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SPECIAL FOCUS PAPER

AI-Enabled Creativity: Effects on Divergent and Convergent Thinking among Higher Education Students

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ABSTRACT

This study aimed to analyse the impacts of artificial intelligence (AI) enabled creativity on divergent and convergent thinking among higher education students, focusing on how key factors—cognition, behaviour, interaction, ethics, and emotion—shape creative outcomes. The AI tools integration with academic environments has enhanced how students generate ideas, solve problems, and express originality. However, AI influences on critical cognitive processes and ethical considerations associated with creativity evidence are limited. The research adopts a quantitative approach, surveying a diverse sample of higher education students across various disciplines and institutions. Data were collected using a standardised questionnaire based on a Likert scale, covering variables such as divergence, convergence, metacognition, dependency, risk-taking, feedback, collaboration, transparency, confidence, and implementation. Structural equation modelling (SEM) was used to test the proposed relationships between these constructs. The findings reveal significant positive effects of cognition on emotion and behaviour, and of behaviour on creativity, while ethics and interaction showed complex, partly indirect pathways influencing creative outcomes. The model fit indices confirmed the robustness of the proposed framework, with acceptable values for CMIN/DF, RMSEA, and CFI. The study emphasises the need for educational institutions to design AI-integrated learning environments that promote ethical engagement, emotional well-being, and critical thinking. The results provide actionable insights for curriculum designers, educators, and policymakers seeking to harness AI for fostering student creativity while safeguarding academic integrity.

KEYWORDS

artificial intelligence (AI)-cognitive, AI-creativity, AI-behaviour, AI-interaction, AI-ethics, AI-emotion, innovative process, quality education work

1 INTRODUCTION

Rapid progression in artificial intelligence (AI) has catalysed a restructuring of educational, creative, and scholarly ecosystems. From large language model (LLM) based chatbots and automated writing evaluation (AWE) platforms to affect-aware

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tutoring, multimodal composition tools, and recommendation engines for mental health and motivation [28], an expanding socio-technical assemblage now mediates how learners generate, refine, and disseminate ideas [5]. Within this landscape, emergent scholarship documents simultaneous augmentation and displacement dynamics: cognitive scaffolding, personalisation, fluency acceleration, and affective regulation are juxtaposed with risks of over-reliance, diminished critical appraisal, attenuated human interaction, privacy exposure, and ethical ambiguity [9]. To interpret these dualities rigorously, fine-grained conceptualisation of learner experience variables is required across cognition, behaviour, interaction, ethics, emotion, and creativity—dimensions foundational to sustainable, human-centred AI integration [7].

The present literature review foregrounds six focal constructs, each operationalised through an internally coherent set of sub-dimensions that can be articulated as scale item propositions for future empirical modelling: Cognition, Behaviour Interaction, Ethics, Emotion and Creativity [19]. These item statements encapsulate theoretically salient learner self-regulatory and socio-cognitive processes activated or modified by AI mediation. They also align with multi-component models of creative cognition emphasising idea generation (divergent thinking), evaluative selection (convergent thinking) [3], reflective monitoring (metacognition), and elaborative development (creative production), while integrating affective (confidence/engagement) and ethical (ownership/transparency) moderators [8].

Typological differentiation between academically orientated LLM chatbots (e.g., ChatGPT) and socio-emotional or therapeutic agents (e.g., Replika, Woebot) underscores why nuanced construct specification matters. Academic agents' emphasise epistemic efficiency—accelerating information retrieval, summarisation, and drafting—thereby intensifying divergence and convergence affordances but also potentially heightening dependency and comparison behaviours [32]. Socio-emotional agents target relational presence and affect regulation, bearing distinct implications for isolation, engagement, and ethical self-disclosure [29]. Conflation of these roles risks maladaptive substitution of human relational scaffolding, which is empirically linked to belonging, motivation, and persistence [25]. Parallel research on AWE verifies tripartite engagement (behavioural, cognitive, emotional), where feedback throughput and revision strategy are shaped by proficiency, motivation, and trust [20].

Across the scholarly writing lifecycle, AI contributes to ideation, structural organisation, literature synthesis, data interpretation, linguistic polishing, and ethical compliance. These affordances map directly onto creativity items (originality, flexibility, elaboration, and implementation) and indirectly modulate behavioural (motivation) and cognitive (divergence/convergence) processes [11]. AI expands meaning-making modalities while potentially inflating cognitive load, amplifying the necessity of learner metacognition to manage prompt iteration and idea pruning [10]. Ethical governance frameworks for responsible, human-centred AI emphasise transparency, fairness, and autonomy—mirrored in the ethics item cluster, plagiarism avoidance [22], transparency, ownership, and honesty—to prevent uncritical internalisation of biased outputs and to sustain epistemic agency [14]. Affective computing advances in emotion detection and adaptive feedback introduce powerful engagement amplification, yet they concomitantly raise privacy, surveillance, and authenticity dilemmas, mediating emotional comparison and isolation dynamics [13].

2 REVIEW OF LITERATURE

2.1 Cognitive

Cognitive engagement with AI in education and creativity involves four key processes: divergence, convergence, criticism, and metacognition [43]. Divergence focuses on generating diverse ideas with AI through prompts, rephrasing, and multimodal inputs, enabling faster brainstorming compared to traditional feedback. Convergence involves selecting the best ideas from AI suggestions [34], but risks arise when learners rely on AI summaries without verifying them against academic or practical standards [29]. Criticism strengthens this process by questioning AI outputs for logic, evidence, and ethics, with advanced learners engaging in deeper revisions compared to surface edits by beginners. Metacognition—reflecting on and managing one's interaction with AI—enhances both divergence and convergence, as structured prompting and reflective practices reduce dependency and improve transfer of skills [12]. While AI accelerates tasks like brainstorming, composition, and problem-solving, excessive options can increase cognitive load, requiring metacognitive filtering. Risks include overdependence, bias reinforcement, and memory decline, which can be mitigated through practices like fact-checking, peer review, and AI audits [30].

2.2 Behaviour

Behavioural dynamics involve how learners use AI tools, their motivation, risk-taking behaviour, and response to feedback. The behaviour construct includes four aspects: dependency [27], motivation, risk-taking, and feedback [18]. Dependency can be positive when it improves workflow but problematic when it replaces independent thinking, leading to "AIholic" tendencies [32]. To counter this, strategies like delaying AI use encourage personal problem-solving first. AI often enhances motivation by providing quick feedback, faster progress, and linguistic support, especially for beginners or non-native speakers. However, if students feel forced to use AI, motivation becomes less genuine [16]. AI also encourages risk-taking by reducing fear of failure through rapid iterations and creative experimentation, though over-reliance on AI suggestions may limit originality [40]. Effective behaviour involves selective adoption of AI feedback rather than blindly accepting all suggestions [12].

2.3 Interaction

The interaction construct includes four elements: usage, prompting, personalisation, and collaboration. Frequent AI use can build skill in crafting better prompts, but without reflective strategies, learners may stick to shallow, generic queries [31]. Personalisation allows AI to adapt content, pace, or feedback to individual needs, boosting engagement [4]. Collaboration improves when AI helps share ideas or equalises participation, yet it can also lead to over-reliance on AI or a single "prompt expert" in groups [36]. AI tools work as support tools and should not replace human interaction [41]. Strategies like group prompt refinement and role rotation (ideator, verifier, and synthesiser) help ensure collaborative learning. Future research could track interaction patterns (e.g., prompt depth, peer-AI negotiation, etc.) using combined logs and peer communications [14].

2.4 Ethics

The ethics construct includes four elements: plagiarism avoidance, transparency, ownership [23], and honesty (truthfully representing AI-assisted work) [17]. Avoiding plagiarism now means not just avoiding copying but also preventing hidden paraphrasing or using fabricated references [8]. Ownership emphasises actively shaping AI output into unique work, while honesty ensures accurate acknowledgement of AI's role. Ethical behaviour can be measured through scenario-based studies, with factors like metacognition (awareness of AI limits) and emotional states (e.g., overconfidence) influencing decisions [2]. Educators can promote ethics by requiring "AI usage statements" and reflective explanations of how students verified AI content [4].

2.5 Emotion

The emotion construct—comprising confidence, comparison, isolation, and engagement—shapes how learners persist, take creative risks, and collaborate [15]. Comparing personal ideas with AI can inspire refinement and creativity, but unfavourable comparisons may lower self-belief and originality. Engagement rises with AI's interactive and adaptive feedback, though over-reliance on gamified stimulation can shift motivation from intrinsic curiosity to external rewards [37]. Emotional dimensions interact—confidence may reduce or increase isolation depending on peer involvement—and cultural factors influence responses, with collectivist learners more sensitive to the loss of social study norms. Integrating AI with peer collaboration strategies can preserve engagement and confidence while mitigating isolation [6].

2.6 Creativity

AI influences creativity across ideation, variation, selection, elaboration, and implementation. The creativity construct includes four items—originality, flexibility, elaboration, and implementation—aligned with Torrance and Amabile's creativity dimensions for human–AI co-creation [21]. AI can boost originality through techniques like prompt chaining and style transfer but may also reduce uniqueness due to its reliance on common patterns [24]. Flexibility improves as AI enables quick shifts in perspectives or problem framing across different contexts. For elaboration, AI provides examples, analogies, and structural outlines to deepen ideas [26]. In implementation, AI aids in producing concrete outputs like drafts, presentations, prototypes, and citations through tools such as code generation, formatting, and accessibility features [1].

3 RESEARCH FRAMEWORK

3.1 Research problem

With the rapid integration of AI tools in higher education, there is growing interest in how these technologies influence students' cognitive and creative abilities. While

AI-assisted platforms offer new possibilities for idea generation, problem-solving, and academic work, there remains limited understanding of their actual impact on key dimensions of creativity, particularly divergent and convergent thinking. Furthermore, the AI tool interplay between cognition, behaviour, interaction patterns, ethical considerations, emotional responses, and creativity is understudied. These factors (such as feedback, motivation, risk-taking, metacognition, collaboration, transparency, and emotional engagement) contribute to or hinder students' creative outputs when using AI tools. In addition, demographic variables (age, gender, education level, field of study, AI proficiency) and institutional contexts may further influence these outcomes. The lack of empirical evidence on these relationships creates a gap in designing effective AI-supported learning environments that foster genuine creativity rather than mere replication or plagiarism.

3.2 Research gap

The AI integration with higher education is advancing rapidly, but research on their direct and indirect influence on student creativity, especially on divergent and convergent thinking, remains limited and fragmented. While existing studies address AI's role in enhancing academic productivity or providing personalised learning, there is a research gap on:

How AI-enabled learning affects critical components of creativity, such as originality, flexibility, elaboration, and implementation. The interaction of cognitive (e.g., metacognition, criticism, etc.), behavioural (e.g., motivation, risk-taking, etc.), ethical (e.g., transparency, plagiarism, etc.), emotional (e.g., confidence, engagement, etc.), and interactional (e.g., collaboration, personalisation, etc.) factors in shaping AI-driven creative performance?

How demographic and contextual variables (such as age, gender, level of education, field of study, AI tool usage frequency, and access to digital infrastructure) moderate or mediate the relationship between AI usage and creative outcomes?

How AI impacts on idea generation (divergence), and idea refinement and application (convergence), which are critical for academic and real-world problem-solving?

This gap limits our ability to design AI-supported educational interventions that genuinely foster student creativity rather than promote superficial outputs.

3.3 Objectives

- To examine significant differences in creativity outcomes (e.g., originality, flexibility, elaboration, implementation, etc.) based on socio-demographic characteristics such as age, gender, education, field of study, AI proficiency, and type of institution using multiple ANOVA.
- To analyse the predictive influence of factors like feedback, dependency, motivation, risk-taking, divergence, convergence, criticism, and metacognition on students' creativity using multiple regression analysis.
- To identify and validate the underlying factor structure of AI-assisted creativity components (cognition, behaviour, interaction, ethics, emotion, and creativity) using factor analysis.
- To evaluate the structural relationships between AI with cognition, behaviour, interaction, ethics, emotion, and creativity among higher education students.

3.4 Methodology and model framework

This study employs a descriptive methodology to examine the impacts of AI enabled creativity, focusing specifically on divergent and convergent thinking among higher education students. The study targets students from various institutions, including universities, engineering colleges, arts and science colleges, medical colleges, and international institutions. A stratified random sampling was verified with 274 higher education students. Data is collected through a structured Likert-scale questionnaire, covering six key constructs: cognition, behaviour, interaction, ethics, emotion, and creativity. The data analysis involves percentage analysis for demographic profiling, multivariate ANOVA to explore group differences, multiple regression analysis to identify significant predictors, factor analysis to identify the key variables, and structural equation modelling (SEM) to test the hypothesised relationships among variables.

The model framework for this study on AI-Assisted Creativity: Effects on Divergent and Convergent Thinking [35] Among Higher Education Students is designed to explore the relationships between cognitive, behavioural, interactional, ethical, and emotional factors and their combined influence on students' creativity outcomes [34]. The framework positions cognition (including divergence, convergence, criticism, and metacognition) [38]. Behaviour (dependency, motivation, risk-taking, and feedback) [37], interaction (usage, prompting, personalisation, and collaboration) [39], ethics (plagiarism, transparency, ownership, and honesty) [42], and emotion (confidence, comparison, isolation, and engagement) are key independent constructs [33].

3.5 Hypotheses of the study

H1: Cognition (divergence, convergence, criticism, and metacognition) has a significant impact on creativity among higher education students using AI tools.

H2: Behaviour (dependency, motivation, risk-taking, feedback) significantly influences the creativity outcomes of students assisted by AI.

H3: Interaction (usage, prompting, personalisation, collaboration) significantly effects on students' creativity in AI learning environment.

H4: Ethics (plagiarism, transparency, ownership, honesty) shows a significant relationship with creativity when students engage with AI tools.

H5: Emotion (confidence, comparison, isolation, engagement) significantly affects the creativity of students supported by AI tools.

H6: Cognition and emotion have a significant relationship in shaping creativity and learning.

H7: Behaviour significant influences between cognition and creativity among higher education students.

H8: Emotion significant influences between interaction and creativity.

H9: Ethics significant influences between behaviour and creativity.

H10: There are significant differences in creativity levels based on demographic characteristics.

4 DATA ANALYSIS

4.1 Characteristics of demographic profile (N = 274)

The demographic characteristics including age, gender, education level, field of study, type of institution and type of location. Its composition of 274 students reveals that a majority (52.6%) are between the ages of 21–23 years, followed by 36.1% in the 18–20 years category, indicating a predominantly young population. In terms of education, most participants are postgraduates (39.1%) and undergraduates (32.8%), suggesting a well-educated sample. The gender category shows those 53.3% males and 46.7% females. The respondents mainly come from science and technology (46.7%), with notable representation from arts and humanities (24.5%) and business and management (24.1%). Most respondents are studying in engineering colleges (37.6%) and universities (27.7%), and the sample comprises individuals from diverse locations, with the highest proportion from rural areas (43.1%), followed by urban (29.9%) and semi-urban (27.0%) settings. This indicates a varied and inclusive sample across age, education, field of study, institution type, gender, and location.

4.2 Multivariate effects of education, field of study, and engagement frequency on creativity

The analysis of creativity outcomes with respect to education level, field of study, and frequency of engagement. It highlights the variations in creativity dimensions across these demographic and engagement factors.

The ANOVA table indicates that the overall model significantly explains variations in creativity ($F(38, 235) = 4.994$, $p < .001$), 44.7% of the variance ($R^2 = .447$). Among the main effects, frequency of engagement shows a highly significant impact on creativity ($F = 19.380$, $p < .001$, Partial Eta Squared = .248), suggesting it is a strong predictor. However, education ($p = .521$) and field of study ($p = 1.000$) do not have significant effects. Regarding interaction effects, the Education × Frequency interaction is significant ($p < .001$), indicating that the relationship between education level and creativity varies by engagement frequency. Other interaction effects, including Education × Field, Field × Frequency, and the three-way interaction, are not statistically significant. The model's power is high (Observed Power = 1.000) for the significant predictors, confirming confidence in the findings. The Levene's Test indicates a statistically significant result ($F = 5.335$, df1 = 38, df2 = 235, $p = .000$).

The estimated marginal means indicate variations in creativity scores across different levels of education, fields of study, and AI tool usages. Among educational levels, undergraduates ($M = 14.57$) and postgraduates ($M = 14.32$) report higher creativity compared to those with polytechnic ($M = 12.26$), diploma ($M = 13.15$), or doctorate qualifications ($M = 11.28$). Field of study: students from arts and humanities have average creativity ($M = 14.59$), followed by business and management ($M = 13.38$) and science and technology ($M = 13.32$), while the "others" category records the lowest mean ($M = 12.53$). Notably, the frequency of AI tool usage shows a strong positive association with creativity, where weekly ($M = 17.13$) and daily users ($M = 16.66$) demonstrate significantly higher creativity levels compared to those who use AI tools occasionally ($M = 10.83$), monthly ($M = 12.30$), or several times a month ($M = 10.09$). These findings suggest that more frequent engagement with AI tools for academic purposes is associated with enhanced creativity.

Results of Tukey HSD and LSD multiple comparisons on education level and creativity. The multiple comparisons using LSD and Tukey HSD methods reveal that significant differences in creativity exist between various levels of education. While the Tukey test shows no significant at the 0.05 level, the LSD test indicates that undergraduates report significantly higher creativity scores than polytechnic (md = 1.96, p = .007), certificate/diploma holders (md = 1.97, p = .032), and doctorate holders (md = 2.73, p = .014). Similarly, postgraduates demonstrate significantly higher creativity than polytechnic (md = 1.63, p = .021) and doctorate holders (md = 2.40, p = .028). However, comparisons involving certificate/diploma and polytechnic or doctorate holders show no significant differences. These results suggest that individuals with undergraduate and postgraduate education levels tend to display higher creativity than those with lower or higher academic qualifications, possibly reflecting greater engagement with creative academic practices at those education levels.

The Tukey HSD post-hoc analysis identified two homogeneous subsets of education levels based on mean creativity scores. The first subset includes doctorate (M = 11.29), certificate/diploma (M = 12.05), and polytechnic (M = 12.05) respondents, who exhibited relatively lower levels of creativity. The second subset consists of postgraduates (M = 13.68) and undergraduates (M = 14.01), reflecting higher creativity levels. Although there is a visible trend showing increasing creativity with undergraduate and postgraduate education, the significance levels (p > .05) indicate that these differences are not statistically significant across subsets at the 0.05 level.

Multiple comparisons table for creativity based on field of study. The multiple comparisons analysis using both Tukey HSD and LSD methods examined differences in creativity scores across four fields of study. While the Tukey HSD test showed not significant (all p > .05), the more liberal LSD test revealed that students from Arts & Humanities reported significantly higher creativity scores than those in Science & Technology (p = .027) and Others (p = .041). Specifically, the mean difference between Arts & Humanities and Science & Technology was 1.28, and between Arts & Humanities and Others was 2.38. These results suggest that while differences are not strong enough to withstand the stricter Tukey test, there is evidence under LSD that field of study may influence creativity, with Arts & Humanities students demonstrating comparatively higher creativity levels than their peers in technical and miscellaneous disciplines.

The Tukey HSD homogeneous subsets analysis for creativity across different fields of study shows that the mean creativity scores cluster into two non-significantly different subsets. The "Others" group had the lowest mean creativity score (11.77), followed by "Science & Technology" (12.87), and "Business & Management" (13.55), which were grouped in the first subset. "Arts & Humanities" students had the highest mean creativity score (14.15) and were placed in a separate second subset. However, the significance values (.214 and .500) indicate that these groupings are not significant at the 0.05 level.

Analysis of creativity differences by frequency of AI tool usage for academic purposes (Tukey HSD and LSD). The results from both Tukey HSD and LSD post hoc tests reveal significant differences in creativity scores across different frequencies of AI usage. Respondents who used AI tools occasionally had significantly lower creativity scores compared to those who used them weekly and daily, with mean differences of –5.40 and –6.34, respectively (both p < .001). Similarly, participants using AI tools monthly showed significantly lower creativity than those using them weekly (–3.24) and daily (–4.18), also with $p < .001$. The most creative group was those who used AI tools daily, followed closely by weekly users, whereas occasional and monthly users scored the lowest on creativity. These findings suggest a significant relationship between the AI usage and creativity, indicating that more frequent.

The Tukey HSD test grouped participants into three statistically homogeneous subsets based on their frequency of AI tool usage for academic purposes and their corresponding mean creativity scores. Those who used AI tools occasionally had the lowest creativity mean (10.55), forming a distinct group. Users who used AI tools several times a month had a slightly higher mean (11.92), while monthly users formed a transitional group (12.70) and did not differ significantly from either lower or higher usage groups. The highest creativity scores were observed among weekly (15.95) and daily users (16.89), indicating that frequent AI tool usage is associated with significantly greater creativity. Although the significance values across subsets (.363, .838, .725) suggest some overlap, the increasing trend in creativity with higher usage frequency is clearly evident.

4.3 Identification of key factors supporting AI-assisted creativity model

The results of the KMO and Bartlett's Test sampling adequacy is 0.855, and Bartlett's Test of Sphericity is highly significant (Chi-square = 3123.161, df = 276, $p < 0.001$).

The Total Variance indicates that six factors were extracted using the Maximum Likelihood method (14 iterations). Initially, the first factor had an eigenvalue of 6.999, explaining 29.161% of the total variance. After extraction and rotation, the six retained factors collectively account for approximately 55.71%. The rotation method helps redistribute the variance more evenly across factors, with the first rotated factor now explaining 13.566%, and the others contributing between 3.1% and 12.4%. This demonstrates a strong underlying factor structure, validating the appropriateness of conducting factor analysis for this data. The first factor was characterised by high loadings on *Prompting* (0.516), *Personalisation* (0.417), *Usage* (0.590), *Collaboration* (0.521), *Plagiarism* (0.557), *Transparency* (0.742), *Ownership* (0.649), and *Honesty* (0.601). The second factor showed strong associations with *Dependency* (0.749), *Motivation* (0.819), *Risk taking* (0.779), and *Feedback* (0.847). The third factor loaded on *Confidence* (0.729), *Comparison* (0.718), *Isolation* (0.555), and *Engagement* (0.681). The fourth factor was defined by *Originality* (0.590), *Flexibility* (0.680), *Elaboration* (0.748), and *Implementation* (0.871). The fifth factor included contributions from *Divergence* (0.673) and *Convergence* (0.416), while the sixth factor showed notable loadings on *Metacognition* (0.491) and a weak negative loading for *Divergence* (–0.052). These results indicate a clear multi-dimensional structure underpinning the measured constructs related to creativity.

4.4 AI-assisted predictive modelling of creativity: regression analysis

Model fit analysis of feedback, dependency, risk taking, and motivation on creativity (regression). The regression analysis results indicate that the model, which includes *Feedback*, *Dependency*, *Risk taking*, and *Motivation* as predictors, explains 8.1% variance in *Creativity* ($R^2 = 0.081$), adjusted R^2 of 0.067, ($F (4, 269) = 5.893$, $p < 0.001$) significantly. The SE is 4.60, and the Watson statistic is 0.899 points.

The ANOVA results for the regression model show that the combined effect of *Feedback*, *Dependency*, *Risk taking*, and *Motivation* on *Creativity* is significant ($F (4, 269) = 5.893$, $p < 0.001$). The model accounts for a regression SS of 499.594, a residual SS is 5701.049, total SS of 6200.642. It shows that the predictors together explain a meaningful, though modest, portion of the variability in creativity scores.

The regression analysis reveals that among the predictors, *Motivation* has a significant negative influence on *Creativity* ($B = –1.064$, $t = –3.255$, $p = 0.001$), suggesting that higher levels of motivation (as measured) are associated with lower creativity scores in this model. *Feedback* shows a positive but marginally non-significant effect ($B = 0.624$, $t = 1.747$, $p = 0.082$). Both *Dependency* ($B = –0.322$, $t = –0.997$, $p = 0.320$) and *Risk taking* ($B = –0.019$, $t = –0.057$, $p = 0.955$) do not significantly predict creativity.

Model fit analysis of metacognition, criticism, convergence, and divergence on creativity (regression). The regression model examining the impact of *Metacognition*, *Criticism*, *Convergence*, and *Divergence* on *Creativity* $R = 0.282$, 8% ($R^2 = 0.080$), with an adjusted R^2 of 0.066, 6.6% of after adjusting variances, SE is 4.61 and significant ($F (4, 269) = 5.813$, $p < 0.001$).

The ANOVA results for the regression model with *Metacognition*, *Criticism*, *Convergence*, and *Divergence* as predictors of *Creativity* indicate that the model is significant ($F (4, 269) = 5.813$, $p < 0.001$). The regression SS is 493.36, the residual SS is 5707.28, mean square for regression is 123.34, compared to 21.22 for the residual. The regression analysis for *Creativity* using *Divergence*, *Convergence*, *Criticism*, and *Metacognition* as predictors shows that *Criticism* is the only significant predictor ($B = –0.614$, $\beta = –0.203$, $t = –3.038$, $p = 0.003$), indicating a negative relationship with creativity. The other variables—*Divergence* ($B = –0.198$, $p = 0.493$), *Convergence* ($B = –0.115$, $p = 0.606$), and *Metacognition* ($B = –0.256$, $p = 0.311$)—do not significantly predict creativity. The collinearity statistics show no concerns, with VIF values below 2 for all predictors, suggesting multicollinearity is not an issue in the model.

AI-assisted creativity and cognitive dimensions: a SEM approach. The present study explores the impact of AI-enabled creativity on divergent and convergent thinking among higher education students, using SEM. The direct and indirect impacts among key constructs are cognition, behaviour, interaction, ethics, emotion, and creativity. By employing SEM, the study aims to provide empirical evidence that can inform educational institutions on fostering responsible and effective AI-assisted learning environments that enhance both divergent and convergent thinking. The model fit indices for AI-Assisted Creativity, highlighting the adequacy of the structural equation model in capturing the relationships between divergent and convergent thinking.

- H1: Ethics has a significant influence on interaction.
- H2: Cognition has a significant impact on emotion.
- H3: Ethics has a significant impact on emotion.
- H4: Interaction has a significant impact on emotion.
- H5: Cognition has a significant impact on behaviour.
- H6: Emotion has a significant impact on behaviour.
- H7: Behaviour has a significant impact on creativity.

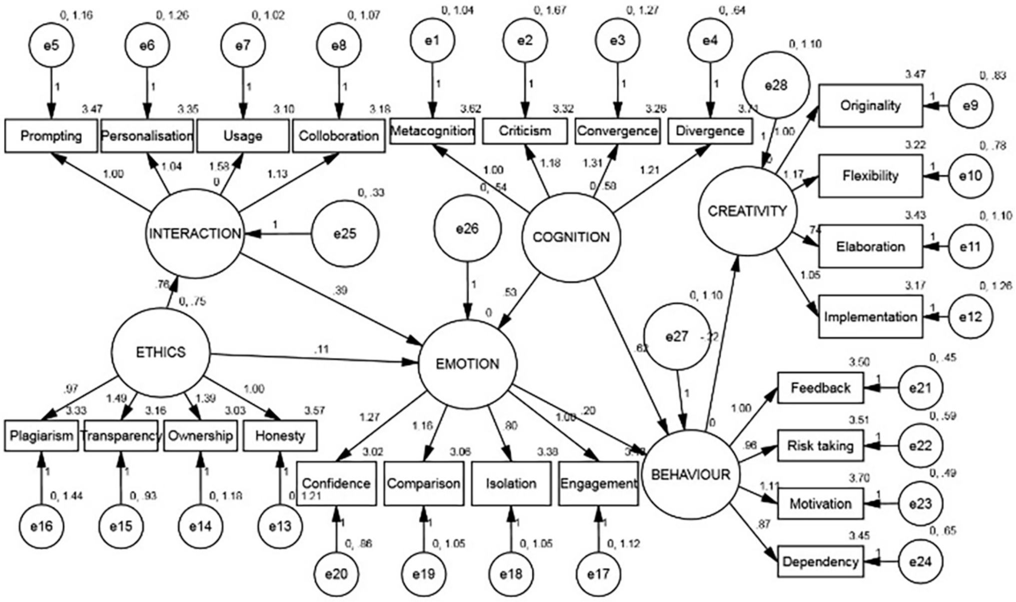

Fig. 1. AI-enabled creativity model

The structural equation model reveals several significant relationships among the variables. Interaction is strongly influenced by ethics (estimate = 0.759, CR = 7.192, $p < .001$), indicating that higher ethical considerations substantially enhance interaction levels. Emotion is significantly predicted by Cognition (estimate = 0.530, CR = 5.116, $p < .001$) and interaction (estimate = 0.391, CR = 2.841, $p = .004$), suggesting both cognitive processes and interpersonal dynamics play important roles in shaping emotional responses. However, the Ethics on Emotion is not impact (estimate = 0.110, CR = 0.827, $p = .408$), implying ethics influences emotion more indirectly via interaction or cognition. Behaviour is significantly influenced by Cognition (estimate = 0.623, CR = 4.625, $p < .001$) and Emotion (estimate = 0.205, CR = 2.137, $p = .033$), highlighting that both thought processes and emotional states contribute to behavioural outcomes. Interestingly, Creativity is negatively predicted by behaviour (estimate = –0.225, CR = –3.591, $p < .001$), indicating that the behavioural patterns measured in this model may hinder creative expression. Overall, these results point to complex interdependencies, where ethics, cognition, and interaction jointly shape emotional and behavioural outcomes, with implications for fostering or limiting creativity.

The SEM indices are Chi-square (CMIN) value is 656.225 (df = 245, $p = .000$), showing a significant result, which is common with larger samples. The relative chi-square (CMIN/DF) is 2.678, which falls within the acceptable range (below 3). The RMSEA is .078 with a 90% confidence interval of .071 to .086, indicating a reasonable error of approximation, though the PCLOSE value of .000 suggests the model is not a close fit. Incremental fit indices like NFI (.797), RFI (.771), IFI (.862), TLI (.843), and CFI (.861) are slightly below the preferred .90 threshold, suggesting the model fits the data moderately well but could be improved. Parsimony indices (PRATIO = .888, PNFI = .707, PCFI = .764) and information criteria (AIC = 814.225, ECVI = 2.983) indicate the model is more efficient and predictive than the independence model. Figure 1 illustrates the structural model of AI-assisted creativity, showcasing the pathways between divergent and convergent thinking components.

5 DISCUSSION

The present study aimed to explore the various factors that influence creativity in an academic or organisational setting, with particular focus on the interaction between individual characteristics (such as motivation, risk-taking, and ethics) [19], cognitive processes, and external feedback mechanisms [30]. The results indicated that respondents' usage of AI tools for academic or creative purposes varied in frequency, with a considerable proportion engaging only occasionally or monthly, suggesting that while AI tools are available [18], their consistent integration into creative tasks is still emerging. The frequency of AI tool usage had a significant impact on creativity scores, with those engaging weekly or daily demonstrating higher creativity levels compared to occasional or monthly users [33]. In terms of regression analysis, creativity ($R^2 = 0.08$), with variables such as motivation showing a significant negative effect, whereas feedback exhibited a positive influence that approached significance. This suggests that while intrinsic factors like motivation are essential [28], they may not always directly predict creativity unless paired with enabling external conditions such as constructive feedback [38]. The factor analysis provided further insights, identifying key latent factors like feedback, ownership, engagement, and originality as important dimensions underpinning creativity [38]. The high KMO value (0.855) confirmed sampling adequacy, and the rotated solution explained a substantial proportion of the variance, validating the multidimensional structure of creativity-related attributes in the sample [13].

Ethics was found to significantly predict interaction, and cognition was a strong driver of both emotion and behaviour (24), which in turn influenced creativity [5]. Interestingly, the negative path coefficient from behaviour to creativity ($\beta = -0.249$, $p < .001$) suggests that certain behavioural expressions or possibly rigid behavioural patterns might inhibit creative potential, highlighting the complex interplay between action and creative thought. The model demonstrated acceptable fit (CFI = 0.861; RMSEA = 0.078), lending support to the proposed theoretical framework. Collectively, these findings underscore that creativity is shaped by a combination of personal, cognitive, ethical, and interactive elements [42]. They suggest that merely fostering individual traits like motivation or risk-taking may be insufficient without supportive environments that encourage feedback, collaboration, and cognitive engagement [43]. The results call for educational and organisational practices that not only enhance individual capabilities but also structure interactions and ethical guidelines in ways that nurture creativity in the context of increasing AI integration [8].

6 APPLICATION OF THE STUDY

The study provides practical applications of usages of AI and digital tools for educational institutions, organisations, and policy makers. Institutions can integrate AI-based platforms into regular academic and workplace activities, ensuring that students and employees are not merely occasional users but develop sustained engagement that supports innovative thinking. The feedback mechanisms play a crucial role in nurturing creativity. This suggests that organisations and educators should establish structured, timely, and constructive feedback systems that encourage individuals to reflect, iterate, and improve their creative output.

The negative influence of motivation (as identified in the regression model) and behaviour on creativity (as found in the SEM) signals the need to reframe motivation and behavioural strategies in the context of creativity. Rather than emphasising motivation as a standalone driver, institutions should focus on creating supportive environments where motivation aligns with collaborative, flexible, and cognitively stimulating activities that truly enhance creative performance. The identified factors, such as ownership, engagement, originality, and feedback, provide a framework for designing creativity-enhancement programmes. For example, learning modules, workshops, and organisational practices can be structured around these dimensions to build a more innovation-conducive culture. The study's insights can inform policy formulation, particularly in educational and professional development standards, by advocating for balanced approaches that integrate cognitive training, ethical interactions, and technological adoption to advance creative capacities in modern work and learning environments.

7 CONCLUSION

The study comprehensively examined the factors influencing creativity using multiple statistical techniques, yielding insightful results. Percentage analysis highlighted that most respondents showed moderate levels of engagement with AI tools, with variations in frequency and application that suggested differing levels of creative involvement. Multiple ANOVA tests revealed significant differences in creativity scores across groups based on AI usage frequency and related variables, indicating that consistent interaction with AI tools was associated with higher creative outputs. The regression analysis demonstrated that key predictors such as motivation, feedback, dependency, and risk-taking collectively explained a modest but meaningful portion of the variance in creativity ($R^2 \approx 8\%$), though individual predictors like motivation showed significant negative effects, while feedback showed a positive but marginal influence. Factor analysis identified distinct underlying dimensions—such as feedback, ownership, engagement, and originality—confirming the multidimensional structure of creativity-related constructs, with a high sampling adequacy (KMO = 0.855) and well-fitting factor solutions explaining over 55% of variance after rotation. Finally, SEM offered a robust test of causal pathways, revealing that ethics significantly enhanced interaction, cognition influenced both emotion and behaviour, and behaviour in turn negatively affected creativity. The model fit indices (e.g., CFI = 0.861, RMSEA = 0.078) suggested an acceptable model fit, supporting the theoretical relationships proposed. Overall, the findings suggest that fostering creativity requires a balanced focus on ethical frameworks, cognitive stimulation, supportive interactions, and constructive feedback, while cautioning that certain behavioural patterns may inadvertently suppress creative expression. These insights support the educators, organisations, and policy framers in designing interventions that enhance creativity with AI-augmented environments.

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