FROM WORKPLACE TO CLASSROOM: A MIXED METHOD APPROACH TO MEASURING CREATIVITY AND AI-RELATED DISPOSITIONS. THE AICREA SCALE AND QUALITATIVE ANALYSIS ON SME MANAGERS

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ABSTRACT
This study investigates AI-related creativity through a mixed-method design integrating a psychometric scale with a qualitative inquiry on managers of small and medium enterprises. The quantitative strand presents baseline (PRE) findings from the AICREA scale, measuring Cognitive Risk Fear, Imagination, and Thought Complexity in 743 employees of a telecommunications company. Prior AI use emerges as the only significant predictor of baseline creativity, while sociodemographic variables show no significant association. The qualitative strand, based on interviews with eleven SME managers, identifies AI as an enabler rather than a substitute for organizational creativity, with continuous training as a key theme. The two strands converge in suggesting that creativity-related dispositions toward AI depend on organizational and educational conditions rather than stable individual traits, with implications for Digital Affective Literacy and teacher training.

KEYWORDS: AI-related creativity; mixed-method research; AICREA scale; digital affective literacy; organizational creativity

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1. Introduction

The advent of generative artificial intelligence in educational and professional contexts is redefining the relationship between creativity, learning, innovation, and human responsibility, affecting the very conditions, cognitive, affective, and decisional, under which creativity manifests itself. The topic of creativity has traditionally been analyzed through studies on divergent thinking. Guilford contributed to distinguishing divergent from convergent production, recognizing creativity as an observable and measurable construct, not reducible to innate talent (Guilford, 1950). Torrance subsequently operationalized this perspective through assessment tools based on fluency, flexibility, originality, and elaboration (Torrance, 1974). However, the measurement of creativity has remained a complex domain, traversed by different approaches centered on process, person, product, and context (Said-Metwaly, Van den Noortgate, & Kyndt, 2017). Generative AI makes this picture more complex. When a person uses a generative system to produce texts or images, the creative outcome can no longer be attributed exclusively to individual abilities, but takes shape in a space of interaction in which the human subject directs the process and retains critical and authorial responsibility. Recent studies have shown that AI can improve the perceived quality of individual creative products, especially for subjects with lower initial creativity, but can also reduce the overall variety of ideas, generating content homogenization (Doshi & Hauser, 2024); conversely, improvements obtained through language model support do not always translate into stable gains once support is removed (Kumar, Vincentius, Jordan, & Anderson, 2025).

It therefore becomes necessary to distinguish classical creativity from AI-related creativity — the creative capacity that takes shape in the interaction between the

human subject and the generative system (Barandiaran & Pérez-Verdugo, 2025). This is not a matter of considering AI as a substitute for human agency, but of investigating the conditions through which it can function as support, amplifier, or mediating environment for the creative process. This perspective is situated within the area of assisted and augmented cognition, in which the person retains an authorial and decision-making role, while operating within a technologically mediated interaction. Willingness to use AI in creative processes depends on affective and cognitive dispositions. The literature has already investigated forms of anxiety, resistance, and insecurity connected to AI in work and learning contexts (Wang & Wang, 2022; Park, Woo, & Kim, 2024). In the case of AI-mediated creativity, one specific form of resistance appears particularly relevant: cognitive risk fear, the difficulty of inhabiting an environment in which AI may call into question established habits of thought, production, and evaluation, a condition that can either facilitate or hinder openness to interaction with the generative system. The organizational context represents a significant observatory for analyzing these processes. According to Amabile's componential model, creativity depends on individual abilities, motivation, creative processes, and environmental conditions that either enable or hinder innovation (Amabile, 1988, 1996). In small and medium enterprises, this dynamic is particularly evident: the adoption of innovative technologies is less formalized than in large organizations and depends to a considerable extent on managers' representations and decisions, making attitudes toward AI directly relevant to the creative climate.

The educational implications concern teacher training and, more broadly, Digital Affective Literacy. AI literacy has been defined as the set of competencies enabling people to understand, critically evaluate, communicate, and collaborate with AI systems (Long & Magerko, 2020). More recent perspectives highlight its multidimensional nature, including affective, behavioral, cognitive, and ethical

aspects (Ng, Wu, Leung, Chiu, & Chu, 2024). Digital Affective Literacy can be understood as the capacity to recognize and regulate one's own emotional and cognitive responses toward AI, transforming fear, resistance, or uncritical fascination into awareness, judgment, and responsibility, a competence central for educators and teachers accompanying students in environments increasingly characterized by human–algorithmic collaboration. Building on these premises, the present contribution aims to investigate whether and how AI-related creativity can be measured and understood through a mixed-method design, integrating a psychometric scale validated on a large organizational sample with a qualitative inquiry on managers from small and medium enterprises. The article is structured as follows: after presenting the theoretical framework (§2), the methodology is described (§3); quantitative and qualitative results are reported (§4), followed by an integrative discussion (§5); the article closes with limitations and future directions (§6).

2. Theoretical Framework: Environment, Dispositions, and AI-Augmented Creativity

To understand how AI intervenes in organizational creative processes, it is necessary to integrate two complementary theoretical models, capable of accounting for both the individual and environmental dimensions of the construct The *Dynamic Componential Model of Creativity and Innovation* (Amabile & Pratt, 2016) conceptualizes creativity not as a stable personality trait, but as a dynamic process resulting from the continuous interaction between individual characteristics and environmental factors. The model identifies three components of individual creativity: intrinsic task motivation, domain-relevant skills, and *creativity-relevant processes* (the cognitive processes relevant to creativity) — the cross-cutting cognitive heuristics (tolerance for ambiguity, propensity for cognitive

risk, ideational fluency, capacity to connect distant concepts) that translate Guilford's and Torrance's divergent thinking into the organizational context. It is precisely the *creativity-relevant processes* that constitute the component most sensitive to environmental influences, and it is on these processes that the introduction of generative AI tools, as an environmental factor of unprecedented scope, appears to leave the most significant imprint. This reading is complemented by the interactionist model of Woodman, Sawyer, and Griffin (1993), according to which organizational creativity is never the product of an isolated individual or of the environment alone, but the result of a complex interaction across individual, group, and organizational levels. At this level, pre-existing creative dispositions are not merely an outcome of the environment, but also an antecedent of the choices people make within it: those who already possess greater cognitive flexibility and a greater propensity for ideational risk also tend to adopt new tools such as AI more spontaneously. The integration of these two theoretical frameworks makes it possible to articulate two non-mutually exclusive hypotheses, which run through the entire research design, in both its quantitative and qualitative components:

- the **augmentation hypothesis**, according to which AI, as an environmental factor, acts on *creativity-relevant processes* by enhancing ideational fluency and exploratory propensity: it is AI that makes people more creative;
- the **self-selection hypothesis**, according to which the observed association between AI use and creativity reflects a pre-existing individual characteristic that precedes and drives the adoption of the tool: it is already more creative people who choose to use AI more frequently.

Distinguishing between these two readings is not a purely theoretical exercise: their practical implications for training and organizational policies are profoundly different, and they constitute the thread running through both the quantitative

investigation of the AICREA scale and the qualitative analysis conducted with managers of small and medium enterprises.

3. Methodology

3.1 General Design

The research adopts a convergent mixed-method design (Creswell & Plano Clark, 2018), aimed at integrating quantitative and qualitative evidence in understanding AI-related creativity. The choice of this approach stems from the composite nature of the construct under investigation: AI-related creativity requires a perspective capable of relating individual dispositions, detectable through standardized psychometric instruments, to the way innovation is concretely represented, experienced, and managed in organizational contexts. The two strands share the same theoretical anchoring, the Dynamic Componential Model (Amabile & Pratt, 2016) and the interactionist model of Woodman, Sawyer, and Griffin (1993), but address two distinct populations: the quantitative strand measures individual dispositions in a large organizational sample; the qualitative strand explores managerial representations in a group of SME managers, to whom the translation of technological innovation into concrete practices is particularly entrusted.

3.2 Quantitative Strand

3.2.1 Participants

The sample for the quantitative strand consists of 743 employees of TIM S.p.A., an Italian telecommunications company, recruited during the PRE phase of the AI4CREA project, prior to the systematic and mandatory introduction of the Microsoft Copilot license within the organization. The survey invitation was sent to a total of 1,500 employees, with a response rate of 49.5%. This timing made it

possible to obtain a baseline measurement of dispositions toward AI-related creativity, uncontaminated by systematic exposure to the tool. The gender distribution (N = 738; 5 missing values) shows a clear male predominance (n = 544, 73.7%) compared to the female component (n = 191, 25.9%) and a residual 0.4% (n = 3) who reported another gender category; this distribution does not reflect the gender composition of TIM S.p.A.'s overall workforce, which is more balanced, and therefore constitutes a limitation to the generalizability of the results, which will be addressed in the conclusions. Participants' age ranges from 18 to over 60 years, with the 51–60 age bracket being the most represented (n = 401, 54.3%). The distribution by professional role (N = 738) shows a marked concentration of Senior profiles (n = 630, 85.4%), compared to far less represented Mid-Level (n = 81, 11.0%) and Junior (n = 27, 3.6%) profiles, a composition consistent with the organizational structure of a large, mature company. Finally, with regard to the frequency of prior use of AI tools (N = 737), only 5.8% of participants reported never having used them and 6.9% reported rarely having done so, compared to a majority reporting at least occasional use ("sometimes": 42.1%; "often": 25.5%; "very often": 19.7%): the sample, therefore, is not approaching AI for the first time, but presents an already internally differentiated prior experience.

3.2.2 Instrument

AI-related creativity was measured using the AICREA scale (*AI-augmented CREAtivity*), an instrument specifically developed to capture *creativity-relevant processes* (Amabile & Pratt, 2016) in organizational contexts where artificial intelligence is present or being adopted. The construction of the instrument draws on the classic dimensions of divergent thinking theorized by Guilford (1950) and operationalized by Torrance (1974), fluency, flexibility, originality, and elaboration, translated into items specific to the AI-augmented work context.

The version subjected to item analysis consisted of 16 items distributed across four subscales (Cognitive Risk Fear, Curiosity, Imagination, Thought Complexity), the outcomes of this procedure, reported in section 4.1, led to a final structure of 10 items on a 5-point Likert scale (1 = *strongly disagree*; 5 = *strongly agree*), distributed across three subscales:

- **Cognitive Risk Fear** (4 items) — the subscale's historical label, retained for continuity with earlier phases of the AI4CREA project; the items composing it are, however, worded in a positive direction, capturing the subject's openness and willingness to explore alternative, even unusual, solutions with AI support, without fear of judgment or failure. Higher scores on the subscale therefore indicate greater propensity for cognitive risk, and not, as the name might superficially suggest, greater fear: the label identifies the psychological pole investigated by the construct (the attitude toward cognitive risk associated with AI use), not the scoring direction of the items.
- **Imagination** (2 items) — concerns the subject's generative and associative capacity, in continuity with the dimensions of fluency and elaboration identified by Torrance (1974).
- **Thought Complexity** (4 items) — refers to tolerance of ambiguity, divergent reasoning, and willingness to engage with non-linear problems, recalling the dimension of cognitive flexibility theorized by Guilford (1950).

Overall, the scale makes it possible to capture AI-related creativity as a composite disposition, in which properly cognitive creative abilities and affective regulation are closely interconnected.

3.2.3 Procedure

Administration took place through an online survey based on a self-report questionnaire, anonymously and on a voluntary basis, with the operational support of TIM S.p.A.'s Human Resources department. Data collection was conducted ensuring a measurement uncontaminated by exposure to the AI-augmented application, in accordance with the PRE-POST longitudinal design of the AI4CREA project, of which the present contribution reports only the results of the PRE phase.

3.2.4 Data Analysis

The main statistical analyses were conducted using IBM SPSS Statistics (v. 25) and were organized into three levels. The first level concerned the item analysis of the scale, conducted through item diagnostics (corrected item-total correlations, α-if-deleted), the estimation of subscale internal consistency (Cronbach's α), and the verification of semantic coherence between direct and reverse-scored items. The second level concerned the verification of baseline homogeneity with respect to the main sociodemographic and organizational variables, through between-group comparisons conducted with both ANOVA (for continuous variables) and the non-parametric Kruskal-Wallis test (for ordinal variables). The third level concerned the identification of predictors of baseline creativity, through a two-block hierarchical multiple regression, in which the first block included only sociodemographic and organizational variables (gender, age, education, seniority, professional role) and the second added the frequency of prior AI use, making it possible to isolate its specific contribution net of basic individual characteristics. An additional robustness analysis, based on multiple imputation of missing data, was conducted in Python (see § 4.1.3).

3.3 Qualitative Strand

3.3.1 Participants

The qualitative strand involved eleven managers from small and medium enterprises and organizations connected to innovation, selected with the collaboration of a consultancy firm specializing in SME support. Unlike the TIM S.p.A. sample, participants here hold senior roles or bear direct responsibility for decision-making processes, a characteristic consistent with the aim of investigating how attitudes toward AI, at this level, may affect the creative climate and the organization's capacity to translate ideas into innovative processes (Amabile, 1988, 1996).

3.3.2 Instrument

Data were collected through an *ad hoc* semi-structured interview, organized into four thematic sections. he first section explores idea generation and innovation in business processes, drawing on the constructs of fluency, flexibility, originality, and elaboration (Guilford, 1950; Torrance, 1974). The second section investigates the relationship between AI, creativity, and decision-making. The third explores challenges and opportunities for leaders, focusing on managerial competencies and creative motivation. The fourth concerns the role of universities in training for creativity and AI.

3.3.3 Procedure

The interviews were conducted individually, in a semi-structured format, allowing room for spontaneous elaboration on the part of interviewees while maintaining the four-section protocol as a constant point of reference.

3.3.4 Data Analysis

The interviews were analyzed through a descriptive-interpretive thematic coding procedure, inspired by the approach of Braun and Clarke (2006), carried out in two phases.

In the first phase, responses were organized according to the areas of the interview protocol; in the second phase, cross-cutting thematic clusters were identified, relating to idea generation, problem solving, organizational flexibility, project elaboration, the role of AI as a support for creativity, and the centrality of continuous training. This procedure made it possible to relate managers' representations to the theoretical dimensions of creativity and to the construct of AI-related creativity, in dialogue with the findings of the quantitative strand.

4. Results

4.1 Quantitative Results

4.1.1 Item Analysis and Internal Consistency

The initial version of the AICREA scale, comprising 16 items distributed across four subscales (Cognitive Risk Fear, Curiosity, Imagination, Thought Complexity), was subjected to item analysis on the overall sample (N = 743 recruited cases). For each subscale, corrected item-total correlations and the α-if-deleted index were calculated on a listwise basis, with a number of valid cases specific to each subscale, depending on the pattern of missing data on the respective items: Cognitive Risk Fear, N = 707; Curiosity, N = 730; Imagination, N = 723; Thought Complexity, N = 721 .

The initial 16-item version was subjected to preliminary item analysis. The Curiosity subscale was entirely removed due to a negative overall α, caused by negative item-total correlations for items DA and DB. In the Imagination subscale, item DE showed a strongly negative item-total correlation (−.792) and was removed; item DF was subsequently removed due to a comparatively lower item-total correlation, yielding a final 2-item subscale. In the Thought Complexity subscale, item DI showed a near-zero item-total correlation (.011) but was retained for theoretical coverage, following DeVellis (2017) and Clark and Watson (1995). The Cognitive Risk Fear subscale was retained in its original 4-item form."

The final structure, comprising 10 items distributed across three subscales, shows the internal consistency indices reported in Table 1.

Table 1: Internal consistency of the AICREA scale — final structure

Subscale	N items	*N*	Cronbach's α
Cognitive Risk Fear	4	707	.782
Imagination	2	726	.830
Thought Complexity	4	721	.588
Total AICREA scale	**10**	**701**	—

Note. Cronbach's α: index of internal consistency. Acceptability threshold: α ≥ .60; good consistency threshold: α ≥ .70. *N* varies across subscales due to the pattern of missing data on the respective items (listwise calculation per subscale); the *N* for the total scale (701) corresponds to cases with all 10 final items complete.

The Thought Complexity subscale shows a value below the conventional acceptability threshold (α = .588), attributable to the multidimensional nature of

the construct, which includes heterogeneous cognitive processes (rapid elaboration, management of multiple strategies, flexibility) with lower internal covariance compared to more unitary dimensions such as Imagination. This psychometric limitation is discussed more extensively in § 6, among the study's limitations.

4.1.2 Baseline Homogeneity

The analyses reported in this section and the next require that each participant have a complete score on the 10-item AICREA scale (see § 4.1.1); the *N* is therefore reduced from 738 (sample descriptives in § 3.2.1) to 701 cases, corresponding to subjects with all 10 final items complete. Baseline homogeneity with respect to the main sociodemographic and organizational variables was verified through between-group comparisons, conducted with both ANOVA and the non-parametric Kruskal-Wallis test (Table 2).

Table 2: Baseline homogeneity — between-group comparisons on AICREA scores

Variable	***N***	***k***	***F***	***df***	***p* (ANOVA)**	**η²**	***H***	***p* (K-W)**
Gender	701	3	0.406	2, 698	.667	.001	0.392	.822
Age	701	6	0.573	5, 695	.721	.004	2.987	.702
Education	701	7	0.572	6, 694	.753	.005	6.262	.394
Seniority	701	5	0.053	4, 696	.995	.000	0.174	.996
Professional role	701	3	1.225	2, 698	.294	.003	3.295	.193

Note. F = one-way ANOVA F statistic; η² = eta squared; *H* = Kruskal-Wallis statistic; *k* = number of groups compared.

None of the variables considered produces significant differences in AICREA scores, according to either statistical criterion employed (all $p > .05$; $\eta^2 \leq .005$). The convergence between the parametric and non-parametric tests strengthens the robustness of the result.

4.1.3 Predictors of Baseline Creativity

Baseline creativity were identified through a two-block hierarchical multiple regression (*N* = 697 Predictors complete cases), with the overall AICREA scale score as the dependent variable. Model 1 includes sociodemographic and organizational variables (gender, age, education, seniority, professional role). Model 2 adds the frequency of prior AI use. *Model 1 does not explain a significant proportion of variance in AICREA scores,* $R^2 = .007$, $F(5, 691) = 0.91$, $p = .475$. *Model 2 explains 12.5% of the overall variance,* $R^2 = .125$, $F(6, 690) = 16.49$, $p < .001$, $\Delta R^2 = .118$ *(Table 3).*

Table 3: Hierarchical multiple regression — Model 2

Predictor	**β***	**95% CI**	***t***	***p***
Prior AI use	.357	[.284, .429]	9.68	< .001
Professional role	−.094	[−.191, .004]	−1.88	.060
Seniority	.093	[−.010, .195]	1.78	.076
Age	.054	[−.046, .153]	1.06	.290
Gender	.007	[−.065, .078]	0.18	.856
Education	−.003	[−.075, .069]	−.08	.935

Note. N = 697. β* = standardized coefficient. R^2 Model 1 = .007; R^2 Model 2 = .125.

In Model 2, prior AI use is the only significant predictor at the $p < .001$ level (β* = .357); its 95% confidence interval does not include zero. Professional role (β* = −.094, $p = .060$) and seniority (β* = .093, $p = .076$) show coefficients in the expected direction, with confidence intervals that include zero, and do not reach conventional statistical significance. Gender, age, and education show no association with AICREA scores ($p > .05$). Multicollinearity among the Model 2 predictors, assessed through the variance inflation factor (VIF), revealed no concerns: all values range between 1.03 and 2.15, well below the conventional threshold of 5 generally adopted in the literature, even for seniority and age, which are moderately correlated with each other and with professional role for conceptually expected reasons.

Mean AICREA scores by frequency category of prior AI use: $M = 3.35$ (never), $M = 3.41$ (rarely), $M = 3.57$ (sometimes), $M = 3.80$ (often), $M = 4.04$ (very often). Difference between extremes: 0.70 points.

The analyses reported above were conducted excluding cases with missing data (listwise deletion). To verify their robustness, the same analyses were repeated on a complete dataset ($N = 743$) obtained through multiple imputation (Multiple Imputation by Chained Equations, implemented with IterativeImputer, scikit-learn). The results obtained with this method substantially confirm those just reported: prior AI use is confirmed as the only significant predictor (β* = .352, $p < .001$), while professional role (β* = −.091, $p = .060$) and seniority (β* = .086, $p = .093$) remain marginal, failing to reach conventional significance — an outcome consistent with that obtained through listwise deletion, which reinforces the reliability of the conclusion adopted here regarding the non-significance of these two predictors.

4.1.4 Interpretation of Quantitative Results in Light of the Theoretical Models

The central finding of the PRE phase is that prior AI use is the only significant predictor of baseline creativity, while none of the sociodemographic and organizational variables considered reaches conventional significance. Model 1, including only control variables, explains no significant variance ($R^2 = .007$); it is only with the addition of prior AI use that the model gains explanatory power ($R^2 = .125$), indicating that basic individual characteristics, in isolation, are not predictive of AI-related creativity in this sample

The Dynamic Componential Model (Amabile & Pratt, 2016), introduced in § 2, identifies *creativity-relevant processes* — ideational fluency, propensity for cognitive risk, the capacity to connect distant concepts — as the component of individual creativity most sensitive to environmental influences, that is, the one on which the work environment exerts the greatest force. From this perspective, the introduction of generative AI tools into organizational contexts does not constitute a mere technological innovation, but an environmental factor of unprecedented scope, one that interacts directly with the processes of idea generation, solution elaboration, and connection between distant concepts, rather than with the resources or timing of work.

This reading finds support in the literature: Jia, Luo, Fang, and Liao (2024) showed experimentally that AI assistance on a specific task increases workers' creativity in subsequent tasks, a finding consistent with the hypothesis that interaction with AI activates exploratory cognitive processes. The present result moves in the same direction, but within a real organizational context, on a large scale, and at a stage prior to the systematic introduction of the tool into the organization. However, on the basis of the PRE-phase data alone, the question of the causal direction of the observed association remains open. The cross-sectional design does not allow us to

distinguish between two alternative readings, both introduced in § 2: the augmentation hypothesis, according to which it is AI use that enhances *creativity-relevant processes* over time, and the self-selection hypothesis, according to which it is people already endowed with greater cognitive flexibility and exploratory propensity who more spontaneously adopt AI, making creativity an antecedent, rather than a consequence, of tool use — a reading anchored in the interactionist model of Woodman, Sawyer, and Griffin (1993). Causal disambiguation between the two hypotheses is left to the comparison between the PRE and POST measurements, planned within the longitudinal design of the AI4CREA project on the same sample of 743 employees.

The remaining variables included in Model 2 show a more nuanced picture: gender, age, and education do not reach statistical significance and show coefficients of negligible magnitude ($p > .29$), while professional role and seniority, although not reaching conventional significance, sit at a marginal threshold ($p = .060$ and $p = .076$) with coefficients in the theoretically expected direction. This picture confirms what already emerged in Model 1: AI-related creativity, in this sample, is specifically associated with the frequency of prior exposure to the tool, while the contribution of sociodemographic characteristics and organizational seniority remains, at present, insufficiently robust to be considered a consolidated finding.

4.2 Qualitative Results

The analysis of the interviews returns a picture in which creativity is represented predominantly as a situated, organizational process, rather than as an isolated individual quality. The companies involved describe idea generation as a relevant phase of innovation processes and report, in many cases, fostering spaces for discussion, listening, and shared deliberation. Practices such as brainstorming, meetings, focus groups, dialogue among colleagues, and moments of collective

evaluation recur frequently: creativity is promoted above all through participatory environments in which an idea can be expressed, discussed, and progressively reworked.

A first finding concerns the centrality of ideational fluency: organizations appear to value the ability to produce many ideas, even when these initially appear unconventional or not immediately applicable — an element that directly recalls the tradition of divergent thinking (Guilford, 1950; Torrance, 1974). A second element concerns the operational definition of creativity, often associated by interviewees with the capacity to solve concrete problems: client requests, technical constraints, market shifts, process digitalization, product adaptation, time reduction. In this perspective, creativity does not coincide with the abstract production of original ideas, but with the capacity to generate solutions that are applicable and consistent with the needs of the context.

Flexibility represents one of the most recurrent thematic clusters: interviewees describe processes of continuous adaptation — modifying products or services according to the client, reusing previously tested solutions, moving across application sectors, reconfiguring digital tools, responding to regulatory or market constraints — showing how innovation often develops through the capacity to reorganize processes, roles, and competencies according to emerging conditions. This is complemented by a finding concerning the transition from idea to project: ideas do not remain solely at the generative stage, but are progressively transformed into operational proposals through feasibility analysis, technical discussion, prototyping, testing, and validation. This dimension of elaboration shows organizations' capacity to carry the initial insight through a path of verification and testing.

With regard to the role of artificial intelligence, the interviews show a predominantly positive, but not substitutive, representation. AI is described as a support for creativity and efficiency — in some cases as a virtual colleague, in others as a tutor, an optimization tool, a support for individual brainstorming, an accelerator in information retrieval, code writing, software development, data analysis, or the search for visual references. What clearly emerges is that AI is interpreted primarily as an enabler of organizational creativity, not as a substitute for human responsibility.

Finally, the interviews highlight the role of continuous training: many participants refer to internal academies, AI-related courses, technical and scientific research, study of documentation, and consultation with external collaborators. Creativity thus appears to be fueled by lifelong learning processes and forms of interdisciplinary collaboration, in which the presence of technical, design, artistic, and managerial competencies fosters cross-fertilization between different perspectives and supports the construction of more articulated solutions.

5. Integrative Discussion

The two strands of the research converge on a central point: artificial intelligence is represented, in neither the quantitative nor the qualitative data, as a substitute for human creativity, but as an environmental condition that enables or hinders its expression depending on how it is encountered, used, and accompanied by adequate organizational practices.

At the quantitative level, prior AI use proved to be the only robust predictor of baseline creativity, independent of the sociodemographic and organizational characteristics of TIM S.p.A. employees. At the qualitative level, SME managers describe AI in terms substantially consistent with this finding: a tool that acts as a

virtual colleague, tutor, or accelerator of ideational processes, without replacing human decision-making responsibility. This reading is consistent with recent evidence on AI adoption in small and medium enterprises, where intentional — rather than passive — exposure to AI tools has been shown to function as a strategic lever for innovation and competitiveness (Yesuf et al., 2025). The convergence reinforces the plausibility of the augmentation hypothesis (see § 2) — the idea that exposure to AI may enhance *creativity-relevant processes* over time — without ruling out the self-selection hypothesis, whose causal disambiguation is left to the PRE-POST longitudinal design of the AI4CREA project.

A particularly significant point of convergence concerns training. In the qualitative strand, continuous training emerges as one of the most recurrent thematic clusters: internal academies, AI-specific courses, and interdisciplinary collaboration are described as conditions that fuel organizational creativity. In the quantitative strand, the pattern relating to professional role and seniority — while not reaching conventional significance — moves in a direction consistent with the hypothesis that less structured AI exposure may be associated with less favorable creative dispositions. Read together, both levels suggest that differences in AI-related creative dispositions depend on organizational and training conditions rather than stable individual characteristics.

It is at this convergence that the most directly educational implication is located. If AI-related creativity is not a fixed trait but a context-sensitive disposition, as indicated by both the Dynamic Componential Model (Amabile & Pratt, 2016) and the managers interviewed, then Digital Affective Literacy (see § 1) cannot be limited to the transmission of technical skills. It requires training environments capable of addressing the affective component of the relationship with AI — cognitive risk fear, resistance, hesitation in the face of a tool perceived as a threat to professional

autonomy — alongside the cognitive competencies of imagination and thought complexity. The continuous training practices described by the managers interviewed (internal academies, dedicated pathways, interdisciplinary exchange) constitute, in this sense, a repertoire transferable from the organizational to the educational context, useful for rethinking teacher and educator training within the tension between technological resistance and uncritical adoption of AI, transforming that tension into a conscious object of pedagogical work, rather than an obstacle to be removed or an opportunity to be embraced without reservation.

6. Conclusions and Limitations

The present contribution investigated AI-related creativity through a mixed-method design integrating a psychometric measure on a large organizational sample with a qualitative inquiry on a group of managers from small and medium enterprises. The two levels of evidence converge in indicating artificial intelligence not as a substitute for human creativity, but as an environmental factor that can either enable or hinder it depending on the conditions — affective, cognitive, and organizational — under which it is encountered. This conclusion, however, must be read in light of certain limitations concerning both the research design and the preliminary nature of some of the analyses conducted.

A first limitation concerns the procedure adopted for developing the AICREA scale. The analyses reported here (item-total correlations, α-if-deleted, internal consistency) constitute a preliminary item analysis, not a full psychometric validation: no exploratory factor analysis or sampling adequacy tests were conducted, and both remain necessary to establish the instrument's dimensional structure, to be addressed in a more extensive validation elsewhere. The three-

factor structure adopted here should be regarded as provisional. The Curiosity subscale, entirely removed due to systematic psychometric inconsistency (see § 4.1.1), may still be theoretically relevant to AI-related creativity; its current operationalization simply did not perform satisfactorily in this sample, and a reformulation tested on an independent sample is needed before ruling out its role. A similar caveat applies to the Imagination subscale, reduced from 4 to 2 items after removing DE (psychometric inconsistency) and DF (lower item-total correlation). Although the 2-item subscale shows good internal consistency (α = .830), this reduced structure narrows the construct's coverage relative to the other two 4-item subscales; item reformulation and expansion on an independent sample would strengthen its representativeness."

A further caveat concerns the Thought Complexity subscale, which, although retained in its original 4-item form, shows internal consistency below the conventional acceptability threshold (α = .588). This value did not, at this stage, justify the removal of any item, given the intrinsically multidimensional nature of the construct; it nonetheless remains an indication that the subscale would benefit from item refinement in future studies, aimed at improving its internal homogeneity.

A second limitation concerns the quantitative sample. Sample size was not determined a priori through a power analysis, but corresponds to the employees who voluntarily took part in the PRE-phase survey, out of 1,500 invited (response rate: 49.5%); the large N (743) makes underpowering for the main effect unlikely, though this remains a concern for smaller effects such as professional role. The gender distribution (73.7% male) does not reflect TIM S.p.A.'s overall workforce, and the concentration of Senior profiles (85.4%) limits generalizability to populations with a different age and professional distribution. The pattern relating

to professional role and seniority sits at a significance threshold not always reached unequivocally, and would warrant verification on larger or more balanced samples. The choice of listwise deletion over more sophisticated imputation techniques was nonetheless subjected to a robustness check, with substantially convergent results (see § 4.1.3)."

A third limitation concerns the cross-sectional nature of the PRE phase. As discussed in § 4.1.4, the association between prior AI use and baseline creativity cannot establish causal direction, leaving open both the augmentation and self-selection hypotheses. Only the POST phase of the AI4CREA longitudinal design, currently underway, will help disambiguate this relationship

A fourth limitation concerns the heterogeneity between the two samples of the mixed-method design. TIM S.p.A. employees and the SME managers interviewed differ in organizational scale, professional role, and degree of decision-making responsibility: a choice that made it possible to observe AI-related creativity at two complementary organizational levels, but one that calls for caution in interpreting the convergence between the quantitative and qualitative results as evidence of a unitary phenomenon, rather than as a plausible parallel between different contexts.

Despite these limitations, the contribution offers elements useful for future research and practice. The AICREA scale warrants more extensive validation, and the PRE-POST design will clarify the causal direction of the relationship between AI exposure and creativity. Training for AI-related creativity cannot be limited to technical skills but must address the affective component of the relationship with AI, in line with Digital Affective Literacy (§ 1) — an indication relevant both for professional development and for the initial training of teachers and educators.

Ethical considerations. Ethical considerations. Data collection in both strands was conducted in compliance with ethical principles for research involving human subjects. Quantitative data were collected by TIM S.p.A.'s Human Resources department on a voluntary and anonymous basis, in accordance with Regulation (EU) 2016/679 (GDPR), with participants free to skip items or withdraw. Qualitative data were collected with informed consent regarding research purposes and the anonymous, aggregated use of interview content.

Declaration on the use of artificial intelligence tools. In preparing this manuscript, a generative artificial intelligence assistant was used as support for editorial work.

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