table 3). The centroid values for the creative thinking dimension are comparatively high, indicating that students in this cluster perceive themselves as highly capable of generating ideas, exploring artistic concepts, and elaborating creative work. In contrast, their AI tool usage in art creation is relatively low compared to other clusters. Similarly, their attitudes toward AI in art education are moderate rather than strongly positive. This pattern indicates a cautious or selective perspective toward AI integration in creative practice. Their digital art self-efficacy scores are also relatively low suggesting limited confidence in using digital tools for artistic production.

DISCUSSION AND CONCLUSIONS

This study identified four different student profiles through K-means clustering, each showing unique patterns in creative thinking, AI tool usage, attitudes toward AI in art education, and digital self-efficacy. Cluster 2 emerged as the most digitally fluent and technologically engaged group, consistently scoring highest across AI usage and confidence measures. In contrast, Cluster 4 demonstrated the strongest creative thinking abilities but reported the lowest levels of AI engagement and digital confidence, which shows a preference for traditional artistic methods. Cluster 1 represented the least engaged group, demonstrating consistently low scores across creative thinking, AI tool usage, attitudes toward AI, and digital self-efficacy. Cluster 3 comprised the largest group of students and showed average performance across all constructs, demonstrating a transitional profile with neutral attitudes and moderate engagement. These findings were supported across statistical and visual analyses, including centroid comparisons (Table 3), item-level plots (Figure 2), cluster distributions (Figure 3), and PCA biplots (Figure 4), which reinforces the reliability of the cluster typologies and their relevance to educational planning.

Interpretation of Cluster Profiles

Cluster 1, labeled "Disengaged Learners," demonstrated consistently low scores across all dimensions of the survey, including creative thinking skills, AI tool usage, attitudes toward AI in art education, and digital art self-efficacy. This pattern suggests that students in this cluster show limited engagement with both creative exploration and AI-supported artistic practices. Their low digital confidence and minimal use of AI tools may indicate insufficient exposure to AI technologies or a lack of motivation to integrate them into their creative processes. For these students, foundational instructional support that gradually develops both creative skills and digital literacy may be necessary before they can effectively participate in AI-integrated art learning environments.

Cluster 2, the "Practical Technophiles," exhibited the highest scores in AI tool usage, digital art self-efficacy, and attitudes toward AI in art education, indicating strong technological engagement and confidence. Students in this group appear highly comfortable incorporating AI tools into their creative workflows and experimenting with new digital possibilities. Their profile aligns with findings by Wang et al. (2023) and Lee et al. (2023), who suggest that students with higher perceived AI competence are more willing to explore, iterate, and apply AI technologies in creative contexts. These learners are well positioned to benefit from advanced AI-integrated instructional approaches and may also act as early adopters or peer mentors in technology-rich creative learning environments.

Cluster 3, labeled "Balanced Creatives," demonstrated moderate scores across all dimensions of the survey, indicating a relatively balanced orientation toward both traditional artistic practices and AI-supported creativity. These students show a reasonable level of creative thinking and some engagement with AI tools, although neither dimension appears particularly dominant. Their moderate attitudes toward AI suggest openness combined with a degree of caution or uncertainty. As noted by Zawacki-Richter et al. (2019), adoption of emerging technologies in education often occurs gradually, and students may require guided experiences to meaningfully integrate these tools into their existing creative practices. Structured activities that combine traditional artistic processes with guided AI exploration may help this group strengthen both their creative confidence and technological competence.

Cluster 4, in contrast, represents "Creative Traditionalists," who demonstrated the highest levels of creative thinking while reporting relatively low AI tool usage and lower digital art self-efficacy. This pattern suggests that these students possess strong creative abilities but prefer more conventional artistic approaches rather than technology-mediated processes. Their cautious engagement with AI may reflect concerns frequently discussed in the literature regarding the potential impact of AI on artistic authenticity, authorship, and originality (Carceller, 2024; McCormack et al., 2019). Rather than lacking technical ability, these students may hold philosophical or aesthetic preferences rooted in traditional studio practices. For this group, hybrid pedagogical approaches that combine manual creative work with selective AI integration may help bridge traditional artistic values with emerging digital tools (Leonard, 2023).

Together, these clusters show that creative thinking in AI-supported art education is not monolithic. Rather, it is shaped by a confluence of digital confidence, cognitive preferences, prior experience, and conceptual frameworks about what creativity means. As students collaborate with generative tools like DALL·E and Midjourney, their role shifts from solitary creator to co-designer, a transformation that requires differentiated instructional approaches specifically designed for each cluster's readiness and disposition (Park, 2023; Verganti et al., 2020).

To ensure the trustworthiness of the cluster profiles derived from this study, we triangulated quantitative clustering results with visual and theoretical validation techniques. The use of the Gap Statistic method in determining the optimal number of clusters provided an objective basis for model selection. Furthermore, we presented both tabular centroid data and PCA-based visualizations to support the interpretability of each group, following best practices in cluster analysis transparency (Hair et al., 2019). The discussion of each profile was not limited to descriptive patterns but was critically interpreted using established frameworks in design creativity and co-creation, particularly theories emphasizing the hybrid nature of AI-human ideation (McCormack et al., 2019; Park, 2023; Verganti et al., 2020). This alignment between empirical patterns and theoretical constructs enhances the explanatory validity of the study and reinforces its relevance to the field of design cognition and AI-supported creative education.

IMPLICATIONS

Implications for Pedagogy and Curriculum

The identification of four distinct student profiles provides actionable offers for designing pedagogical strategies and curriculum models that support both creativity and digital fluency in AI-integrated art education. The diversity of learners revealed in this study shows that a one-size-fits-all approach to instructional design may inadvertently exclude or demotivate segments of the student population. Instead, differentiated and responsive teaching practices are needed to accommodate students' varying degrees of creative engagement, attitudes toward AI, and digital self-efficacy.

For students in Cluster 2 (Practical Technophiles), who exhibit high confidence in AI tools and digital environments, curriculum developers can incorporate advanced generative AI tools and emphasize project-based learning. These learners are well-positioned to engage in experimental, autonomous tasks that require iterative thinking and digital fluency. Instructors might introduce activities involving multi-modal creation, AI remixing, or collaborative design challenges where students push the creative boundaries of emerging technologies (Bedir Erişti & Freedman, 2024).

In contrast, Cluster 4 (Creative Traditionalists) requires a more scaffolded and transitional approach. While these students possess strong creative thinking skills, their low digital self-efficacy and tool usage suggest a potential reluctance toward AI. Educators should consider hybrid instructional models that blend analog and digital processes, such as beginning with hand-drawn sketches that are later enhanced using AI tools (NAEA, 2023).). These learners may also benefit from reflective discussions on the philosophical and ethical implications of AI in art, allowing them to voice concerns and develop critical digital literacy without feeling pressured to abandon traditional practices (Gupta, 2023; McCormack et al., 2019; Leonard, 2023).

Cluster 1 (Disengaged Learners) may require foundational pedagogical support before they can effectively engage with AI-integrated art education. Instructors should prioritize activities that gradually build both creative confidence and digital literacy through guided and low-pressure learning experiences. Structured tasks that introduce AI tools in simple and supportive ways may help reduce hesitation and increase familiarity with digital creative environments. Additionally, collaborative learning settings and scaffolded practice opportunities may encourage these students to develop both creative engagement and confidence in using emerging technologies.

Cluster 3 (Balanced Creatives) represents a pivotal group for intervention. Their average scores across all domains show that they may neither resist nor fully embrace AI unless instructional supports are intentionally designed. These students could benefit from structured exposure to AI through low-stakes activities, clear demonstrations, and collaborative exercises that emphasize AI as a supportive, rather than substitutive, creative partner. Embedding short, guided AI explorations into foundational courses may also help these students build confidence gradually.

Contributions to the Field

This study offers several key contributions to the interdisciplinary fields of art education, educational technology, and AI integration in higher education. First and foremost, it provides empirical evidence of student diversity in AI-supported creative learning, using a cluster analysis approach that moves beyond average-based generalizations. By identifying four distinct learner profiles, the study shows the heterogeneity of student experiences in digital and artistic domains. Such a typology is rarely addressed in existing literature, which tends to focus on either the technological affordances of AI or broad student outcomes without differentiating learner subgroups.

Second, the study advances theoretical understanding by bridging models of creative thinking with technology acceptance frameworks. While previous research has examined creativity (Runco & Jaeger, 2012; Torrance, 1974) and AI adoption (Davis, 1989; Venkatesh et al., 2003) in isolation, this study integrates these perspectives to explore how attitudes, confidence, and tool usage interact with creative capacities. This integrated approach supports calls from scholars such as Kim (2006) and Wang et al. (2023) to develop more nuanced, context-sensitive frameworks for understanding creativity in AI-enhanced learning environments.

Third, the research provides a region-specific contribution by focusing on university students in Kazakhstan, a context that is underrepresented in global educational technology discourse. In doing so, the study enriches the international literature with perspectives from Central Asia, a region experiencing rapid digital transformation but lacking empirical findings about how students are adapting to these changes in creative disciplines. This adds a valuable cultural dimension to existing work on AI in art education, which is often limited to Western contexts.

Finally, the findings have practical value for educators and curriculum designers by offering data-driven guidance for differentiated instruction. Rather than treating all students as equally prepared for AI integration, the study outlines tailored pedagogical approaches that align with specific learner needs. This contribution is particularly timely as institutions worldwide grapple with how to integrate generative AI tools into creative learning while safeguarding students' sense of authorship, identity, and agency.

In the context of design creativity, the study offers a rare empirical perspective on student engagement with algorithmic co-creativity. Existing scholarship has debated the epistemological and ontological shifts introduced by AI in creative processes (McCormack et al., 2019; Irbite & Strode, 2021), yet few studies have mapped how students themselves navigate these tensions in real educational settings. Our findings show that students' perceptions of AI as either a tool, a co-creator, or a threat are deeply intertwined with their creative dispositions and digital competencies. This typology adds granularity to the understanding of creativity in the post-digital design classroom and supports the emerging view that design creativity must now be studied through distributed, techno-social models rather than purely cognitive or individual frameworks (Gil-Glazer, 2020; Leonard, 2023).

Limitations

This study has several limitations that should be acknowledged. First, the study relied exclusively on self-reported data, which are subject to biases such as social desirability and over- or underestimation of competencies. Triangulating survey data with observational or log-based data (e.g., tool interaction metrics) could improve the validity of the findings. Second, although exploratory factor analysis supported the proposed four-factor structure, a confirmatory factor analysis (CFA) was not conducted in the present study. Future research should validate the instrument using CFA with an independent sample to further confirm the factorial structure and strengthen the psychometric robustness of the scale. Third, although the study focused on four key dimensions, creative thinking, AI usage, attitudes toward AI, and digital self-efficacy, it did not fully examine external factors such as prior technology exposure, access to resources, or instructor practices, which could significantly influence student experiences and profiles. Fourth, the clustering approach offers a descriptive rather than causal explanation. The study does not explain why students fall into particular clusters or how instructional interventions might cause movement between clusters over time. Fifith limitation concerns the reliance on self-reported creative thinking measures. While such instruments are widely used to capture students' perceptions and beliefs about their creative abilities, they do not directly assess demonstrated creative performance or the quality of artistic products. Future research could complement self-report data with performance-based assessments, portfolio evaluations, or expert ratings of student artwork to provide a more comprehensive understanding of creativity in AI-supported art education.

Suggestions for Future Research

Building on the findings and limitations of this study, several important directions for future research are proposed to increase our understanding of AI integration in art education and to improve pedagogical practices. First, future studies should incorporate mixed-methods approaches that combine quantitative surveys with qualitative data such as interviews, focus groups, or student portfolio analyses. Such methods would provide better findings for the reasoning, emotions, and contextual factors that shape student attitudes and creative behaviors in AI-supported settings (Guidi et al., 2026). Second, researchers should explore the impact of specific pedagogical interventions on different learner profiles. Experimental or quasi-experimental designs could test the effectiveness of targeted teaching strategies, such as peer mentoring, hybrid analog-digital workflows, or ethical AI modules, on students' creative performance, confidence, and engagement. Third, integrating behavioral and performance-based data, such as digital footprint analysis, AI tool interaction logs, or assessments of student-generated artworks, would complement self-report measures and provide more objective indicators of learning.

Conclusions

This study explored the formation of creative thinking, digital self-efficacy, AI tool usage, and attitudes toward AI among university students in art education, using a cluster analysis approach to reveal underlying learner profiles. The results identified four distinct clusters and we named them as "Disengaged Learners, Practical Technophiles, Balanced Creatives, and Creative Traditionalists".

The use of AI in creative disciplines is not experienced uniformly; rather, students engage with these tools based on their confidence, values, prior exposure, and creative identity. While some students view AI as an enabler of creative exploration, others perceive it as a challenge to traditional artistic authenticity. This diversity indicates the need for differentiated pedagogical strategies that respect and build upon students' existing dispositions.

By combining findings from clustering techniques, survey data, and current literature, the study contributes a scalable framework for instructors and curriculum developers aiming to support varied student needs in AI-integrated learning environments. It also shows the importance of preparing learners to use AI tools and to critically engage with their possibilities, limitations, and ethical implications.

In a rapidly evolving educational context, improving both creative capacity and digital competence is essential. This study proposes a foundation for more inclusive and responsive practices that help students thrive as creative thinkers and responsible users of AI in the arts.

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