

Exploring the Role of Generative Artificial Intelligence in Creative Thinking Processes: results from a preliminary study.

Eugenia Treglia ¹, Anna Maria Mariani ¹ and Michele Vindigni ^{2, *1}

¹ Università Telematica Pegaso; eugenia.treglia@unipegaso.it,
annamaria.mariani@unipegaso.it;

² Università Degli Studi di Brescia; michele.vindigni@unibs.it

* Correspondence: eugenia.treglia@unipegaso.it

Abstract: Creativity is widely recognized as a key competence in higher education and is closely related to higher-order cognitive processes such as analysis, evaluation, and creation. Recent developments in generative Artificial Intelligence (GenAI) challenge traditional views of creativity as an exclusively human capacity, raising questions about its influence on students' creative thinking. This preliminary study investigates the impact of GenAI on higher-order thinking processes in university students, with specific reference to the Create dimension of the revised Bloom's taxonomy. A quasi-experimental design with two independent groups was employed. Fifty-six undergraduate students completed an authentic creative task based on the analysis and reinterpretation of a disciplinary text; only one group was allowed to use GenAI during the analytical phases preceding creative production. Data were collected through a structured creative performance rubric, the creativity module of the A.S.K. test, and a questionnaire assessing familiarity with AI-based tools. Results showed no statistically significant differences in creative performance between students who used GenAI and those who did not, although a small positive trend emerged in the experimental group. Significant positive correlations were found between creative performance and familiarity with AI, particularly in content creation and problem-solving skills. Creative potential measured by the A.S.K. test was also moderately associated with actual performance. Overall, findings suggest that GenAI does not directly enhance creativity but may act as a cognitive amplifier when integrated in a reflective and informed manner, with relevant implications for educational design in higher education.



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1. Introduction

In recent years, creativity has been recognized as a key competence of the 21st century across multiple domains, including education, as it is closely related to the ability to generate new, useful, and applicable ideas for solving complex problems and producing meaningful knowledge (Amabile, 1983; Treglia, 2020; Patston et al., 2021).

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In academic contexts, these competences are particularly relevant when interpreted in relation to higher-order thinking processes, as described in the revised Bloom's cognitive taxonomy (Anderson & Krathwohl, 2001), and especially to the Create dimension, which involves the reorganization, transformation, and original production of content. The Create level presupposes and integrates all other levels of the taxonomy, namely: using knowledge (Remember), understanding it (Understand), applying it to new contexts (Apply), critically breaking it down (Analyze), and reflecting on and judging it (Evaluate).

Recent developments in Generative Artificial Intelligence (GenAI) are challenging the traditional conception of creativity as an exclusively human attribute, introducing new scenarios of interaction between human agents and algorithmic systems capable of learning, synthesizing information, and producing texts, images, code, and other creative artifacts (Brown et al., 2020; Skilton & Hovsepian, 2018; World Bank, 2018). In particular, generative models are distinguished by their ability to combine pre-existing data to produce outputs that are new and seemingly original, assuming an increasingly relevant role in processes of ideation and creative production (Dong et al., 2017; Elgammal et al., 2017).

Although from a computational standpoint, contemporary generative AI systems do not possess intentionality or autonomous creative agency, as their outputs are produced through probabilistic inference over large-scale training data rather than through goal-directed cognitive processes (Bender et al., 2021; Floridi et al., 2018), within educational contexts, such systems may still be meaningfully interpreted as functionally collaborative agents, insofar as they participate in human creative processes by supporting specific cognitive operations such as exploration, recombination, and representational transformation. This distinction between intentional agency and functional agency is particularly relevant when interpreting creativity within the Create dimension of the revised Bloom's taxonomy. While generative AI does not "create" in a human sense, it can contribute to creative activity by mediating analytical and re-elaborative phases that precede or accompany original production, without displacing the learner's evaluative and decision-making role.

Within educational contexts, the use of GenAI represents an emerging area of research with the potential to profoundly influence teaching-learning models, pedagogical strategies, and the ways in which students construct knowledge (Popenici & Kerr, 2017; Gabriel, 2024). The literature highlights how these technologies may offer significant support for personalized learning, writing, brainstorming, and idea exploration, potentially contributing to the development of creative and metacognitive skills among university students (Zawacki-Richter et al., 2019; Remian, 2019).

However, the interaction between GenAI and creativity raises important questions regarding the impact of these technologies on deep cognitive processes, particularly divergent thinking, conceptual re-elaboration, and problem finding, which are central components of the creative phase of thinking (Csikszentmihalyi, 1988; Reiter-Palmon & Robinson, 2009). Some studies emphasize the risk that uncritical use of digital technologies may negatively affect fundamental cognitive functions, such as memory and deep reflection, which are essential for authentic creative processes (Greenfield, 2009; Treglia, 2020).

From this perspective, GenAI can be interpreted not as a substitute for human creativity, but as a collaborative functional agent capable of supporting certain phases of the creative process, particularly exploration, the generation of alternatives, and the reorganization of information, while leaving humans a central role in problem definition, critical evaluation, and the final validation of creative products (Boden, 2016; Glăveanu, 2020; Goutham Srinivas et al., 2025).

In light of these considerations, it appears necessary to systematically investigate how the use of Generative Artificial Intelligence influences higher-order thinking processes in university students, with specific reference to the Create dimension of Bloom's taxonomy. Understanding whether and how GenAI supports, transforms, or inhibits creative re-elaboration, synthesis, and original production represents a crucial challenge for contemporary higher education and constitutes the central objective of the present study.

2. Materials and Methods

This study aims to investigate the role of generative Artificial Intelligence in higher-order thinking processes among university students, with specific reference to the Create dimension of the revised Bloom's taxonomy. By comparing creative performance under conditions with and without AI support and examining individual differences in AI familiarity, the study seeks to explore whether generative AI functions primarily as a neutral tool or as a cognitive facilitator in students' creative re-elaboration, synthesis, and original knowledge production within higher education contexts.

2.1 Research Design

The study is based on a quasi-experimental design with two independent groups, developed to compare the effect of Artificial Intelligence while keeping all other elements of the proposed activity constant. The sample, composed of university students, was randomly assigned to either an experimental group or a control group. Random assignment was employed to reduce selection bias and to minimize the potential influence of motivational factors or prior familiarity with AI on group membership. All participants were assigned an anonymous identification code, consisting of the first two letters of the surname, the first two letters of the given name, and the last two digits of the year of birth. This code was used to ensure data confidentiality and to allow accurate integration across the different research instruments.

The activity followed a common structure for both groups. Each participant read the text "Tribal Economy: When Not Doing Becomes Abundance" by Matteo Minelli (2015) and responded to three questions calibrated at different levels of Bloom's taxonomy: two questions targeting Analysis and Evaluation and one question targeting Creation. The experimental condition differed solely in the opportunity granted to the experimental group to use AI tools when responding to the first two questions; by contrast, the control group completed the entire activity without any form of digital support.

As part of the research protocol, a creative production task was included to assess students' ability to re-elaborate complex information and transform it into a concise, original, and contextually appropriate communicative output. Unlike the structured

subtests of the creative module of the A.S.K. test, this task was designed as an authentic activity closely aligned with real-world digital communication contexts. After reading and analyzing the text “Tribal Economy: When Not Doing Becomes Abundance” by Matteo Minelli (2015), all participants - regardless of group assignment - were asked to produce a social media post, choosing among Instagram, X/Twitter, or Facebook. The task required participants to: (1) identify and synthesize the core message of the text by selecting its most relevant conceptual elements; (2) re-elaborate the content in a personal and creative manner, avoiding simple paraphrasing and instead favoring original interpretations and connections with contemporary issues; (3) adopt a communicative style consistent with the selected platform, characterized by brevity, immediacy, engagement, and effectiveness in terms of social communication; and (4) stimulate audience reflection, particularly on the key concepts of the text, namely the idea of “abundance” understood not as accumulation but as balance, the value of “not doing” as a sustainable strategy, and the alternative perspective offered by tribal societies in contrast to the Western productivist model.

A methodological consideration concerns the nature of students’ interaction with generative AI systems. In line with recent developments of the DIGCOMP framework, which explicitly addresses competencies related to Artificial Intelligence use, AI-related proficiency cannot be reduced to mere access to technological tools, but involves a set of interaction skills that mediate human–AI collaboration.

These interaction skills include the ability to formulate effective prompts, iteratively refine requests, critically interpret and evaluate AI-generated outputs, and strategically integrate them into one’s own cognitive and communicative processes. Such competencies are closely related to the DIGCOMP areas of Digital content creation, Problem solving, and higher-level aspects of Information and data literacy. While the experimental design necessarily operationalizes AI use as a dichotomous condition for control purposes, qualitative differences in interaction strategies are expected to play a role in shaping cognitive outcomes.

2.2 Sample

The sample consisted of 56 undergraduate students, evenly distributed by gender, with a mean age of 21 years; approximately 80% of the participants were aged 21 or younger. Participants were recruited through convenience sampling during regular university coursework.

With regard to academic background, 45% of the participants were enrolled in the first year of the quantitative–economic program in Economics and Data Analysis, while 54% were third-year students in Business Economics. One participant was enrolled in a Master’s degree program in Management Engineering, representing an isolated case within the overall distribution. Given its marginal incidence, this participant was retained in the analyses.

2.3 Instruments

Data collection was conducted through an online questionnaire administered via digital platforms (PsyToolkit and/or Google Forms). The questionnaire was

structured into multiple sections and complemented by specific forms designed for the experimental group. The instruments used are described below.

- **Demographic Information and Identification Code:** an initial section collected basic demographic information (age, gender, and degree program) and required participants to generate a unique identification code by combining the first two letters of their surname, the first two letters of their given name, and the last two digits of their year of birth. This code ensured participant anonymity while allowing the integration of data across different measures (A.S.K., questionnaires, and task performance).
- **AI Familiarity Questionnaire (DIGCOMP-based):** to assess participants' perceived familiarity and competence in the use of AI-based tools, a set of 10 items was developed based on the latest version 3.0 of the European DIGCOMP framework, recently reworked to focus on AI skills, with two items for each of the five competence areas: Information and data literacy, Communication and collaboration, Digital content creation, Safety, Problem solving. Each item described a specific behavior or use of AI (e.g., information search, evaluation of reliability, use in collaborative contexts, personal data management, integration of AI tools for problem solving) and was rated on a 5-point scale (0 = Never; 1 = Basic; 2 = Intermediate; 3 = Advanced; 4 = Expert), supported by descriptors clarifying the progressive levels of proficiency.
- **A.S.K. Questionnaire (Creative Thinking Module):** the test by Shuler & Hell (2009) was administered in its creative thinking component, which consists of four subtests (e.g., hypothesis generation, category creation, conditional structure, sentence invention). Raw scores were subsequently converted into standardized scores and percentiles based on the normative tables provided in the test manual, differentiated by adult age group and gender. The overall standardized creativity score was used to classify participants into performance bands (below average, average, above average).
- **Disciplinary Reading Text and Comprehension Tasks:** all participants were presented with the text "L'economia tribale: quando il non fare diventa abbondanza" ("Tribal economy: when not doing becomes abundance") by Matteo Minelli (2015), selected for its conceptual density and its potential to stimulate reflections on economics, work, society, and models of development. Based on the text, the following tasks were developed:
 - Five multiple-choice questions targeting Analysis and Evaluation (two of which were used in the main task, with and without AI support), constructed in accordance with the higher levels of Bloom's taxonomy;
 - One Creation task, consisting of the production of a social media post (Instagram, X/Twitter, or Facebook) of up to 800 characters, including a title/slogan and a concise yet creative reworking of the concepts of "economy of abundance" and "not doing" in contemporary society.
- **Creative Production Evaluation Rubric:** scoring rubric consistent with the Create level of the revised Bloom's cognitive taxonomy was used to assess the creative production. The rubric included four indicators: conceptual re-elaboration, originality and synthesis of the message, thematic relevance, and linguistic appropriateness and communicative tone. Each indicator was rated on a

four-point ordinal scale (0–3), resulting in a maximum total score of 12 points. The rubric enabled a structured analysis of the creative, communicative, and critical re-elaboration skills activated by the proposed task.

3. Results

Data were analyzed using descriptive, inferential, and correlational statistics. Descriptive analyses were conducted to summarize participants' characteristics, digital competencies related to AI use, and creative performance. Group differences were examined through independent-samples comparisons, with effect sizes calculated to estimate the magnitude of observed differences. Pearson's correlations were computed to investigate the relationships between AI familiarity, creative potential (A.S.K.), and creative task performance. All analyses were conducted using an alpha level of .05, with effect sizes considered alongside statistical significance due to the exploratory nature of the study.

3.1. Digital Competence Results

Overall, students demonstrated an intermediate level of digital competence ($M = 1.73$). Approximately 46–45% of participants reported using AI effectively for information search and evaluation, while more than 50% integrated AI tools into problem-solving activities.

However, notable weaknesses emerged in specific areas. In collaborative activities, 34% of students remained at a basic level of competence, and only 5% reached an expert level. Similarly, in areas related to copyright management and transparency, 36% of participants were positioned at the lowest competence level.

Taken together, these findings outline a functional operational profile characterized by adequate intermediate skills but limited advanced and strategic competencies in the use of AI.

3.2. Creative Performance Results

Descriptive statistics for the creative performance scores are reported in Table 1.

Table 1. Means and Standard Deviations for Total_Create Scores by Group.

Group	N	Mean	Std. Dev.
Group A – with AI	28	8.21	1.97
Group B – without digital tools	28	7.64	1.94

Group A showed a slightly higher mean score than Group B (+0.57 points), suggesting a potential contribution of AI in supporting processes of re-elaboration and formulation of the creative post.

The comparison between groups on the Create performance indicated that participants who used AI obtained a marginally higher mean score than those who completed the task without AI support (8.21 vs. 7.64). However, this difference was not statistically significant ($p = .31$), and the effect size was small (Cohen's $d = 0.26$),

indicating that the use of AI did not result in a clear advantage or in the expected decrement in creative performance.

3.3. ASK Creativity Module

The analysis of standardized scores from the A.S.K. Creativity Module allowed participants to be classified into three performance levels: below average (standard score < 93), average (93–107), and above average (>107). The distribution of participants across these categories, stratified by gender, is presented in Table 2.

Considering the total sample, the majority of participants fell within the average range (66.07%), while 17.86% were classified as above average and 16.07% as below average. Gender-based analyses revealed noteworthy differences. Among male participants, nearly three quarters of the sample (74.07%) were classified within the average range, with smaller proportions falling above average (14.81%) and below average (11.11%).

In contrast, the female group showed a more balanced distribution across the three performance levels: 55.56% were classified as average, while 22.22% fell both above and below the average range. In other words, compared to male participants, female participants exhibited greater variability in creativity levels, with higher representation in the extreme categories (both above and below average).

Table 2. Distribution of Standardized Creativity Scores by Performance Level and Gender

Category	Male (n)	Male (%)	Female (n)	Female (%)	Total (n)	Total (%)
Below Avg. 16.07%	3	11.11%	6	22.22%	9	
Average. 66.07%	20	74.07%	15	55.56%	37	
Above Avg. 17.86%	4	14.81%	6	22.22%	10	

Overall, the results indicate that the sample predominantly exhibited normative levels of creativity, with a subset of participants demonstrating elevated performance. Gender-based distributions further suggest different patterns across male and female participants, with males tending to cluster around mean values and females showing greater heterogeneity in standardized creativity scores.

3.4. Correlation analysis results

The correlational analysis revealed a positive and statistically significant association between the overall score on the AI Familiarity Questionnaire (DIGCOMP) and creative performance as assessed through the analytic scoring rubric ($r = .46$, $p < .001$). This association indicates that higher levels of perceived familiarity and competence in the use of AI-based tools are associated with better performance on creation tasks.

When examining the individual DIGCOMP domains, the strongest correlations emerged for Digital content creation ($r = .51$, $p < .001$) and Problem solving ($r = .48$, $p < .001$). More moderate, yet still statistically significant, relationships were observed for Information and data literacy ($r = .34$, $p < .01$), Communication and collaboration ($r = .31$, $p < .01$), and Safety ($r = .29$, $p < .05$).

Overall, these findings suggest that competence in the use of AI, particularly in domains oriented toward production and problem solving, is associated with a higher level of activation of higher-order thinking processes related to the Create dimension of Bloom's taxonomy.

3.5. Relationship Between Creative Potential (A.S.K.) and Actual Creative Performance

The analysis of the relationship between standardized scores obtained from the A.S.K. Creativity Module and creative performance evaluated through the analytic rubric revealed a positive, moderate, and statistically significant association ($r = .42$, $p < .01$). This result suggests a tendency whereby higher levels of creative potential, as measured by the standardized instrument, are accompanied by moderately better performance on the proposed creation task.

However, the variability observed within individual performance bands indicates that creative potential does not automatically translate into high performance. Although a higher proportion of students with above-average A.S.K. scores was observed among those achieving higher scores on the creative task, the relationship appears to be influenced by additional factors, such as task context, communicative skills, and the re-elaboration strategies adopted.

Overall, the findings indicate a partial correspondence between creative potential and actual creative performance, highlighting the need for further investigation in future studies.

4. Discussion

The findings of the present study contribute to the ongoing debate on the role of generative Artificial Intelligence (GenAI) in higher-order thinking processes, offering a nuanced picture that cannot be reduced to simplistic or deterministic interpretations. In line with recent literature, the results indicate that the use of AI does not lead to a direct or automatic increase in creative performance. This is supported by the absence of statistically significant differences between the group that used AI during the analytical phases of the task and the group that completed the activity without digital support.

This finding suggests that creativity, understood as the ability to re-elaborate information, synthesize ideas, and produce original content, remains strongly dependent on individuals' cognitive and decision-making processes rather than on

access to technological tools per se. In this sense, the results align with perspectives that conceptualize creativity as a complex, situated process requiring intentional engagement, rather than as an outcome that can be easily enhanced through technological assistance alone.

At the same time, the correlational analyses provide important complementary insights. Higher levels of familiarity with AI, particularly competencies related to digital content creation and problem solving, were significantly associated with better creative performance. These results indicate that it is not occasional or unreflective use of AI that makes a difference, but rather a more mature and conscious integration of AI into cognitive processes. From this perspective, AI appears to function as an enabling or supportive tool, capable of facilitating certain phases of higher-order thinking - such as exploration, reorganization, and generation of alternatives - without replacing human creative agency.

From an interactional perspective, these findings also help clarify why no statistically significant differences emerged between the two groups. While access to generative AI was experimentally controlled, the quality of human-AI interaction was not directly observable or standardized, and likely varied substantially across participants.

In this sense, the significant correlations between DIGCOMP-based AI familiarity and creative performance suggest that interaction skills function as a latent moderating variable. Rather than exerting a uniform effect, generative AI appears to amplify higher-order thinking processes only when learners are able to engage with it through strategic prompting, critical evaluation of outputs, and purposeful integration into their own reasoning. This interaction-dependent dynamic may account for the observed pattern of results, in which competence-related differences emerge more clearly than condition-based effects.

Another relevant aspect concerns the relationship between creative potential, as measured by the A.S.K. Creativity Module, and actual creative performance. The moderate association observed between these dimensions confirms that creative potential does not automatically translate into high-level performance. This partial correspondence highlights the role of contextual, motivational, and communicative factors in shaping creative outcomes. The authentic task employed in this study, closely aligned with real-world digital communication practices, seems to capture not only latent creative abilities but also the capacity to activate and apply them in a situated and functional manner.

Taken together, these findings underscore the importance of considering creativity as a dynamic interaction between individual potential, contextual conditions, and strategic use of tools, rather than as a fixed trait or a technology-driven outcome.

5. Limitations

Some limitations of the present study should be acknowledged. First, the relatively small sample size and the use of convenience sampling limit the generalizability of the findings. In addition, the sample was largely composed of students from economics-related programs, which may restrict the applicability of the results to other disciplinary contexts.

Second, familiarity with AI was assessed through self-reported measures, which may be influenced by subjective bias. Finally, the quasi-experimental design does not

allow for strong causal inferences regarding the effects of AI use on creative performance; therefore, the results should be interpreted as indicative of associations rather than causal relationships.

6. Conclusions

Overall, the results suggest that generative Artificial Intelligence should not be understood as a direct enhancer of creativity, but rather as an expanded cognitive context within which students may exercise, modulate, or even inhibit their higher-order thinking processes. AI emerges not as a substitute for human creativity, but as a potential amplifier whose impact depends largely on users' competencies, awareness, and intentional use.

From an educational perspective, these findings reinforce the need to design learning activities that promote reflective and strategic engagement with AI tools. Rather than encouraging cognitive delegation, instructional practices should aim to support students in developing the skills necessary to integrate AI meaningfully into processes of analysis, evaluation, and creation, in line with the Create dimension of Bloom's taxonomy.

The interpretation of generative AI as a "cognitive amplifier" can be further refined by drawing on concepts from informatics and cognitive systems research. In particular, generative AI systems can be understood as human-in-the-loop computational tools that extend cognitive capacity through controlled forms of cognitive offloading and distributed cognition, rather than as autonomous problem solvers.

In this framework, amplification does not occur automatically through exposure to AI-generated content, but emerges from an active interaction cycle in which the human user retains responsibility for goal setting, evaluation, and decision-making. The AI system contributes by accelerating exploratory processes, offering alternative representations, or supporting linguistic and conceptual restructuring, while higher-order cognitive control remains firmly human-driven.

This interpretation aligns with the empirical findings of the present study, which suggest that generative AI may support creative performance only when integrated in a reflective and competent manner. The notion of amplification, therefore, should be understood as conditional and competence-dependent, reinforcing the idea that pedagogical effectiveness lies not in technological delegation but in the intentional orchestration of human–AI interaction.

Finally, the exploratory nature of the study calls for further research. Future studies involving larger samples, more diverse disciplinary contexts, and longitudinal designs could deepen understanding of how individual characteristics, instructional design, and sustained exposure to AI-mediated tasks interact in shaping creative thinking in higher education.

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