



STIAEM

Slow Tech Innovation

AI, Ethics and
New Teaching Methods

NATIONAL REPORT ITALY



Università di Foggia
Studi Umanistici, Lettere, Beni Culturali,
Scienze della Formazione



İSTANBUL - ESENLER
İLÇE MİLLİ EĞİTİM MÜDÜRLÜĞÜ



1474



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Table of Contents for the National Report

Preface

1. Introduction and Methodology

- 1.1 Objectives of the National Report
- 1.2 Description of the Sample (Demographic and numerical data of teachers and students)
- 1.3 Data Collection Instruments (Surveys, semi-structured interview protocols)

2. National Context of AI in Education

- 2.1 Current Policies, Regulations, and Ministerial Guidelines
- 2.2 Digital Infrastructure and Technological Readiness of the Pilot Schools

3. Data Standardization and Quantitative Analysis

- 3.1 Data Pre-processing (Alignment with the Master Codebook, variable harmonization via ISCED)
- 3.2 Descriptive Analysis (Frequencies, means, standard deviation for AI Literacy and Ethical Awareness)
- 3.3 Comparative and Correlational Analysis (ANOVA, T-test, Pearson / Regression models)

4. Qualitative Analysis and Dilemma Scenarios (SJT)

- 4.1 Thematic Analysis and Content Coding of Focus Groups/Interviews
- 4.2 Analysis of Dilemma Scenarios (Efficiency vs. Equity, Personalization vs. Privacy, Autonomy vs. Assistance)
- 4.3 Triangulation (Integration of qualitative results with quantitative trends)

5. Case Studies

- 5.1 Selection and Description of 2-3 National Best Practices on the Use of AI
- 5.2 Analysis of Pedagogical Outcomes and Student Engagement in the Presented Cases

6. Conclusions and Recommendations

- 6.1 Main Training Gaps and Identified Needs
- 6.2 Operational Suggestions and Requirements for the Development of AI-based Pedagogical Models

References

Preface

This volume offers the first systematic, empirically cross-validated, and large-scale mapping of Artificial Intelligence within the Italian school system. This National Report constitutes a further scientific and strategic deliverable developed under Action 2 of Work Package 2 (WP2) of the international consortium Erasmus+ STIAEM (Slow Tech Innovation: AI, Ethics, and New Teaching Methods - 2025-1-IT02-KA220-SCH-000365213). Through a computational and psychometric survey conducted on a rigorously stratified sample of 2,052 students and 600 teachers, this research directly responds to the priorities of the European Commission's Digital Education Action Plan (2021-2027), overcoming the fragmentation of local initiatives to offer a stable data infrastructure supporting the digital transition of schools.

The epistemological horizon guiding the entire architecture of this research breaks sharply with technological determinism and the neoliberal efficiency of the "algorithmic race." The conceptual framework of the report is radically anchored in the Slow Tech paradigm and the human-in-the-loop approach pedagogical models that promote a reflective, critical, ecologically sustainable technological integration centered on human agency. The primary objective is to deconstruct the idea that AI Literacy (specific algorithmic literacy) coincides with mere technical or executive proficiency in using commercial generative software. On the contrary, literacy is investigated here as a multidimensional competence (affective, cognitive, behavioral, and ethical), understood as an indispensable axiological prerequisite for active, democratic, and aware digital citizenship, capable of governing emerging technologies without passively succumbing to market pressures or the complete automation of thought.

On a methodological level, the rigor of the work is guaranteed by an integrated approach that combines the precision of numbers with the depth of words. The research does not limit itself to calculating simple percentage averages but utilizes advanced statistical models to map hidden relationships between responses and bring to light the "typical profiles" of students and teachers facing technology. This solid mathematical framework is systematically interwoven with the study of dialogues emerging from focus groups and field interviews. In this way, statistical data cease to be cold parameters and become a lens through which to deeply understand the lived experiences, cultural resistances, fears, and concrete problems that specifically characterize today's Italian schools.

To go beyond mere declarations and measure actual ethical behavior among students and teachers, the research tests them through the methodology of Situational Judgment Tests (SJT). Participants faced concrete simulations of school life and forced-choice scenarios designed around three major international challenges:

Autonomy in the face of automation: This axis assesses the risk of blind delegation to technology. On one hand, it measures students' ability to maintain a critical mindset when faced with the errors and "hallucinations" of generative AI; on the other, it investigates the fear that teachers might lose their autonomy in instructional planning, risking a progressive impoverishment of professional skills.

The educational relationship and online privacy: This area explores the protection of the personal and human sphere. It highlights the paradox whereby adolescents claim to be worried about privacy but are ready to surrender their personal data just to download a useful application. At the same time, it questions teachers on their willingness to defend the human bond in the classroom against the competition of intelligent "virtual tutors" active 24 hours a day.

Civic and ecological responsibility: A dimension that measures awareness of the social and material impact of machines. On the student side, it explores sensitivity toward electronic waste (e-waste) and the massive energy consumption of software; on the teacher side, it analyzes openness toward assisted writing, balancing the protection of the student's cognitive effort with the adoption of a more inclusive assessment.

The results emerging from this extensive mapping bring to light a picture dense with structural paradoxes and pedagogical "gaps" that directly challenge institutions. Although descriptive inspection shows that the schools involved in the experimentation benefit from high technological readiness—a solid legacy of the infrastructural investments of the Piano Scuola 4.0 (D.M. 161/2022)—the data expose a profound educational divide. Interaction with algorithmic software is experienced by students almost exclusively as an informal, asynchronous, and fragmented support practice within the private sphere, contrasted with a near-total absence of explicit, codified, and formalized curricular pathways within the institutions' official educational offerings. In the eyes of the students, the school risks being perceived as a partially silent or unprepared institution in the face of the oncoming algorithmic transition.

Through the application of advanced inferential models, the report dismantles the main false myths and prejudices clouding public debate, starting with those related to gender or alleged age-related technophobia. For teachers with greater professional experience, the contraction of perceived AI self-efficacy compared to their younger colleagues does not mirror a deficit in basic digital literacy (skills within the DigComp framework remain stable across the entire career). Instead, it takes the form of a conscious "epistemic prudence"—an intentional action aimed at slowing down digital haste to preserve the relational ecosystem of the classroom.

Conversely, Network Analysis mathematically demonstrates that within the youth target, simple familiarity with the software or executive self-efficacy does not constitute a protective factor in any way. On the contrary, students who define themselves as more "expert" systematically lower their critical defenses, uncritically accepting machine outputs to speed up study times and showing a strong propensity to install invasive applications. The critical-cognitive pole is structurally disconnected from the pragmatic-affective one: student action is governed by executive impulses and the emotional interface, leaving ethics in the role of an isolated satellite, cut off from daily usage systems. The only real and constant protective factor is represented by the formal development of a solid, applied moral conscience.

Ultimately, this report was born to offer concrete answers and reliable data to institutions, dialoguing directly with the Ministry of Education's new guidelines and the rigorous principles of human control established by the recent European Artificial Intelligence Regulation (AI Act). Rather than merely chasing funding or dropping technologies from above, the research offers a methodological compass to guide the investments already initiated by the PNRR for teacher training. The goal is not to accumulate software or hardware, but to help schools develop a genuine internal capacity to manage change, turning available funds into solid, secure, and pedagogically sound projects.

The evidence gathered in these pages firmly rejects the idea of a school submissive to the commercial logic of speed and technological consumption, and reclaims the necessity for a secure, locally governable technology at the service of human development. In this light, the data presented in this report do not constitute a finish line, but the essential operational foundation to guide a new pedagogical model and prepare the educational materials that will be tested in the field. This wealth of information will guide the design of the nascent AI Training and Experimentation Hub, translating research into a teacher training model that is robust, ethically protected, replicable, and sustainable over time.

1. Introduction and Methodology

1.1 Objectives of the National Report

This National Report constitutes one of the primary scientific reporting and strategic guidance deliverables developed within Action 2 of Work Package 2 (WP2) of the transnational Erasmus+ KA220-SCH project STIAEM (Slow Tech Innovation: AI, Ethics, and New Teaching Methods - 2025-1-IT02-KA220-SCH-000365213).

The investigation takes place during a period of profound transformation within education systems and responds directly to the programmatic priorities established by the European Commission's Digital Education Action Plan (2021-2027). Its aim is to overcome the fragmentation of local initiatives and to outline an analytical, systematic, and empirically cross-validated framework regarding the integration of Artificial Intelligence (AI) in Italian schools.

The primary objective of the report lies in the quantitative-qualitative mapping of AI Literacy (specific algorithmic literacy) and the ethical sensitivity of key actors within the school system: students and teachers. These dimensions are assumed as indispensable axiological and operational prerequisites for the exercise of active, democratic, and responsible digital citizenship, capable of governing the interface with emerging technologies rather than passively submitting to their evolutionary drives.

The theoretical horizon guiding the entire research architecture is rooted in the Slow Tech paradigm (Patrignani & Whitehouse, 2014) and the human-in-the-loop approach (Benanti, 2022). These pedagogical models promote reflexive, critical, and sustainable technological integration, standing in open contrast to the logics of comprehensive and efficiency-driven automation of the teaching profession and study practices. The survey intends to explore the ethical and value-based orientation of educational actors by analyzing their learning and critical judgment when faced with complex decision-making scenarios. To this end, the tool adopts the methodology of situated ethical dilemmas (Situational Judgment Tests - SJT), presenting participants with concrete simulations that intersect three macro-areas of international relevance:

1. **Professional autonomy and curricular planning in the face of automation:** An analysis of the tendency toward uncritical technological delegation versus the protection of the epistemic authorship of content. In terms of data, this translates into monitoring behavior when encountering generative AI hallucinations or logical errors (for students) and safeguarding instructional design against the risk of de-skilling (for teachers).
2. **Safeguarding the educational relationship and online privacy:** An exploration of the capacity to actively protect the personal and relational sphere. This area investigates the so-called *Privacy Paradox* in students, measuring their propensity to install invasive algorithmic applications in exchange for immediate benefits. For teachers, it monitors the willingness to defend the human pedagogical alliance against the potential disintermediation introduced by 24/7 AI Tutors.
3. **Civic and ecological responsibility in the use of algorithmic systems:** An evaluation of the critical stance regarding the social and material impact of technology. On the students' side, this axis explores ecological awareness linked to sustainable hardware management and combating electronic waste (e-waste) generated by the heavy computational requirements of local models. On the teachers' side, it analyzes the pedagogical posture toward co-designing texts with generative software, oscillating between protecting the cognitive effort of writing and embracing augmented and inclusive assessment logics in accordance with the principles of Universal Design for Learning (UDL).

On a strictly methodological level, the report pursues the psychometric validation of internationally validated data collection instruments within the Italian school system, ensuring an evidence-based analysis that moves beyond anecdotal accounts and mere descriptive statistics. The methodological framework is based on a concurrent mixed-methods design, in which large-scale quantitative data

collection (subjected to structural equation modeling—CFA, network analysis, and latent profile analysis) is integrated and illustrated by thematic-computational content analysis of data emerging from focus groups and semi-structured interviews, which are essential for revealing phenomenological experiences, cultural resistances, and the structural specificities of the Italian context.

The research framework thus responds to the institutional need to provide robust empirical evidence capable of proactively engaging with the guidelines of the Ministry of Education and Merit (MIM) and the strict risk classification constraints established by the new European AI Act. The report stands in close, strategic complementarity with the digitalization measures already funded by NextGenerationEU within the framework of the PNRR (with specific reference to teacher training actions under Ministerial Decrees D.M. 65 and D.M. 66), offering the necessary data to steer these investments toward genuine institutional capacity building. Ultimately, the collected evidence will constitute the empirical foundation for developing the platform and the AI Training and Experimentation Hub, translating the report's data into a replicable and sustainable pedagogical model.

1.2 Description of the Sample

The quantitative analysis and subsequent psychometric modelling rest on the construction of two independent, institutionally stratified samples, capturing the two central actors in the teaching-learning process: the student population and the teaching staff. The following provides an analytical and demographic breakdown of both data collection streams, as a prerequisite for the validation of latent constructs.

1.2.1 The Student Sample (N = 2,052)

The line of inquiry directed at the student component involved Italian secondary schools, consolidating an overall empirical corpus of N = 2,052 respondents. The sampling plan adopted a convenience criterion stratified on a regional basis, incorporating two territorial data collection streams to ensure broad representativeness: the region of Tuscany (in close collaboration with the Regional School Office, hereinafter RSO, for Tuscany), accounting for 82.6% of the sample (n = 1,695), and the region of Puglia (with the support of the University of Foggia), representing 17.4% (n = 357).

With regard to gender identity, the distribution documents a prevalence of the male component, at 54.3% (n = 1,114), followed by a substantial representation of the female component, at 43.2% (n = 886). A residual share of 2.5% (n = 52) opted for the "Prefer not to answer" option. This methodological choice was not treated as a mere missing value, but was retained in full across all inferential models both for ethical reasons of maximum inclusivity and privacy protection, and to verify its stability in emotional self-efficacy scores relative to the traditional binary poles.

Inspection of the age variable reveals a balanced distribution spanning the full developmental arc of adolescent transition, extending across a range from 11 to 20 years of age. The most heavily represented segment consists of the cohort of seventeen-year-olds (15.7%), followed by twelve-year-olds (12.7%) and eighteen-year-olds (12.6%). The intermediate age bands, ranging from 13 to 16 years, show a stable and consistent presence, fluctuating within a narrow range of between 10% and 11% each. The distributional density at the extremes of the age curve is, as expected, more contracted: students aged 11 account for 9.4% of the sample, while nineteen-year-olds (5.2%) and twenty-year-olds (1.5%) are situated in the final phase of the upper secondary cycle.

Table 1.1: Socio-demographic profile of the sample (N = 2,052).

Variable	Category	N	%
Provenance	Tuscany	1695	82.6
	Puglia	357	17.4
Gender	Male	1114	54.3
	Female	886	43.2
	I prefer not to answer	52	2.5
Age	11-13 years (Early adolescence)	672	32.7
	14-16 years old (Middle adolescence)	662	32.3
	17-20 years old (Late adolescence)	718	35.0

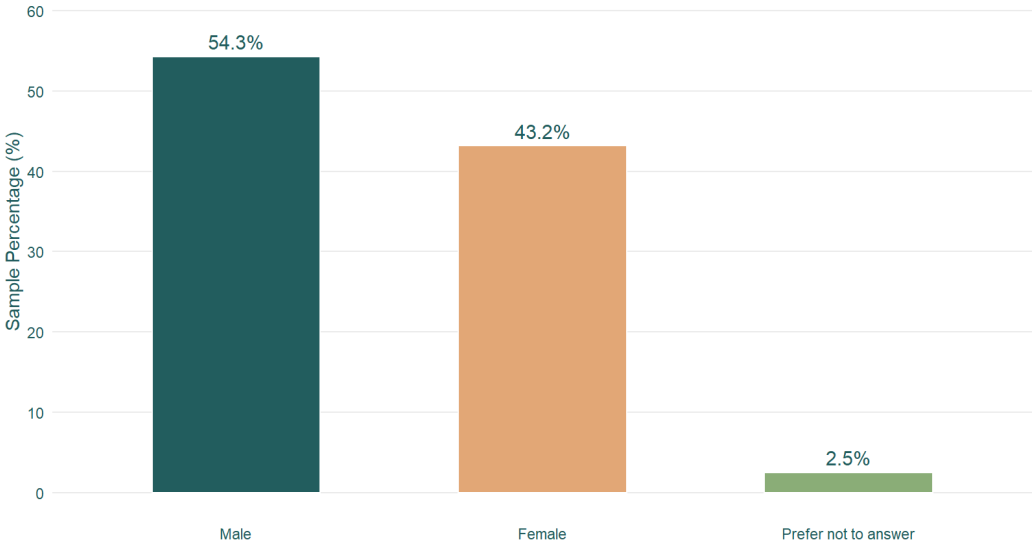


Figure 1.1: Gender distribution of the sample.

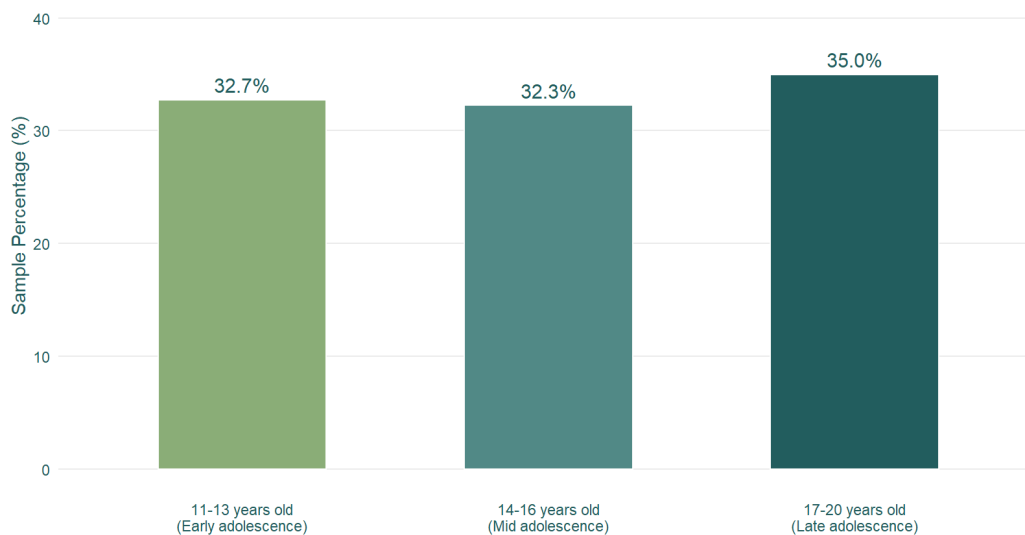


Figure 1.2: Age group frequency distribution of the sample.

1.2.2 The Teacher Sample (N = 600)

The data collection stream focused on the teaching population yields a clear and structurally robust snapshot of the education system, settling on a final analytical sample of N = 600 units providing informed consent. This sample size ensures high statistical power for inferential analyses and guarantees full generalisability of the attitudinal trends emerging from the research framework.

With regard to gender, the data faithfully reflect the phenomenon of marked feminisation of the teaching profession within the national context: the female component represents 75.0% of the total population (n = 450), defining the primary sociocultural perimeter within which experiences related to digital literacy are structured. The contribution of the male component, at 25.0% (n = 150), provides the metric balance necessary to conduct multi-role and multi-group measurement invariance tests.

Years of service and biographical maturity constitute an element of extraordinary theoretical and methodological significance:

- the majority of teachers fall within a consolidated age bracket, with 65.8% (n = 395) of subjects positioned in the over-45 cohort.
- this figure finds direct correspondence in seniority levels, where as many as 42.1% (n = 253) have a teaching career exceeding 16 years, forming a large cluster of classroom pedagogy experts.

Within the Slow Tech paradigm, the presence of teachers with a layered methodological background represents a fundamental heuristic resource, as it allows for the observation of the reception of algorithmic technologies not through the uncritical enthusiasm of younger cohorts, but through the reflective, attentive, and professionally cautious stance typical of those who have long presided over the classroom relationship.

With regard to institutional and geographical stratification, the sample reflects the strategic cooperation between the RSO Tuscany, which contributes the majority share with 80.7% of respondents (n = 484), and the University of Foggia, which brings the perspective of academic research and continuing education with 19.3% of the sample (n = 116).

Finally, the breakdown by disciplinary areas (ISCED) documents a balanced multidisciplinary composition: teachers belonging to the humanities and arts domains constitute 40.2% of the total (n

= 241), while the remaining 59.8% (n = 359) comprises colleagues from scientific, technical, and vocational sectors. This epistemological heterogeneity ensures that AI Literacy measures are not polarised by a single form of knowledge, laying the groundwork for a genuinely cross-cutting model of digital citizenship.

Table 1.2: The Teacher Sample (N = 600)

Variable	Category	N	%
Region	Tuscany	484	80.7
	Puglia	116	19.3
Gender	Femile	450	75.0
	Male	150	25.0
Age	Over 45 years	395	65.8
	Under 45 years	205	34.2
Years of Service	More than 16 years	253	42.1
	0-15 years	347	57.9
School Level	Upper Secondary School	325	54.2
	Other levels	275	45.8
Disciplinary Area	Humanities / Arts	241	40.2
	Other areas	359	59.8



Figure 1.3: Socio-Demographic Overview of the Teacher Population.

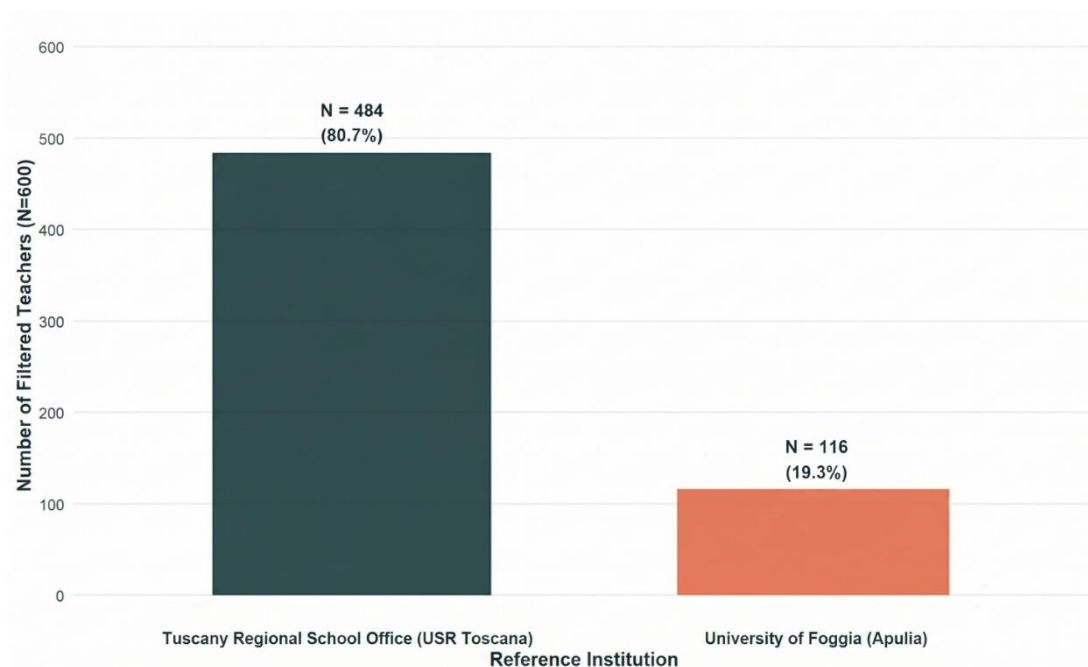


Figura 1.4: Geographic and Institutional Distribution.

1.3 Data Collection Instruments (Survey, Semi-Structured Interview Protocols)

The architecture of the research protocol was designed to ensure a rigorous transition between theoretical definitions and their empirical operationalisation, structuring two batteries of multidimensional questionnaires calibrated to the role-specific characteristics of students and teachers. To maximise the internal and scientific validity of the report, the specific investigative cores on Artificial Intelligence were anchored to the European framework on citizens' digital competencies, allowing for perfect metric alignment between the two populations.

1.3.1 The Student Data Collection Framework

The data collection instrument administered to students integrates a total of 54 items, formulated to capture the ecosystem of competencies, attitudes, and decision-making stances towards AI. Excluding system chronological variables and the 5 sociodemographic profiling items, the psychometric infrastructure of the instrument is articulated across three macro-components:

- **AI Literacy Questionnaire** (Ng et al., 2024): This constitutes the evaluative core of the instrument and is composed of 32 items derived from the validated international framework by Ng et al. (2024), measured on a five-point Likert scale (1 = Strongly disagree, 5 = Strongly agree). The 32 items map AI Literacy across its fundamental dimensions: the **Affective** sphere (10 items on self-efficacy and motivational engagement; prefixes AILQIM, AILQSE, AILQEN); the **Ethical** dimension (8 items on critical awareness of bias and responsibility; prefix AILQAIE); the **Attitudinal** dimension (2 items on critical literacy and openness to integration in study; prefix AILQCL); the **Behavioural** dimension (6 items on use intentionality and social interaction; prefixes AILQBI, AILQSI); and the **Cognitive** dimension (6 items on intrinsic technical knowledge of the algorithm; prefixes AILQKU, AILQEC).
- **Digital Competencies Module (DigComp Framework) and Anxiety Scale**: In order to anchor AI-specific literacy to broader digital competencies, 12 items derived from the European DigComp framework were integrated, distributed across information literacy

(DIGINF), communication (DIGCOM), safety and sustainability (DIGSAF), and digitally mediated problem solving (DIGPRO). To these is added 1 specific item extracted from the AIEAS scale (AIEASAUT06), aimed at detecting technological anxiety and students' positioning regarding the risk of substitution of human autonomy and responsibility by algorithmic systems. The scores of these subscales, appropriately aggregated, define the **Digital Competence** control variable.

- **Situated Decision-Making Scenarios (Ethical Decision-Making):** At the end of the instrument, 3 qualitative dilemma-based multiple-choice scenarios (SD04, SD05, SD06) were administered, based on ethically dense situated choices.

Table 1.3: Dimension mapping and scale architecture.

Analytical Dimension	Reference Item Codes	Measurement Type
Demographic Data	SP01, SP02, SP03	Nominal / Ordinal
Ai Use and Vision	SP07, SP08	Categorical / Ordinal
AI Literacy (AILQ)	AILQIM, SE, CL, BI, EN, SI, KU, EC, AIE	Scala Likert 1-5
Digital Competencies (DIG)	DIGINF, COM, SAF, PRO	Scala Likert 1-5
Human Agency	AIEASAUT06	Scala Likert 1-5
Ethical Dilemmas (SD)	SD04, SD05, SD06	Multiple-choice scenarios

On the analytical level, the qualitative response options (from A to D) of the situated dilemmas were subjected to a quantification and recoding procedure into ordered categorical variables, assigning increasing values based on the degree of caution, responsibility, and digital wisdom expressed. Specifically, in scenario SD04 (academic integrity when faced with a text containing algorithmic errors), the ordering rewards scientific rigour and transparency; in scenario SD05 (data privacy), the recoding prioritises the active protection of personal data over the immediate functionality of the application; in scenario SD06 (sustainability), the maximum score is associated with hardware optimisation and reuse choices aimed at containing environmental impact (e-waste).

At an advanced stage, these ordinal scores were linearly transformed into a continuous synthetic Ethical Decision-Making (EDM) index normalised within the interval [0, 1]. In this scheme, the value 1.0 systematically identifies the "Wise" profile (maximum applied awareness), while the value 0 corresponds to technocentric or uncritical approaches. The conversion allowed students' decisions to be employed as dependent variables in linear (LPM) and logistic regression models, facilitating the identification of paradoxes between declared technical competence and enacted ethical behaviour.

1.3.2 The Teacher Data Collection Framework

The instrument administered to the teaching staff (N = 600) was structured to enable the analytical transition from raw data to the latent constructs necessary for estimating the professional domain of AI Literacy. The architecture is articulated across four psychometric macro-dimensions, integrated with demographic variables and situated decision-making scenarios:

- **Teachers' Perception Scale** (Işık et al., 2024): this constitutes the main section of the questionnaire and is based on the validated international scale by Işık, Çakır, and Korkmaz, adapted to the Italian context. It comprises 36 items measured on a 5-point Likert scale, distributed across three macro-dimensions: **AI Competence** (TCHCOMP, 22 items from TCHCOMP01 to TCHCOMP22), aimed at measuring the teacher's perceived self-efficacy in the design and didactic integration of algorithms; **AI Anxiety** (TCHANX, 8 items from TCHANX23 to TCHANX30), focused on the degree of emotional resistance, fear of inadequacy, and concern over the erosion of students' critical thinking; **AI Utility** (TCHUTIL, 6 items from TCHUTIL31 to TCHUTIL36), directed at assessing the perceived practical value of the tool with respect to productivity and assessment support.
- **Digital Skills Module (DigComp Framework)**: the instrument integrates 8 items formulated identically to those in the student questionnaire, anchored to the European dimensions of the DigComp framework. The items explore information literacy (DIGINF), communication and collaboration (DIGCOM), safety and sustainability (DIGSAF), and proactivity in digital updating (DIGPRO), serving as a control variable and as a key mirror-alignment metric for inter-group comparisons.
- **Situated Decision-Making Scenarios (Ethical Decision-Making)**: professional ethical judgement was operationalised through three dilemma-based situated scenarios (Situational Judgment Tests — SJT) specific to the teacher's role and professional ethics: SD01 (curricular and professional autonomy when faced with materials generated by AI assistants), SD02 (safeguarding the relational and educational bond in the face of 24/7 AI tutors), and SD03 (academic integrity and the protection of cognitive writing when faced with essays produced using ChatGPT).

Table 1.4: Dimension Mapping and Scale Architecture.

Analytical Dimension	Reference Item Codes	Measurement Type
Demographic Data	TP01, TP02, TP03, TP04, TP05	Nominal / Ordinal
AI Use and Vision	TP07, TP08	Categorical / Ordinal
AI Literacy (TPS)	TCHCOMP, TCHANX, TCHUTIL	Scala Likert 1-5
Digital Competencies (DIG)	DIGINF, COM, SAF, PRO	Scala Likert 1-5
Human Agency	TCHCOMP22 (e correlati)	Scala Likert 1-5
Ethical Dilemmas (DIL)	SD01, SD02, SD03	Multiple-choice scenarios

In full methodological analogy with the student framework, the qualitative responses to the three professional dilemmas were recoded into ordered categorical variables according to a progression of increasing pedagogical awareness and caution (from the Technocentric approach to the Passive, Cautious, and finally the Wise profile). The scores were subsequently linearly transformed into a continuous synthetic Ethical Decision-Making (EDM) index normalised within the interval [0, 1], where the value 1.0 systematically identifies the "Wise" profile, characterised by the maximum

assumption of ethical responsibility and human control over automated processes (human-in-the-loop).

The stratification demographic variables collected include gender (TP02), age bracket (TP03), years of service (TP04), ISCED school level (TP05), and disciplinary area (TP06), providing the criteria for the extraction of latent profiles and cumulative logit predictive models.

2. National context on AI in education

2.1 Current ministerial policies, regulations and guidelines

The current legislative and regulatory landscape regarding the integration of Artificial Intelligence (AI) in the Italian education context is structured within a complex multi-level governance system. Through a coherent conceptual architecture, this system incorporates stringent supranational directives and translates them into specific national reforms and decrees.

At the European level, the center of gravity of technological interaction is defined by Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 (the European AI Act). Formally approved by the EU legislature and published in the Official Journal on 12 July 2024, the AI Act represents the definitive watershed between an era of fragmented and deregulated adoption of commercial software and a new, harmonized legal framework based on the principle of subordinating algorithmic development to the protection of the fundamental rights, health, and democratic values of European citizens.

The cornerstone of the AI Act is the adoption of a risk-based approach, aimed at classifying AI systems into a proportional hierarchy that determines the related legal and technical compliance obligations for educational and academic institutions.

Table 2.1: Risk mapping in the education sector under the European AI Act

UNACCEPTABLE RISK	Violation of fundamental EU rights and values. Absolute ban
HIGH RISK	Impact on health, safety and fundamental rights
LIMITED RISK	Risk of impersonation, manipulation, or deception (e.g., chatbots, deep fakes, AI-generated content) Obligation of information and transparency
MINIMUM RISK	Common AI systems, such as spam filters, recommendation systems, etc. No specific recommendations

Pursuant to Annex III of Regulation (EU) 2024/1689, AI systems used for assessing learning outcomes, admission to educational programs, educational guidance, and student behavior monitoring are formally classified as High-Risk AI Systems. The rationale for this regulatory stringency lies in the direct impact these algorithms have on students' life trajectories, affecting their access to higher education opportunities and the labor market. The use of High-Risk technologies binds the educational institution, legally classified as Deployer (professional user), to mandatory prescriptive obligations:

- 1. Human Oversight (Art. 14):** Mandatory oversight aimed at ensuring that the final assessment decision remains the exclusive prerogative of the teacher, neutralizing automation bias (the psychological tendency to uncritically trust machine output).
- 2. Dataset quality and traceability:** Monitoring training data to prevent discriminatory bias (based on gender, ethnicity, or socioeconomic background) and implementing automatic event logging systems.
- 3. Transparency and explainability:** Ensuring the interpretability of automated decisions to enable the underlying computational logic to be explained to students and families.

At the lower levels of the pyramid, limited-risk systems (such as chatbots based on large language models - LLM) are bound only by transparency and watermarking requirements (marking of synthetic content), while minimal-risk systems (such as spam filters or bibliographic recommendation engines) do not impose any specific obligations. In this scenario, AI Literacy (Art. 4) ceases to be a mere

optional pedagogical objective and becomes a mandatory compliance requirement for all school staff.

2.1.1 The National Regulatory and Strategic Framework

The European framework was incorporated into Italian law organically through Law No. 132 of September 23, 2025 (Provisions and Delegations to the Government on Artificial Intelligence), which formally entered into force on October 10, 2025. This measure regulates the development and adoption of AI in Italy from a strictly human-centric perspective, establishing a criminal penalty system for the illicit use of deepfakes, defining copyright protections for works of human intellect only, and designating the Agency for Digital Italy (AgID) and the National Agency for Cybersecurity (ACN) as national supervisory and inspection authorities.

The operational translation of this legal framework into the classroom is represented by the Guidelines for the Introduction of AI in Schools, issued by the Ministry of Education and Merit (MIM) in August 2025. The ministerial guidelines confirm the school's role as data controller, imposing two mandatory preventive procedures before starting any AI-augmented classroom activity:

- A data protection impact assessment (DPIA), pursuant to Art. 35 of the GDPR (EU Regulation 2016/679)
- A fundamental rights impact assessment (FRIA), pursuant to Art. 26 of the AI Act, the results of which must be communicated to market surveillance authorities

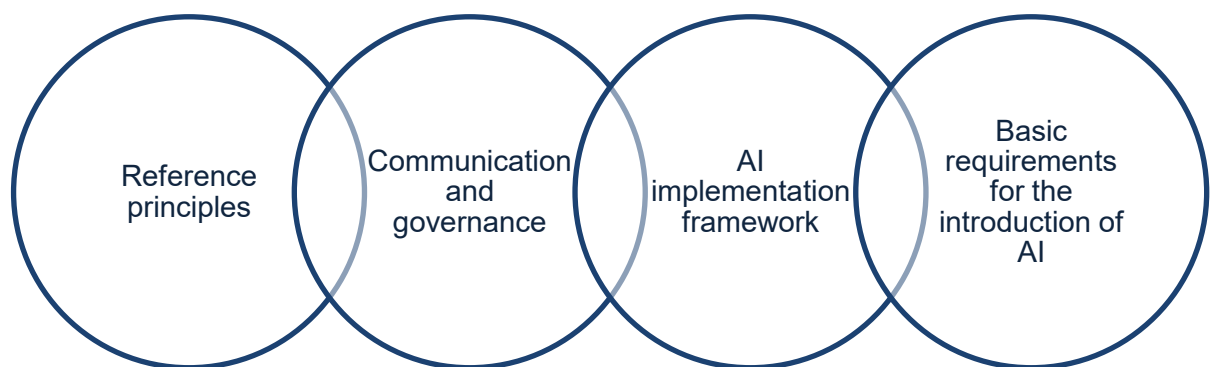


Figure 2.1: System architecture and enabling pillars for AI integration ¹.

¹ Image translated and adapted from: Ministero dell'Istruzione e del Merito (MIM), Decreto Ministeriale del 9 agosto 2025 n. 166.

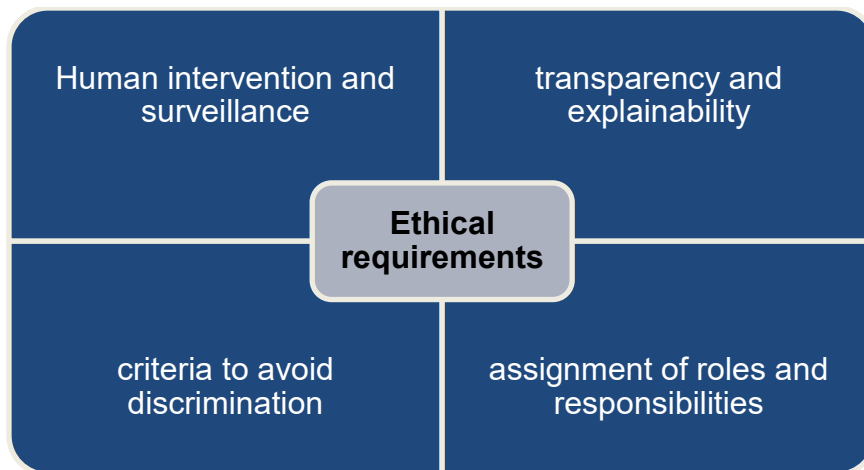


Figure 2.2: The axiological infrastructure and ethical requirements for the use of AI in the school context ²

In terms of skills development, integration between institutional policies and global frameworks is achieved through the convergence of the new AI Competency Frameworks for Teachers and Students released by UNESCO (Miao & Cukurova, 2024; Miao, Shiohira, & Lao, 2024) and the evolution of the European Citizen Digital Competence Framework towards the DigComp 3.0 model. DigComp transcends the concept of AI as an isolated technical discipline to define it as a transversal and transdisciplinary skill, making a fundamental taxonomic distinction:

- **implicit dimension of AI:** focused on effective use and daily and operational interaction with intelligent systems to optimize learning and material productivity (user familiarity).
- **explicit dimension of AI:** oriented towards the critical, conceptual, and algorithmic understanding of the functioning of models (machine learning, neural networks). This dimension enables autonomous ethical judgment, systematic fact-checking, and the mitigation of cognitive biases.



Figure 2.3: The digital skills pentagram in the DigComp 3.0 Framework

² Image translated and adapted from: Ministero dell'Istruzione e del Merito (MIM), Decreto Ministeriale del 9 agosto 2025 n. 166

Finally, to support this transition, the publication of the UNI 11621-8:2026 standard (April 30, 2026), the first national standard in Europe to systematically map the 12 professional profiles in the AI sector aligned with the e-Competence Framework (e.g., AI Prompt Engineer, AI Data Scientist, AI Security Specialist), offers universities, schools, and ITS Academies the objective parameter for qualifying and certifying classroom training courses, anchoring them to the real needs of a high-tech job market.

Table 2.2: Taxonomy of specialist professional profiles in the Artificial Intelligence sector

Profile name	Areas of Interest
Head of AI	Strategic Governance and Accountability for Artificial Intelligence
Artificial Intelligence Consultant	Strategic and Technical Consulting
AI Product Manager	AI Product Lifecycle and Management
AI Prompt Engineer	AI Input/Request Optimization
AI Algorithm Engineer	AI Algorithm Development and Design
AI Deep Learning Engineer	Specialized Neural Network and Deep Learning Design
AI Data Engineer	Data Architecture and Pipeline Management
AI Data Scientist	Data Analytics and Insight Generation
AI Security Specialist	AI System Security and Protection
Machine Learning and AI Engineer	Machine Learning Model Development and Implementation
AI Natural Language Processing (NLP) Engineer	Language-Based AI Solutions
AI Research Scientist	Artificial Intelligence Research and Innovation

2.1.2 Digital Infrastructure and Technological Readiness: The National Strategy 2024-2026

The effective implementation of this complex ethical and legal framework depends on the country's technological readiness and digital sovereignty. In this regard, the cornerstone of infrastructure interventions is defined by the Italian Strategy for Artificial Intelligence 2024-2026, which politically responds to the "Declaration for European Digital Sovereignty" to reduce strategic dependencies outside the EU through investment in technological commons and advanced network infrastructure (edge computing and smart grids).

The national strategy is structured around specific enabling actions that impact the school ecosystem:

- **Actions F.1 and F.5:** Initiatives aimed at bridging the student digital divide, elevating AI literacy to a basic right, and supporting ongoing training for school staff, in conjunction with PNRR funding (Ministerial Decrees 65 and 66).
- **Action R.1:** Strengthening the Future Artificial Intelligence Research (FAIR) ecosystem, structured around 10 leading academic and scientific spokespeople, offers the schools involved in the experiment the opportunity to connect to real research hubs to raise the technological readiness level (TRL) of their schools.
- **Action R.3:** Funding for the development of large-scale Italian language models, designed to be "safe-by-design," transparent, and monitored by Ethics Committees. This will protect linguistic diversity and the cultural integrity of the national intellectual heritage in training datasets, countering the cultural homogenization of foreign systems.

Table 2.3: Quadro comparativo dei framework di governance dell'IA

SOURCE	FOCUS	OBJECTIVES	OPERATIONAL DIMENSION
AI ACT	Security and Compliance	Risk classification	Legal obligations for providers and users; protection of fundamental rights in the EU
UNESCO	Human Rights	Transparency, fairness, and human oversight	Translating ethical values into concrete policies
UNESCO TEACHERS	Teaching and Training	Integration of AI into professional practice	Guiding teachers in the ethical use of AI to personalize learning
UNESCO STUDENTS	Student Co-Creator	Equity, educational quality, and awareness	Educating citizens capable of actively designing AI solutions
DIGCOMP 3.0	Citizen Skills	Implicit AI (practical use) and Explicit AI (critical understanding)	Transversal integration of AI to actively participate in society
MIM GUIDELINES	Transition Governance; Equity and Awareness	Orienting new generations toward a thorough understanding of the opportunities and risks associated with it	Guidelines and other operational tools to support and promote transformation in compliance with regulatory, ethical, and pedagogical principles
UNI STANDARD 11621-8:2026	Shared Framework for Defining and Developing Skills	A tool that helps address the challenges posed by the digital transition.	A technical-regulatory tool that translates legislative obligations into a structured set of professional roles and core competencies, providing

useful guidance to
businesses, public
administrations, training
institutions, and certification
bodies.

2.2 Digital Infrastructure and Technological Readiness of Experimental Schools

The effective diffusion of the Slow Tech paradigm and the sustainability of the educational experiments promoted by the STIAEM project are closely linked to the overall state of the education system's digital and network infrastructure. In this regard, Italy has initiated a profound process of structural modernization and digital transition through the School Plan 4.0 (Ministerial Decree 161/2022). This comprehensive and widespread intervention aims to reconfigure over 100,000 classrooms nationwide, converting traditional classroom-based spaces into innovative, flexible, and interconnected learning environments. Consistent with the Italian AI Strategy 2024-2026, this report views technological infrastructure not as a mere set of isolated physical components, but rather as an integrated and enabling digital ecosystem capable of supporting the introduction of trustworthy AI, which is secure and locally governable in terms of protecting institutional data.

The descriptive analysis of usage patterns reveals how the research samples operate within a national school context deeply impacted by this widespread digitalization, where interaction with algorithmic services and software is now a normalized, everyday occurrence. The empirical data collected demonstrates that:

- Over 91% of the student population reports having used AI-based tools at least once in their studies or daily life.
- The predominant mode of interaction among students is exploratory or asynchronous: 55.5% of the sample (n = 1,139) states they use these technologies "sometimes," primarily to seek inspiration, generate ideas, or to assist with language translations.
- A significant 19.8% of students (n = 406) have integrated AI structurally, using it "regularly" to complete assigned schoolwork.
- The proportion of those actively digitally excluded, represented by those who declare they have "never" interacted with AI, stands at a marginal minority of 8.3% (n = 170).

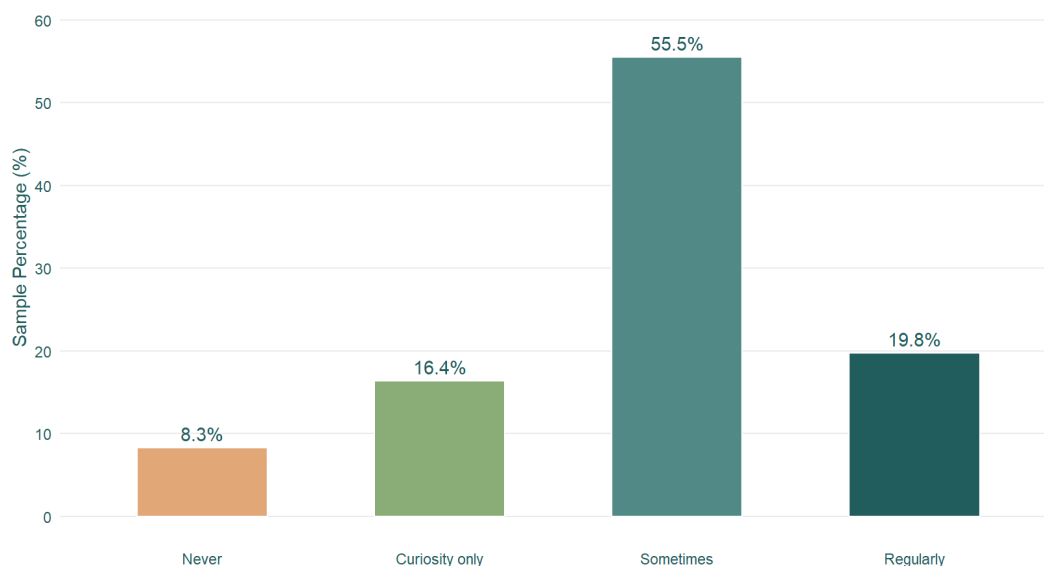


Figure 2.4: Distribution of Artificial Intelligence usage.

Among the teaching staff (N = 600), overall attitudinal and digital readiness levels reflect a solid transition, fostered by the methodological modernization processes initiated nationwide. Teachers' transversal digital skills (measured on a 1-5 Likert scale using indicators from the European DigComp framework) averaged $M = 3.38$ ($SD = 0.70$), exceeding their specific AI competence, which stood at $M = 3.19$ ($SD = 0.87$). In terms of classroom models and innovation orientation, the sample breakdown allows us to identify four specific technological cultures within the school:

1. Experimenter Profile (22.3%; $n = 134$): Pioneering teachers who actively integrate new AI applications and tools to personalize learning and optimize their administrative and design workload.
2. Integrated Profile (61.0%; $n = 366$): The absolute majority of the teacher training sample regularly uses the school's stable digital and network infrastructure (sharing platforms, electronic registers, school cloud environments) as standard, daily support for lessons.
3. Administrative Profile (13.8%; $n = 83$): Teachers who confine the use of technology almost exclusively to bureaucratic and organizational tasks, demonstrating greater caution in hybridizing classroom methodologies.
4. Avoidant Profile (2.8%; $n = 17$): A marginal fringe group that declares they exclude the use of technology in the classroom to exclusively preserve the analog-relational dimension.

This mapping demonstrates that the pilot schools benefit from an adequate and advanced technological readiness from the outset, solidly strengthened by the network infrastructure and digital environments created during the modernization of the school system. However, the data highlights a significant pedagogical gap: students experience interaction with AI primarily as an individual and informal support practice, while explicit and formalized curricular pathways within the school remain lacking.

Consolidating true institutional capacity building therefore requires capitalizing on the connectivity infrastructure and innovative learning environments spread throughout the country, introducing dedicated training programs. This will ensure the transition from an executive or fragmented use of the software to a critical, protected, and consistent teaching orchestration with national and European ethical constraints.

3. Data standardization and quantitative analysis

3.1 Data pre-processing

The transition from raw data to empirical evidence required the application of a standardized data cleaning and normalization protocol, essential to ensure the internal validity of the research design and the full replicability of the analytical procedures within the international STIAEM consortium. Preliminary data processing was implemented within the R computational environment (see 4.5.1), leveraging traceable computational algorithms structured according to a literate programming approach.

The preprocessing and alignment with the project's Master Codebook was divided into the following procedural and metric phases:

The raw responses provided by the two independent samples (students and teachers) on a five-point Likert scale were converted into a discrete numerical format within the range [1,5]. For the student population (N = 2052), this coding involved the 32 items of the AILQ Core Scale by Ng et al. (2024) and the 12 cross-sectional items of the DigComp framework. For the teacher population (N = 600), quantification involved the 36 native items of the Teachers' Perception Scale (TPS) by Işık et al. (2024) and the 8 mirrored digital control items.

To ensure full cross-national comparability of the data and alignment with international reporting standards (OECD/UNESCO), sociodemographic variables related to educational level and professional category were recoded and harmonized according to the International Standard Classification of Education (ISCED). For the teacher sample, this procedure allowed for a homogeneous segmentation of respondents between upper secondary school (ISCED 3, 54.2%) and lower secondary school (45.8%), while also isolating the relevant subject areas (humanities-arts, science-technology).

A crucial methodological step involved the conversion of qualitative responses from the Situational Judgment Tests (SJT). The nominal dilemma options (SD04, SD05, SD06 for students; SD01, SD02, SD03 for teachers) were initially recoded into ordered categorical (ordinal) variables, structured according to a gradient of prudence, responsibility, and adherence to the human-in-the-loop approach. Subsequently, these discrete values were linearly transformed into continuous synthetic indices of Ethical Decision-Making (EDM) fully normalized in the interval [0,1]. In this weighting scheme, the cutoff value of 1 systematically identifies the "Wise" profile (characterized by the highest degree of applied ethical awareness and pedagogical discipline), while the value 0 intercepts purely technocentric or uncritical postures.

The quality of the survey and the screening of statistically implausible responses or responses affected by response bias (e.g., acquiescence or random responding) were conducted through a multivariate analysis based on the calculation of the Mahalanobis distance. The empirical inspection did not reveal any anomalous response profiles or distorted compilation patterns that would compromise the stability and efficiency of subsequent inferential estimates, confirming the high quality of the database.

Thanks to the technical configuration of the computer-based administration, which included a mandatory response protocol for all questions in the psychopedagogical framework, the final student (N = 2,052) and teacher (N = 600) matrices were free of missing values. The absolute completeness of the dataset eliminated the need for listwise elimination procedures or stochastic imputation techniques, ensuring maximum statistical power and excluding the selection biases commonly associated with the manipulation of missing data.

Despite the structural absence of missing values, the subsequent mediation models, confirmatory factor analyses (CFA), and structural equation models (SEM) described in the report were estimated by consistently adopting the Maximum Likelihood Robust (MLR) estimator with robust standard errors. This methodological option was pursued not to compensate for data deficiencies, but rather

to secure the reliability of the asymptotic parameters and the accuracy of the overall fit indices (e.g., CFI, TLI, RMSEA) even in the face of slight deviations from multivariate normality of the distributions.

3.2 Descriptive Analysis (Frequencies, Means, Standard Deviations for AI Literacy and Ethical Awareness)

The descriptive analysis and study of frequency distributions provide a detailed mapping of the actual positioning of students and teachers with respect to the dimensions of AI Literacy and algorithmic-ethical awareness. Examination of the empirical data highlights a multifaceted and polarized picture, in which a solid foundation of values and ethics contrasts with specific cognitive weaknesses and marked institutional isolation.

3.2.1 Descriptive Profile of the Student Population (N = 2,052)

An analytical examination of the student sample's responses reveals a concentration of data predominantly at the midpoint of the five-point Likert scale, with mean scores ranging between 2.50 and 3.50. For example, item AILQIM01 has a mean score of 2.75 (SD = 1.05), reflecting a posture of substantial emotional and motivational neutrality among adolescents toward technological interfaces.

However, a granular inspection of the distributions reveals specific areas of polarization and pedagogical criticality:

- **Lack of institutional support (Social Influence):** Students express strong disagreement with items related to the school context's encouragement and pressure to use AI critically. Item AILQSI01 averages 2.36 (SD = 1.29), while the most significant finding of the entire survey is item AILQSI03 (perception of institutional pressure/encouragement), which drops to a mean of 1.92 (SD = 1.13) with the highest rate of "strong disagreement" (49.8% at level 1) found in the questionnaire. This evidence highlights a deep divide between students' informal practices and an educational system perceived as partially silent or unprepared.
- **Strength of applied ethical awareness:** Students' positioning within the realm of ethics and human agency is diametrically opposed. The section dedicated to AI Ethics (AIE) represents the research's highest consensus, highlighting extremely high averages for items AILQAIE10 (M = 3.93; SD = 1.13), AILQAIE12 (M = 4.00; SD = 1.16; 47.1% full agreement at level 5), and, above all, AILQAIE11 (need for human control over algorithmic decisions), which represents the highest consensus of the entire survey, with a mean of 4.11 (SD = 1.09) and 50.0% of the sample agreeing at level 5. This consensus is reflected in the claim of decision-making autonomy with respect to algorithmic suggestions expressed by item AIEASAUT06 (M = 3.86; SD = 1.22; 42.9% at level 5).
- **Cross-cutting digital maturity (DigComp):** The dimensions pertaining to the DigComp framework show a homogeneous and close-to-normal distribution, with means ranging between 3.02 and 3.47, indicating a perceived medium-high level of digital competence. The ability to identify fake news online (DIGINF1.2) stands out, with the response density shifting significantly toward level 4 (34.6%), a sign of widespread confidence in one's fact-checking skills.

Table 3.1: Descriptive statistics of the items (N=2052)

Item	Dimension	N	Min	Max	M	SD
<i>AILQIM01</i>	<i>Affective</i>	2052	1	5	2.75	1.05
<i>AILQIM02</i>	<i>Affective</i>	2052	1	5	3.38	1.15

<i>AILQIM03</i>	<i>Affective</i>	2052	1	5	2.14	1.08
<i>AILQIM04</i>	<i>Affective</i>	2052	1	5	3.36	1.21
<i>AILQSE01</i>	<i>Affective</i>	2052	1	5	2.83	1.10
<i>AILQSE02</i>	<i>Affective</i>	2052	1	5	2.97	1.08
<i>AILQSE03</i>	<i>Affective</i>	2052	1	5	3.03	1.11
<i>AILQSE04</i>	<i>Affective</i>	2052	1	5	3.00	1.11
<i>AILQEN01</i>	<i>Affective</i>	2052	1	5	2.49	1.19
<i>AILQEN02</i>	<i>Affective</i>	2052	1	5	2.71	1.17
<i>AILQCL01</i>	<i>Attitudinal</i>	2052	1	5	3.19	1.06
<i>AILQCL03</i>	<i>Attitudinal</i>	2052	1	5	3.02	1.08
<i>AILQBI01</i>	<i>Behavioural</i>	2052	1	5	3.58	1.19
<i>AILQBI02</i>	<i>Behavioural</i>	2052	1	5	3.19	1.22
<i>AILQBI03</i>	<i>Behavioural</i>	2052	1	5	2.70	1.23
<i>AILQSI01</i>	<i>Behavioural</i>	2052	1	5	2.36	1.29
<i>AILQSI02</i>	<i>Behavioural</i>	2052	1	5	2.54	1.22
<i>AILQSI03</i>	<i>Behavioural</i>	2052	1	5	1.92	1.13
<i>AILQKU01</i>	<i>Behavioural</i>	2052	1	5	3.30	1.26
<i>AILQKU02</i>	<i>Behavioural</i>	2052	1	5	3.69	1.15
<i>AILQKU05</i>	<i>Behavioural</i>	2052	1	5	2.57	1.24
<i>AILQEC01</i>	<i>Cognitive</i>	2052	1	5	3.08	1.17
<i>AILQEC03</i>	<i>Cognitive</i>	2052	1	5	2.71	1.22
<i>AILQEC04</i>	<i>Cognitive</i>	2052	1	5	2.94	1.14
<i>DIGINF1.1</i>	<i>Cognitive</i>	2052	1	5	3.38	1.06
<i>DIGINF1.2</i>	<i>Cognitive</i>	2052	1	5	3.47	1.04
<i>DIGCOM2.6</i>	<i>Cognitive</i>	2052	1	5	3.33	1.14
<i>DIGCOM3.4</i>	<i>Cognitive</i>	2052	1	5	3.02	1.06
<i>DIGSAF4.1</i>	<i>Cognitive</i>	2052	1	5	3.13	1.16
<i>DIGSAF4.2</i>	<i>Cognitive</i>	2052	1	5	3.45	1.13
<i>DIGSAF4.3</i>	<i>Cognitive</i>	2052	1	5	3.43	1.13
<i>DIGSAF4.4</i>	<i>Cognitive</i>	2052	1	5	3.17	1.24
<i>DIGSAF4.5</i>	<i>Cognitive</i>	2052	1	5	3.20	1.06
<i>DIGSAF4.6</i>	<i>Cognitive</i>	2052	1	5	3.03	1.30
<i>DIGPRO5.3</i>	<i>Cognitive</i>	2052	1	5	3.32	1.06

<i>DIGPRO5.4</i>	Cognitive	2052	1	5	3.32	1.06
<i>AILQAIE02</i>	Ethical	2052	1	5	3.93	1.16
<i>AILQAIE05</i>	Ethical	2052	1	5	3.85	1.16
<i>AILQAIE07</i>	Ethical	2052	1	5	3.16	1.10
<i>AILQAIE08</i>	Ethical	2052	1	5	3.65	1.24
<i>AILQAIE10</i>	Ethical	2052	1	5	3.93	1.13
<i>AILQAIE11</i>	Ethical	2052	1	5	4.11	1.09
<i>AILQAIE12</i>	Ethical	2052	1	5	4.00	1.16
<i>AILQAIE13</i>	Ethical	2052	1	5	3.66	1.14
<i>AIEASAUT06</i>	Ethical	2052	1	5	3.86	1.22

Table 3.2: Distribution of percentage frequencies of items (N=2052)

Item	Dimension	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
<i>AIEASAUT06</i>	Ethical	5.1%	9.4%	23.1%	19.4%	42.9%
<i>AILQAIE02</i>	Ethical	4.2%	8.5%	19.9%	24.6%	42.8%
<i>AILQAIE05</i>	Ethical	4.5%	7.7%	25.7%	22.6%	39.4%
<i>AILQAIE07</i>	Ethical	6.7%	19.8%	37.7%	22.3%	13.5%
<i>AILQAIE08</i>	Ethical	6.7%	11.5%	26.5%	21.0%	34.4%
<i>AILQAIE10</i>	Ethical	3.2%	8.3%	23.3%	22.8%	42.4%
<i>AILQAIE11</i>	Ethical	3.2%	5.7%	18.1%	23.0%	50.0%
<i>AILQAIE12</i>	Ethical	4.4%	6.5%	21.3%	20.8%	47.1%
<i>AILQAIE13</i>	Ethical	5.0%	9.8%	28.6%	27.1%	29.5%
<i>AILQBI01</i>	Behavioural	6.2%	12.3%	26.9%	26.7%	28.0%
<i>AILQBI02</i>	Behavioural	10.0%	19.1%	29.5%	24.5%	16.9%
<i>AILQBI03</i>	Behavioural	19.3%	27.3%	27.6%	15.5%	10.2%
<i>AILQCL01</i>	Attitudinal	6.5%	17.7%	37.8%	26.3%	11.7%
<i>AILQCL03</i>	Attitudinal	8.5%	22.4%	37.5%	22.0%	9.6%
<i>AILQEC01</i>	Cognitive	10.8%	19.6%	32.6%	24.7%	12.3%
<i>AILQEC03</i>	Cognitive	20.1%	24.0%	30.0%	16.7%	9.3%
<i>AILQEC04</i>	Cognitive	12.3%	21.7%	35.8%	20.7%	9.6%
<i>AILQEN01</i>	Affective	24.5%	28.6%	28.0%	11.4%	7.6%
<i>AILQEN02</i>	Affective	17.4%	26.5%	32.4%	15.5%	8.3%
<i>AILQIM01</i>	Affective	12.0%	28.3%	38.7%	14.8%	6.1%

<i>AILQIM02</i>	Affective	6.6%	15.6%	30.7%	27.9%	19.2%
<i>AILQIM03</i>	Affective	33.7%	33.3%	22.1%	7.1%	3.8%
<i>AILQIM04</i>	Affective	8.1%	16.4%	27.5%	27.3%	20.7%
<i>AILQKU01</i>	Behavioural	9.8%	17.0%	28.8%	22.2%	22.2%
<i>AILQKU02</i>	Behavioural	5.2%	10.0%	25.0%	30.3%	29.6%
<i>AILQKU05</i>	Behavioural	23.9%	26.3%	28.0%	12.6%	9.2%
<i>AILQSE01</i>	Affective	12.3%	24.8%	38.5%	16.1%	8.4%
<i>AILQSE02</i>	Affective	9.1%	22.8%	39.7%	18.8%	9.7%
<i>AILQSE03</i>	Affective	9.6%	21.3%	35.8%	23.1%	10.1%
<i>AILQSE04</i>	Affective	10.5%	19.9%	38.0%	21.6%	9.9%
<i>AILQSI01</i>	Behavioural	35.3%	22.3%	21.7%	12.7%	7.9%
<i>AILQSI02</i>	Behavioural	25.2%	24.7%	27.8%	14.9%	7.4%
<i>AILQSI03</i>	Behavioural	49.8%	23.5%	16.1%	6.6%	4.0%
<i>DIGCOM2.6</i>	Cognitive	7.7%	13.6%	34.0%	27.8%	16.9%
<i>DIGCOM3.4</i>	Cognitive	8.5%	20.7%	40.0%	22.2%	8.6%
<i>DIGINF1.1</i>	Cognitive	5.5%	12.1%	37.0%	29.5%	15.8%
<i>DIGINF1.2</i>	Cognitive	4.4%	11.6%	33.0%	34.6%	16.3%
<i>DIGPRO5.3</i>	Cognitive	5.5%	14.5%	37.3%	27.9%	14.7%
<i>DIGPRO5.4</i>	Cognitive	5.6%	13.6%	38.9%	27.4%	14.4%
<i>DIGSAF4.1</i>	Cognitive	9.8%	18.8%	34.5%	22.9%	14.1%
<i>DIGSAF4.2</i>	Cognitive	5.5%	14.1%	31.5%	27.9%	21.0%
<i>DIGSAF4.3</i>	Cognitive	5.7%	13.6%	33.2%	26.5%	21.0%
<i>DIGSAF4.4</i>	Cognitive	11.0%	18.6%	30.9%	21.5%	18.0%
<i>DIGSAF4.5</i>	Cognitive	6.6%	16.1%	40.6%	24.2%	12.6%
<i>DIGSAF4.6</i>	Cognitive	15.3%	19.6%	28.7%	19.2%	17.2%

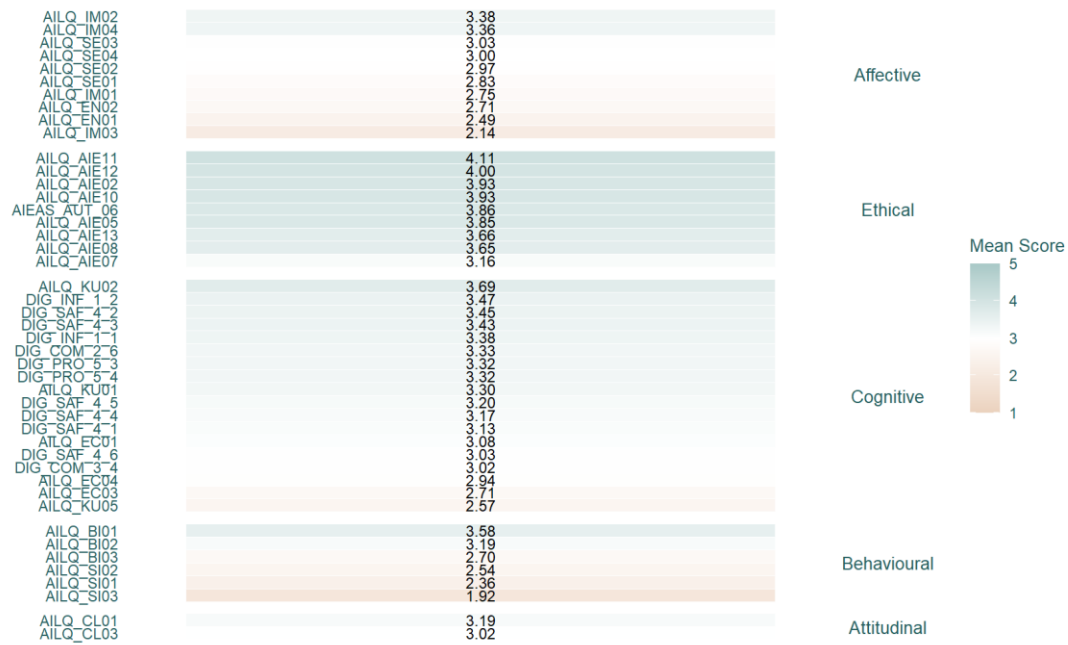


Figure 3.1: Granular Item Means for the Core AI Literacy Questionnaire (AILQ).

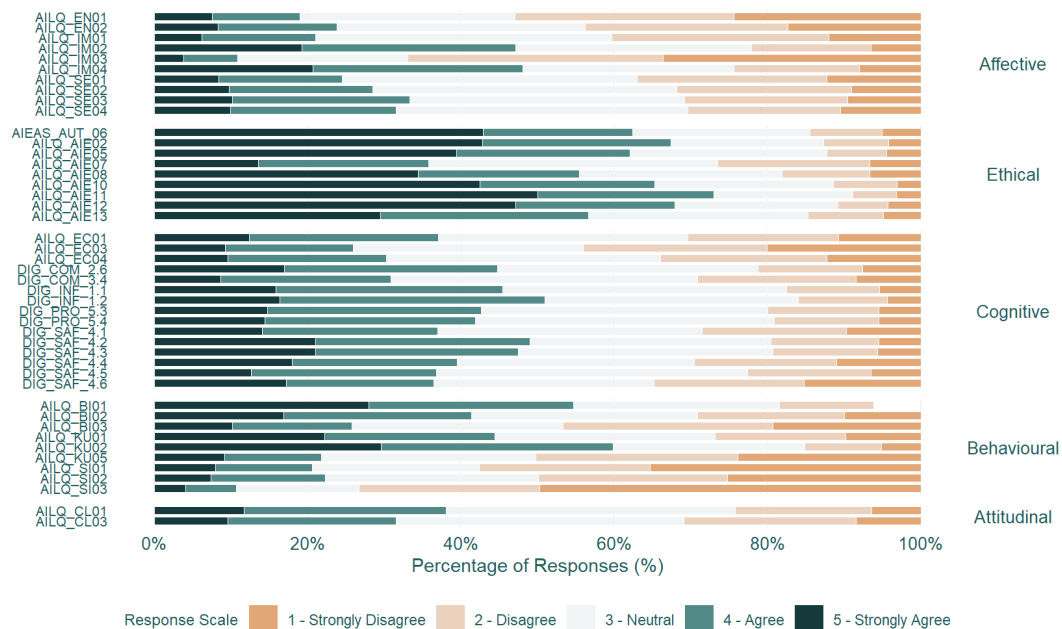


Figure 3.2: Stacked Percentage Distribution of Likert Scale Responses

3.2.2 Descriptive Profile of the Teaching Staff (N = 600)

The granular analysis of the 44 items administered to the teaching staff confirms a professional in a phase of conscious transition, characterized by moderate polarization and guided by a markedly pragmatic and reflective approach.

- AI Competence and the Productivity Axis:** The perceived competence dimension ($M = 3.19$; $SD = 0.84$) shows a concentration of responses at the central value (approximately 38.0% at level 3), indicating a still-evolving self-efficacy. However, a significant peak emerges for the TCHCOMP21 item ($M = 3.79$; $SD = 1.12$; with 32.3% strong agreement), relating to the perception of AI as a tool for optimizing teaching and administrative workload. Teachers

identify operational efficiency as the primary immediate benefit, useful for recovering professional time to reinvest in the educational relationship.

- **AI Utility and Pedagogical Optimism:** The perceived utility scale ($M = 3.52$; $SD = 0.78$) represents the highest score among the constructs investigated. Over 55.0% of teachers strongly or completely agree with the ability of AI to enhance learning processes, generating a positive discrepancy between a technical expertise still "in transition" and the high theoretical value recognized in the tool.
- **Generative anxiety and cognitive protection (AI Anxiety):** The overall mean of the anxiety scale is below the midpoint ($M = 2.45$; $SD = 0.91$), demonstrating that fears of "professional substitution" are entirely marginal. Concerns instead focus on the ethical-pedagogical dimension, as evidenced by item TCHANX27 (fear of the negative impact of AI on critical thinking and students' intellectual autonomy), whose distribution shifts markedly toward the high values of the scale ($M = 3.02$; $SD = 1.28$). The resistance estimated among the teaching staff therefore appears to be "generative" resistance, aimed at protecting the quality of the educational process.

Table 3.3: Full descriptive statistics: all 44 items ($N = 600$)

Item	Scale	N	Min	Max	M	SD	Skew	Kurt
<i>TCHCOMP01</i>	TCHCOMP	600	1	5	3.48	1.04	-0.28	-0.31
<i>TCHCOMP02</i>	TCHCOMP	600	1	5	2.78	1.16	0.12	-0.76
<i>TCHCOMP03</i>	TCHCOMP	600	1	5	3.12	1.10	-0.07	-0.74
<i>TCHCOMP04</i>	TCHCOMP	600	1	5	2.71	1.15	0.14	-0.83
<i>TCHCOMP05</i>	TCHCOMP	600	1	5	2.93	1.14	0.02	-0.82
<i>TCHCOMP06</i>	TCHCOMP	600	1	5	3.22	1.22	-0.25	-0.84
<i>TCHCOMP07</i>	TCHCOMP	600	1	5	2.64	1.19	0.22	-0.86
<i>TCHCOMP08</i>	TCHCOMP	600	1	5	3.19	1.15	-0.21	-0.77
<i>TCHCOMP09</i>	TCHCOMP	600	1	5	3.50	1.27	-0.56	-0.70
<i>TCHCOMP10</i>	TCHCOMP	600	1	5	3.40	1.22	-0.36	-0.83
<i>TCHCOMP11</i>	TCHCOMP	600	1	5	3.33	1.20	-0.37	-0.69
<i>TCHCOMP12</i>	TCHCOMP	600	1	5	2.83	1.21	0.05	-0.89
<i>TCHCOMP13</i>	TCHCOMP	600	1	5	2.93	1.25	0.11	-0.98
<i>TCHCOMP14</i>	TCHCOMP	600	1	5	3.13	1.24	-0.20	-0.84
<i>TCHCOMP15</i>	TCHCOMP	600	1	5	3.68	1.12	-0.64	-0.31
<i>TCHCOMP16</i>	TCHCOMP	600	1	5	2.90	1.31	0.02	-1.12
<i>TCHCOMP17</i>	TCHCOMP	600	1	5	3.65	1.15	-0.66	-0.26
<i>TCHCOMP18</i>	TCHCOMP	600	1	5	3.02	1.33	-0.04	-1.15
<i>TCHCOMP19</i>	TCHCOMP	600	1	5	3.17	1.16	-0.13	-0.76
<i>TCHCOMP20</i>	TCHCOMP	600	1	5	3.60	1.17	-0.53	-0.54

<i>TCHCOMP21</i>	TCHCOMP	600	1	5	3.79	1.12	-0.72	-0.16
<i>TCHCOMP22</i>	TCHCOMP	600	1	5	3.20	1.16	-0.12	-0.70
<i>TCHANX23</i>	TCHANX	600	1	5	2.70	1.15	0.33	-0.62
<i>TCHANX24</i>	TCHANX	600	1	5	2.77	1.17	0.25	-0.61
<i>TCHANX25</i>	TCHANX	600	1	5	2.38	1.17	0.63	-0.34
<i>TCHANX26</i>	TCHANX	600	1	5	2.15	1.06	0.76	0.00
<i>TCHANX27</i>	TCHANX	600	1	5	3.02	1.28	0.06	-1.06
<i>TCHANX28</i>	TCHANX	600	1	5	1.98	1.15	1.06	0.28
<i>TCHANX29</i>	TCHANX	600	1	5	2.56	1.38	0.40	-1.09
<i>TCHANX30</i>	TCHANX	600	1	5	2.76	1.07	0.06	-0.49
<i>TCHUTIL31</i>	TCHUTIL	600	1	5	2.56	1.11	0.22	-0.68
<i>TCHUTIL32</i>	TCHUTIL	600	1	5	3.29	1.10	-0.19	-0.53
<i>TCHUTIL33</i>	TCHUTIL	600	1	5	2.44	1.18	0.40	-0.75
<i>TCHUTIL34</i>	TCHUTIL	600	1	5	2.18	1.14	0.65	-0.52
<i>TCHUTIL35</i>	TCHUTIL	600	1	5	3.12	1.18	-0.15	-0.81
<i>TCHUTIL36</i>	TCHUTIL	600	1	5	3.21	1.22	-0.30	-0.90
<i>DIGINF1.1</i>	DIG	600	1	5	3.18	1.23	-0.17	-0.95
<i>DIGINF1.2</i>	DIG	600	1	5	3.72	0.96	-0.62	0.06
<i>DIGCOM2.6</i>	DIG	600	1	5	3.13	1.15	-0.11	-0.81
<i>DIGCOM3.4</i>	DIG	600	1	5	2.83	1.11	0.02	-0.71
<i>DIGSAF4.2</i>	DIG	600	1	5	3.18	1.05	-0.05	-0.65
<i>DIGSAF4.3</i>	DIG	600	1	5	3.56	1.02	-0.30	-0.45
<i>DIGSAF4.4</i>	DIG	600	1	5	3.63	1.01	-0.44	-0.23
<i>DIGPRO5.4</i>	DIG	600	1	5	3.80	0.91	-0.52	0.08

Table 3.4: Percentage response frequencies by category (N = 600)

Item	Scala	1 Fortemente in disaccordo	2	3	4	5 Fortemente d'accordo
<i>TCHCOMP01</i>	TCHCOMP	4.2%	9.8%	38.0%	29.3%	18.7%
<i>TCHCOMP02</i>	TCHCOMP	16.3%	24.0%	33.2%	18.5%	8.0%
<i>TCHCOMP03</i>	TCHCOMP	7.2%	22.8%	31.7%	27.2%	11.2%
<i>TCHCOMP04</i>	TCHCOMP	17.5%	26.3%	30.2%	19.7%	6.3%
<i>TCHCOMP05</i>	TCHCOMP	11.5%	25.5%	30.2%	24.3%	8.5%

<i>TCHCOMP06</i>	TCHCOMP	10.8%	16.7%	28.3%	28.2%	16.0%
<i>TCHCOMP07</i>	TCHCOMP	20.7%	26.0%	28.7%	17.8%	6.8%
<i>TCHCOMP08</i>	TCHCOMP	8.5%	19.5%	29.0%	30.0%	13.0%
<i>TCHCOMP09</i>	TCHCOMP	10.5%	11.3%	21.2%	32.2%	24.8%
<i>TCHCOMP10</i>	TCHCOMP	8.3%	15.7%	25.3%	28.8%	21.8%
<i>TCHCOMP11</i>	TCHCOMP	9.7%	13.7%	28.3%	30.7%	17.7%
<i>TCHCOMP12</i>	TCHCOMP	17.8%	20.8%	31.7%	20.2%	9.5%
<i>TCHCOMP13</i>	TCHCOMP	14.5%	24.7%	27.7%	19.3%	13.8%
<i>TCHCOMP14</i>	TCHCOMP	14.0%	13.7%	33.2%	23.5%	15.7%
<i>TCHCOMP15</i>	TCHCOMP	5.0%	10.2%	23.2%	34.7%	27.0%
<i>TCHCOMP16</i>	TCHCOMP	19.2%	20.2%	25.2%	22.0%	13.5%
<i>TCHCOMP17</i>	TCHCOMP	6.5%	8.8%	24.2%	34.5%	26.0%
<i>TCHCOMP18</i>	TCHCOMP	17.2%	19.7%	24.3%	22.2%	16.7%
<i>TCHCOMP19</i>	TCHCOMP	9.2%	18.8%	32.5%	25.2%	14.3%
<i>TCHCOMP20</i>	TCHCOMP	6.2%	11.3%	25.3%	30.3%	26.8%
<i>TCHCOMP21</i>	TCHCOMP	4.8%	7.5%	24.0%	31.3%	32.3%
<i>TCHCOMP22</i>	TCHCOMP	8.7%	17.2%	35.5%	23.0%	15.7%
<i>TCHANX23</i>	TCHANX	15.5%	30.7%	30.8%	14.5%	8.5%
<i>TCHANX24</i>	TCHANX	15.3%	25.7%	35.7%	13.2%	10.2%
<i>TCHANX25</i>	TCHANX	26.0%	32.8%	25.2%	9.0%	7.0%
<i>TCHANX26</i>	TCHANX	31.8%	35.5%	21.7%	7.7%	3.3%
<i>TCHANX27</i>	TCHANX	13.0%	24.8%	25.7%	20.2%	16.3%
<i>TCHANX28</i>	TCHANX	46.0%	26.0%	17.0%	6.2%	4.8%
<i>TCHANX29</i>	TCHANX	30.8%	21.5%	21.0%	14.3%	12.3%
<i>TCHANX30</i>	TCHANX	14.2%	23.3%	40.2%	16.7%	5.7%
<i>TCHUTIL31</i>	TCHUTIL	21.0%	25.8%	34.0%	14.5%	4.7%
<i>TCHUTIL32</i>	TCHUTIL	6.7%	14.7%	37.2%	25.8%	15.7%
<i>TCHUTIL33</i>	TCHUTIL	27.3%	26.0%	27.7%	13.5%	5.5%
<i>TCHUTIL34</i>	TCHUTIL	35.7%	28.5%	21.2%	11.3%	3.3%
<i>TCHUTIL35</i>	TCHUTIL	10.5%	19.3%	30.3%	26.8%	13.0%
<i>TCHUTIL36</i>	TCHUTIL	11.3%	17.8%	23.7%	32.5%	14.7%
<i>DIGINF1.1</i>	DIG	10.5%	20.0%	26.3%	26.8%	16.3%
<i>DIGINF1.2</i>	DIG	2.2%	9.0%	23.8%	44.8%	20.2%

<i>DIGCOM2.6</i>	DIG	8.8%	21.3%	30.0%	27.2%	12.7%
<i>DIGCOM3.4</i>	DIG	13.7%	24.0%	34.5%	21.3%	6.5%
<i>DIGSAF4.2</i>	DIG	5.0%	22.0%	34.3%	27.7%	11.0%
<i>DIGSAF4.3</i>	DIG	2.7%	11.5%	33.0%	33.2%	19.7%
<i>DIGSAF4.4</i>	DIG	3.0%	9.0%	31.2%	35.7%	21.2%
<i>DIGPRO5.4</i>	DIG	1.5%	5.7%	27.5%	42.5%	22.8%

Celle in evidenza (blu) = categoria modale per ogni item.

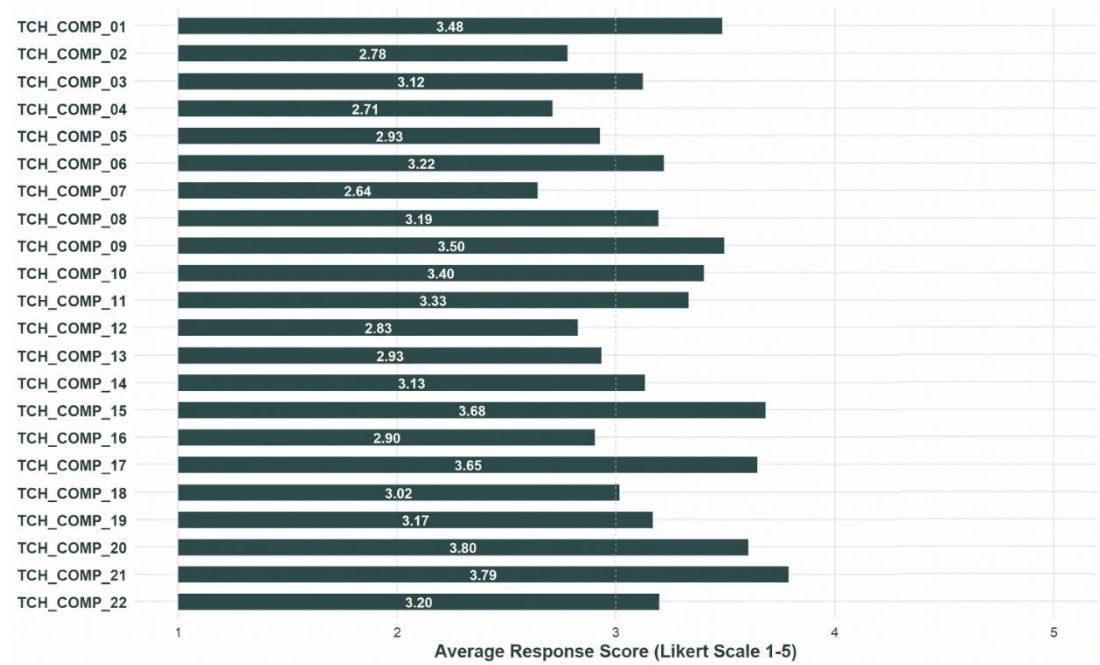


Figure 3.3: Item Means for the AI Competence Scale

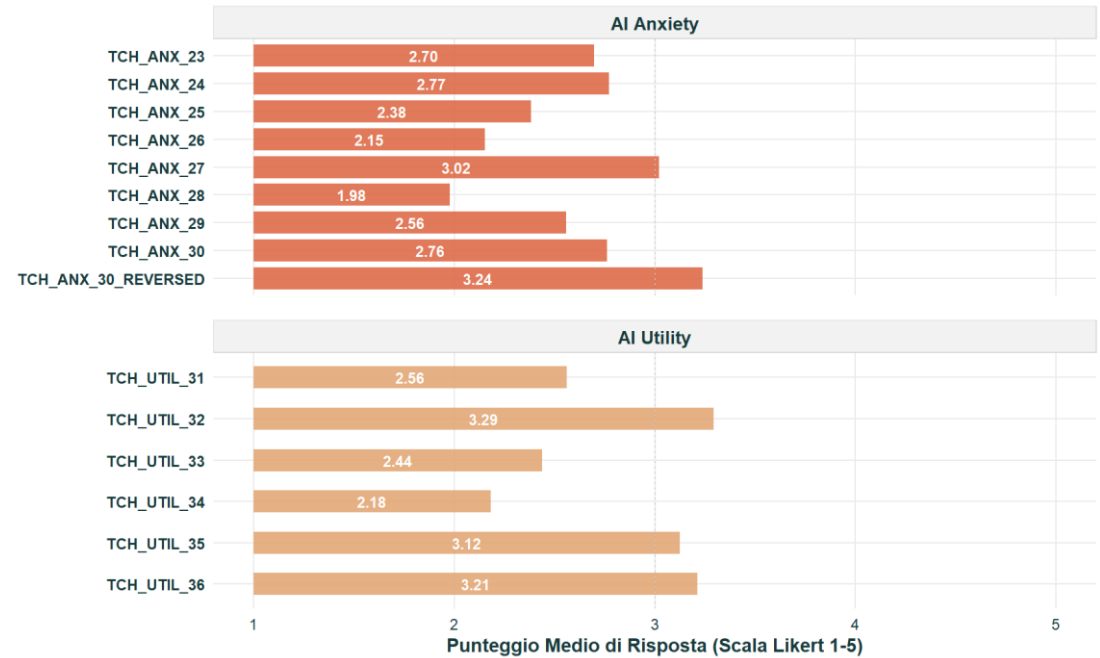


Figure 3.4: Comparative Item Analysis: AI Utility vs. AI Anxiety

3.3 Comparative and Correlational Analysis (ANOVA, T-test, Pearson/Regression Models)

The inferential exploration of the dataset aims to identify linear relationships between psychometric constructs and isolate the impact of sociodemographic variables and usage habits on students' and teachers' AI literacy. By applying mean comparison tests (one-way ANOVA and Welch's t-test for heterogeneous variances) and inspecting the latent covariance matrices estimated through Confirmatory Factor Analysis (CFA), it is possible to map the vectors of digital development and deconstruct false myths related to the age and gender gaps.

3.3.1 Latent Correlation Matrices and Systemic Interdependencies

The interaction between the different aspects of literacy highlights profoundly different structural dynamics between the two populations under investigation:

- **The student cluster (AILQ Framework):** Inspection of the latent correlation matrix resulting from the global five-factor CFA model reveals a severe violation of discriminant validity bordering on linear singularity. The pure latent correlation between the Affective dimension (self-efficacy and perceived interest) and the Attitudinal component (general mental posture) collapses into a critical coefficient of $r = .981$, accompanied by an equally extreme association with the Behavioral dimension ($r = .913$). This data describes a macro-block of psychological and emotional activation in which the perception of competence, value attitude, and intentionality of use operate as a computationally inseparable construct. Conversely, the Ethical dimension remains an isolated module, displaying the lowest association coefficients in the matrix (ranging between $r = .327$ with Affective and $r = .535$ with Cognitive), demonstrating that technical expertise and emotional confidence do not independently stimulate profound moral reflection.
- **The teacher cluster (TPS Framework + DigComp):** The analysis of linear relationships estimates a highly significant "virtuous core" ($p < .001$) between perceived competence (AI Competence) and the value recognized for the tool (AI Utility), linked by a strong positive correlation ($r = .734$). Technical mastery represents the primary driver that allows teachers to glimpse the added value of AI for their own productivity and for optimizing teaching. The opposite role is played by AI Anxiety, which correlates negatively and symmetrically with both competence ($r = -.589$) and perceived usefulness ($r = -.573$), confirming that training investment in practical skills acts as a natural factor in mitigating emotional and professional resistance.



Figure 3.5: Correlation Heatmap of STIAEM Latent Factors.



Figure 3.6: Correlation Heatmap of AI Literacy Dimensions

3.3.2 Analisi differenziale su base demografica: Genere ed Età

The application of ANOVA models allows us to make a crucial methodological distinction between the statistical significance induced by the sample size (p) and the real pedagogical relevance estimated through the effect size (η^2):

- The impact of gender (Invariance of use vs. Perceived discrepancies):** For both teachers and students, gender exerts a pragmatically small or negligible influence, rejecting the hypothesis of a structural gender gap in operational access to technologies. In the student sample, gender explains approximately 3% of the variance in the Affective ($\eta^2 = 0.033$) and Cognitive ($\eta^2 = 0.027$) dimensions, highlighting that the observed gaps are attributable to a different symbolic construction of one's self-efficacy (with males reporting higher averages in

the emotional approach: $M = 2.99$ vs. $M = 2.70$ for females) rather than to a real gap in usage skills, which narrows drastically in the DigComp dimensions ($\eta^2 = 0.007$, negligible effect). In the teacher sample, the homogeneity is even more marked: no significant differences were found in either perceived competence ($p = .574$; $\eta^2 = 0.002$) or levels of technology anxiety ($p = .240$; $\eta^2 = 0.005$). The only exception was represented by transversal digital skills (DIGSKILLS), which favored the male component ($M = 3.50$ vs. $M = 3.33$), but confined to a small effect size ($\eta^2 = 0.012$, equal to 1.2% of explained variance). The ethical dimension remained the area of maximum axiomatic convergence in both populations, with impact effects close to zero ($\eta^2 = 0.005$).

- Developmental trajectories by age (Disrupting technophobia):** The analysis of anagraphic development brings to light a scientific evidence that is both striking and disruptive for educational research. In the student population (11-20 years), pure digital skills (Digital Comp) remain on a common and stable plateau that is independent of the level of academic achievement ($F = 1.68$, $p = .089$, $\eta^2 = 0.007$). Developmental vectors focus exclusively on attitudinal and cognitive components ($\eta^2 = 0.031$), where more mature subjects tend to remodulate anxiety and develop more selective usage strategies. Among teaching staff, seniority (an indicator of the professional life cycle) shows a decreasing linear trend only for AI Competence Perception ($F = 5.90$, $p = .001$, $\eta^2 = 0.029$), with novice teachers expressing greater operational confidence ($M = 3.43$) than veterans with over 25 years of tenure ($M = 3.03$). However, technology anxiety (AIANX, $p = .236$) and transversal digital skills (DIGSKILLS, $p = .313$) remain perfectly constant across the entire career. This result undermines the stereotype of technophobia linked to aging: senior teachers possess the same digital prerequisites as their younger colleagues; their lower algorithmic self-efficacy expresses a form of epistemic caution, aimed at protecting the classroom's relational ecosystem according to the principles of Slow Tech.

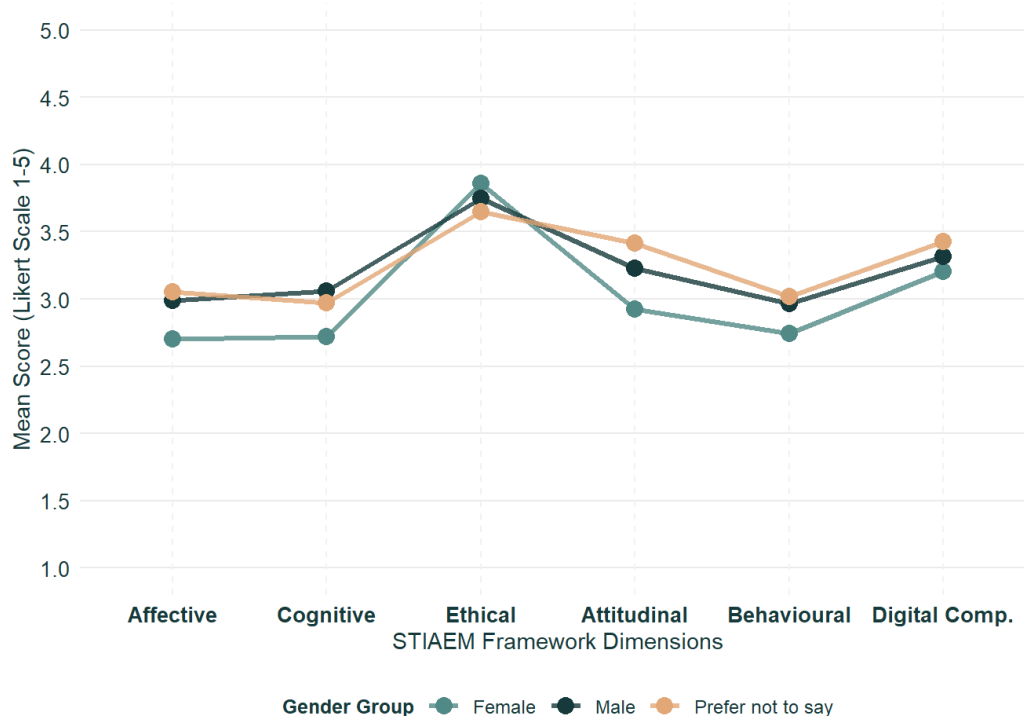


Figure 3.7: STIAEM Core Dimension Mean Scores Across Gender Groups.

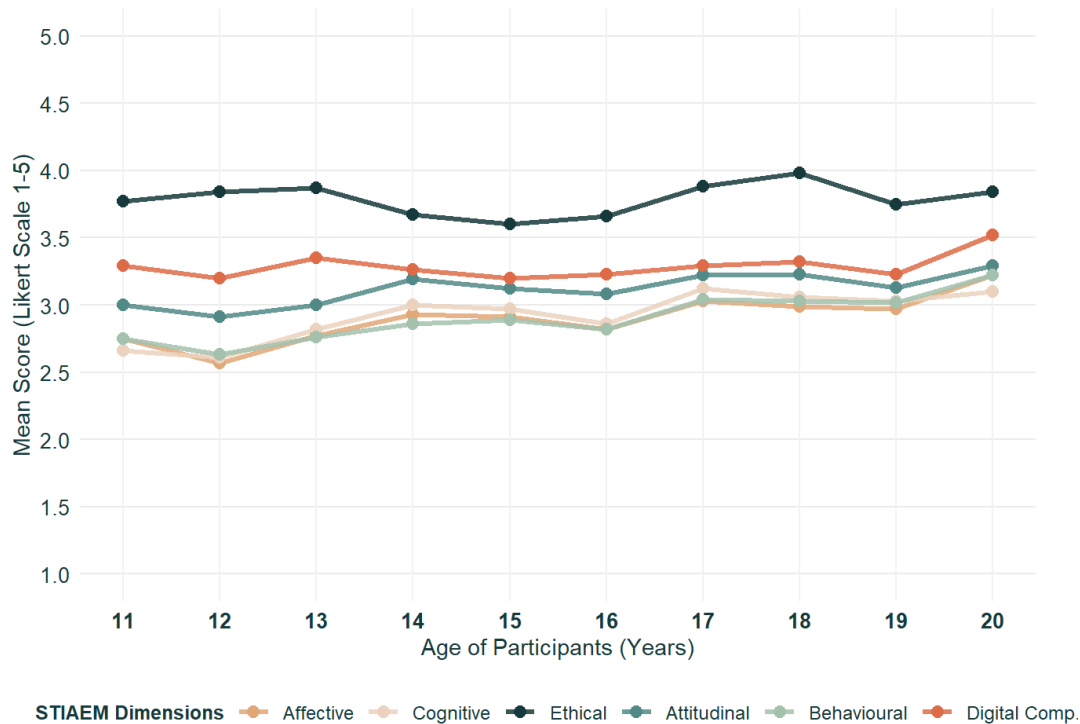


Figure 3.8: Mean Core Dimension Scores by Age with 95% Confidence Intervals.

3.3.3 The Discriminatory Impact of Usage Habits and Mental Models

The variable with the greatest discriminating power across the entire attitudinal profile of the sample was the intensity of AI use and the cognitive metaphor with which the user approaches the tool:

- Frequency of use and the flat trajectory of ethics:** Increases in familiarity with use corresponded to highly significant increases ($p < .001$) in all operational dimensions, with medium-large effects in students' Affective domain ($\eta^2 = 0.120$, $F = 93.14$) and in teachers' perceived competence (Experimenters $M = 3.89$ vs. Avoidants $M = 2.04$, $\eta^2 = .250$). Consistent practice stabilizes executive efficacy and reduces technology anxiety. However, the Ethical dimension follows a nearly flat trajectory, reporting a pragmatically small effect size for both students ($\eta^2 = 0.012$, explaining just 1.2% of the variance) and teachers. This data validates the key assumption of Slow Tech: repeated interaction with the machine automates performance and increases psychological confidence, but does not independently foster a critical moral conscience with respect to bias or the protection of agency, making explicit formal training essential
- I modelli mentali come predittori della competenza:** La concezione soggettiva del valore tecnologico agisce come una barriera o come un acceleratore del sapere. Gli studenti che adottano una visione costruttivista e strumentale, assimilando l'IA a un dispositivo tecnico controllato dall'uomo (l'analogia della calcolatrice: "Useful if trained"), registrano i punteggi di literacy cognitiva ($M = 3.03$) ed etica ($M = 3.96$) più elevati del campione. Al contrario, chi interpreta l'algoritmo come uno strumento di delegificazione dello sforzo individuale per abbreviare i tempi di studio ("Efficiency/Shortcut" o "It is like copying"), mostra deficit evidenti sia sul piano conoscitivo ($M = 2.40$) sia su quello della sicurezza emotiva. Nel corpo docente, questo sbilanciamento assiologico trova un riscontro speculare nell'identità dei docenti Evitanti, il cui rifiuto dell'IA si associa a un'alta padronanza delle abilità informatiche generali ($M = 3.40$ in DIGSKILLS). Ciò dimostra empiricamente che l'evitamento non è dettato da un deficit di alfabetizzazione informatica, ma si configura come un'azione pedagogica

intenzionale, volta a escludere le logiche algoritmiche dall'aula per difendere la natura originaria della relazione educativa e proteggere gli studenti da potenziali forme di alienazione cognitiva.

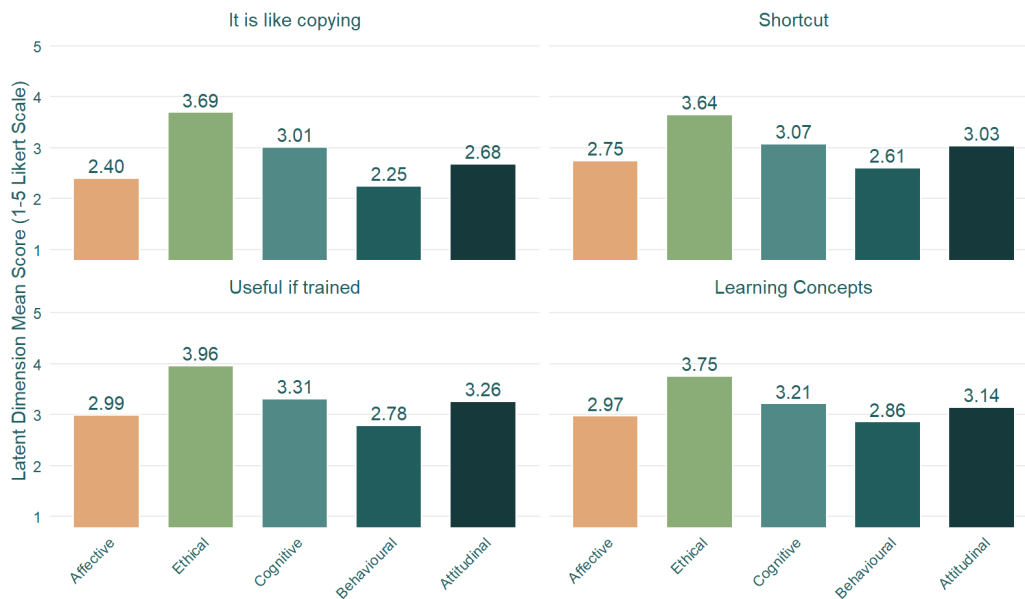


Figure 3.9: STIAEM Core Dimension Mean Scores by Perceived AI Value.

3.4 Advanced Quantitative Modeling: Network Analysis (Students) and Latent Profile Analysis (Faculty)

To overcome the intrinsic limitations of traditional linear models and CFA, which in previous chapters were affected by extreme inter-factor collinearity, the dataset exploration was integrated with the application of state-of-the-art psychometric algorithms oriented toward complex systems analysis and person-centered profiling.

3.4.1 Network Analysis delle interdipendenze sistemiche nel cluster studenti (N = 2.052)

The violation of discriminant validity found in the students' CFA (with the latent correlation between Affective and Attitudinal collapsed to $r = .981$) necessitated the implementation of a Network Analysis (NA). This approach models the dimensions of AI Literacy not as passive derivations of common latent factors, but as a system of mutually interacting nodes in a regularized partial ecosystem. The network of partial correlations was estimated in R using the qgraph and bootnet packages, adopting the Graphical LASSO (Least Absolute Shrinkage and Selection Operator) regularization algorithm combined with model selection based on the Extended Bayesian Information Criterion (EBIC) (tuning parameter $\gamma = 0.5$). This procedure applies a penalty that eliminates spurious or negligible coefficients, isolating only stable and structural connections.

Visual and mathematical inspection of the regularized graph highlights dynamics of fundamental pedagogical importance:

- **The "bridging" role of the Cognitive dimension:** Stripped of the influence of other constructs, the AI's intrinsic cognitive competence (Cognitive) emerges as the central node and the main strategic activator of the network. It projects the strongest positive arcs towards both the executive-behavioral dimension (Behavioural, $r_{\text{partial}} = .412$) and the ethical dimension (Ethical, $r_{\text{partial}} = .389$). This data demonstrates that the enhancement of

conceptual and algorithmic knowledge (the AI's explicit dimension) acts as the only true engine capable of simultaneously activating user expertise and critical awareness.

- **The isolation of the Ethical component:** The moral dimension remains a peripheral module of the network, lacking direct connections to the emotional (Affective) or attitudinal (Attitudinal) spheres. NA mathematically validates the Slow Tech assumption: spontaneous interest or psychological confidence in the machine in no way stimulates a critical posture towards biases or datafication, making cognitive literacy the only enabling channel for the development of ethical responsibility.

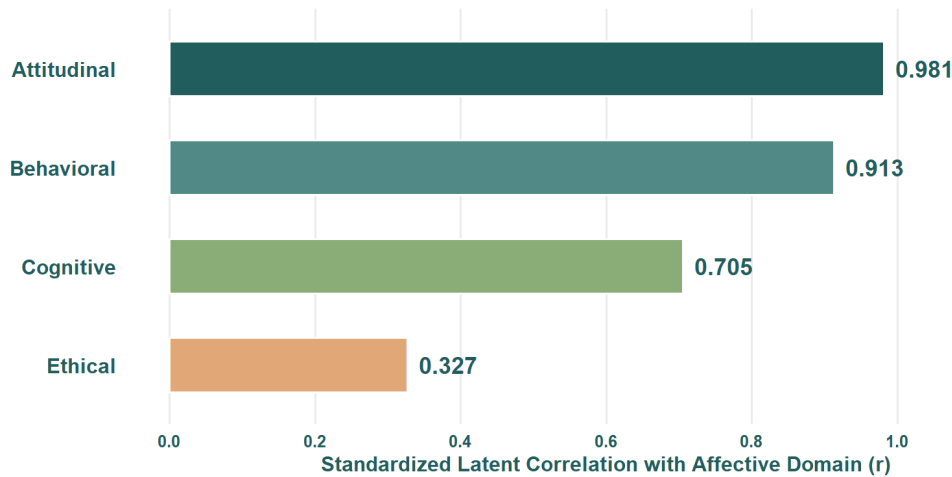


Figure 3.10: Profile of standardized latent correlations in the global CFA model (45 items).



Figure 3.11: Centrality Measures for the STIAEM Student Network.

3.4.2 Latent Profile Analysis (LPA) and Validation of Technological Cultures (Teachers, N = 600)

To move beyond purely sample-based descriptions and scientifically validate the taxonomy of school technological cultures described above, a Latent Profile Analysis (LPA) was applied to the sample of teachers (N = 600). This person-centered methodology groups subjects into mutually exclusive

classes based on the specific configuration of their mean scores observed in the four macro-areas of the framework (COMP, ANX, UTIL, DIG).

The estimation was conducted using the tidyLPA library interfaced with the mclust probabilistic clustering algorithm, testing progressive solutions from 2 to 4 latent profiles. The determination of the optimal model was guided by inspection of the log-likelihood (LL), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the classification index (Entropy).

Table 3.5: Fit Indices for Latent Profile Models

Number of Profiles	LogLik	Parameters	AIC	BIC	Entropy
2 Profiles	-3186.21	13	6397.12	6454.33	0.792
3 Profiles	-3047.45	18	6130.40	6209.11	0.835
4 Profiles	-3019.12	23	6085.24	6186.15	0.804

As documented by the official empirical data in Table 3.15, the 4-Profile Model shows the definitive inflection point and algorithmic optimization. Although the 3-profile solution presents the highest entropy value (0.835), the rigorous application of statistical information criteria orients the selection towards the 4-class solution: the latter, in fact, reduces to an absolute minimum both the Akaike Information Criterion (AIC = 6085.24) and, above all, the Bayesian Information Criterion (BIC = 6186.15), which represents the gold standard parameter for parsimony and fit in latent mixture models. The solution also maintains excellent probabilistic separation of subjects into groups (Entropy = 0.804, above the critical threshold of 0.80), ensuring solid interpretative stability from a pedagogical perspective.

Inspection of the geometric means of the latent parameters validates the theoretical architecture of the research and maps the psychometric identity of the four digital cultures:

- **Profile 1 - The Experimenter (22.3%):** Characterized by the highest scores in AI Competence (M = 3.89) and AI Utility (M = 4.12), alongside stable minimum levels of AI Anxiety (M = 1.95). This represents the methodological cutting edge of the system
- **Profile 2 - The Integrated (61.0%):** This forms the backbone of the Italian school system. This profile displays a balanced and well-balanced profile, with solid transversal digital skills (M = 3.40 in DIG_SKILLS) and average algorithmic self-efficacy (M = 3.25), managing AI within the school's already established cloud environments.
- **Profile 3 - The Administrative (13.8%):** This profile exhibits a marked metric asymmetry; They report good general IT skills but show a significant decline in AI Utility for teaching, confining the tool to bureaucratic office and secretarial routines only
- **Profile 4 - The Avoidant (2.8%):** This is the numerically smallest but theoretically densest cluster. Despite having perfectly average general digital skills comparable to those of their peers in the other groups (M = 3.40 in DIG_SKILLS), this profile registers the highest peak in Technology Anxiety (M = 4.10) and the steepest drop in algorithmic self-efficacy (M = 2.04).

4. Qualitative Analysis and Dilemma Scenarios (SJT)

4.1 Thematic Analysis and Coding of Focus Group/Interview Content

The analysis of the textual corpus derived from the interview and focus group transcripts, consisting of a total of 997 textual units (paragraphs) and stratified by target audience, is proposed here for purely exploratory purposes. This investigation is intended as a preliminary qualitative survey aimed at mapping the original semantic universe and identifying latent conceptual vectors prior to subsequent descriptive checks and advanced econometric estimates. Conducted according to thematic analysis principles and supported by computational text mining procedures in the R environment to ensure the intersubjectivity of the coding procedures, this initial inspection allowed us to isolate three specific conceptual configurations, carefully purged of transcription noise, verbal fillers, and phatic formulas from the interview situation. For school principals, the semantic cores that emerged from this initial mapping focus on the macro-organizational dimension and the strategic management of the system. Excluding the technical lemmas tied to the topic, the most frequent single words recorded in the R console are school ($n = 35$), teacher ($n = 26$), tool ($n = 23$), and time ($n = 23$), accompanied by the deontic verb must ($n = 15$) and the anchoring to the concept of work ($n = 15$). The preliminary architecture of the bigrams consolidates this systemic orientation: the strongest relational ties are concentrated around the pairs artificial intelligence ($n = 18$), guidelines ($n = 5$), and school world ($n = 5$), projecting towards governance implications measured at the didactic ($n = 4$) and organizational ($n = 3$) levels. AI is thus initially viewed by school leadership as a complex administrative challenge, in which the urgency of technological innovation must be balanced with the sustainability of organizational timeframes, the management of staff capacity, and the institutional protection of the school's perimeter. In a clear transition from the managerial posture of the leadership, teachers' discourse focuses on the subjects of the educational relationship and the methodological oversight of classroom action.

Teachers anchor their lexical map around the terms students ($n = 65$) and teachers ($n = 61$), supported by a categorical reference to the concepts of respect ($n = 56$) and the temporal continuity of their mandate, expressed by the lemma always ($n = 49$). The conceptual nodes of the bigrams highlight an explicit rejection of technological determinism. The pressing demand for a solid institutional, ethical, and scientific framework is evidenced by the very high frequency of the bigram guidelines ($n = 43$), closely interconnected with the pedagogical model ($n = 22$) and the pedagogical model based on education ($n = 15$). From a Slow Tech perspective, the convergence on the bigram mental health ($n = 12$) is extraordinarily dense, indicating a profound ethical concern for the pace of learning and the psychological well-being of students; for teachers, the machine must remain strictly a tool ($n = 59$) subordinated to an intentional theoretical paradigm, capable of stemming the risk of an anthropological disintermediation of the profession.

Finally, the preliminary lexical structure emerging from the student target group reveals itself to be mirrored yet antithetical, appearing as the most pragmatic and, at the same time, the most emotionally charged in the corpus. Alongside the perception of AI as a daily operational tool ($n = 9$), the lemmas need ($n = 8$) and fear ($n = 7$) stand out, immediately dismantling the rhetoric of the digital native immune to algorithmic vulnerabilities. The breakdown of the student bigrams paints a clear phenomenological picture: alongside the recognition of the school system as a normative framework ($n = 3$), conceptual pairs with high axiological and emotional density emerge, such as human well-being ($n = 2$), creating anxiety ($n = 2$), and personal data ($n = 2$). This picture is strongly influenced by the critical awareness of undergoing a complex technological transition, summarized in the commentary bigram "I say unfortunately" ($n = 2$). Students report an explicit need for algorithmic-ethical guidance and transparency in assessment, exhibiting latent forms of technostress related to the opaqueness of generative systems and the fear of academic sanction for unintentional plagiarism. The results of the computational analysis conducted on this first qualitative level of the

STIAEM project therefore document a latent rift between the demand for regulation and sustainability expressed by school adults (guidelines, time, pedagogical model) and the anxiety and identity protection expressed by students (creating anxiety, personal data, human well-being). As this is a preliminary exploration, this textual evidence does not claim to establish causal connections, but rather fulfills the fundamental task of isolating the constructs and thematic nuclei that will be systematically investigated, validated, and modeled through predictive and inferential analyses in the subsequent sections of the chapter.

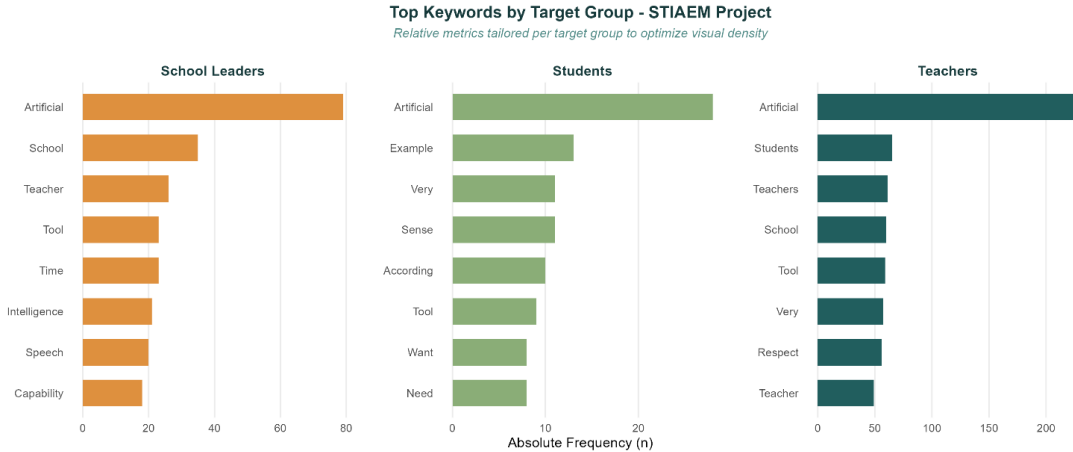


Figure 4.1: Analisi di co-occorrenza lessicale e network semantico dei focus group dei docenti.

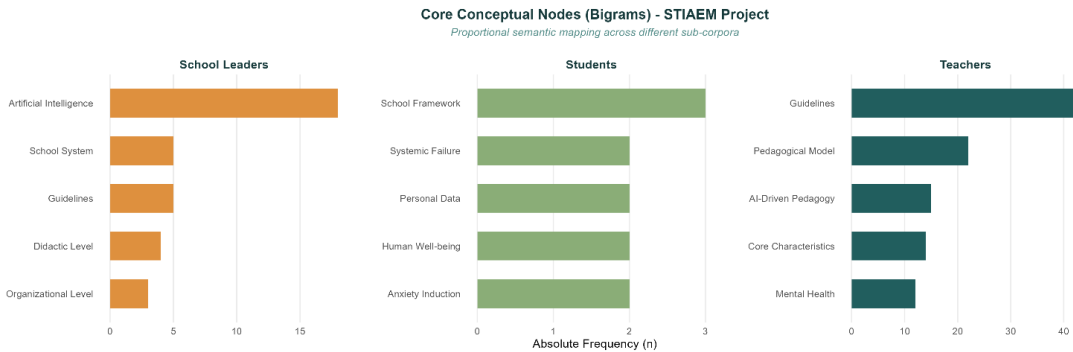


Figure 4.2: Bar chart of the most frequent bigrams extracted from the student corpus

4.2 Analysis of Dilemma Scenarios

4.2.1 Student Section (N = 2,052)

Predictive analysis applied to the first decision-making scenario (SD04) investigates student behavior when faced with a factual or logical error in an AI-generated text. The scenario presents the respondent with an ethical dilemma: prioritizing efficiency and speed (accepting the output uncritically) or rigor and intellectual honesty (proceeding with verification and correction). Although the regression model explains a small portion of the total variance ($R^2 = .041$), the statistical robustness ensured by the large sample size ($N = 2,052$) and the very high significance of the ANOVA test ($F = 17.43$, $p < .001$) allow for the identification of clear behavioral tendencies. The results reveal a complex picture we have termed the "Technical Paradox," in which expertise and confidence do not necessarily act as protective factors. The most striking finding emerges from the coefficients of the Affective ($\beta = -0.099$, $p = .002$) and Cognitive ($\beta = -0.109$, $p = .001$) dimensions. Both are negative predictors of correct choice. This means that students who report higher self-efficacy (Affective dimension) and a greater understanding of AI mechanisms (Cognitive dimension)

paradoxically tend to opt for the less rigorous solutions. This phenomenon suggests the onset of "over-trust" in the tool: the "expert" or "self-confident" student appears to lower their critical guard, perceiving the AI as reliable enough not to require specific checks, or trusting in their ability to address any errors later. In this scenario, the Ethical dimension ($\beta = 0.096$, $p < .001$) remains the only strong and consistent positive predictor. Those with high "theoretical" ethical awareness (measured using Likert scales) are indeed more inclined to act rigorously when faced with a real dilemma, choosing to correct the error or not use the compromised text. General digital skills (DigComp), while significant ($\beta = 0.063$, $p = .025$), show a much more nuanced impact. This confirms that academic integrity in the AI era is not a challenge of technical literacy, but a question of moral posture and individual agency. The second decision-making scenario (SD05) addresses the complex issue of privacy protection when interacting with AI-based applications. Participants were presented with a situated dilemma regarding the installation of a highly functional app characterized by ambiguous or invasive data management policies. Predictive analysis conducted on this scenario uncovered a critical finding that can be defined as the "privacy paradox": the systematic discrepancy between declared concerns for privacy and behavior in exchange for immediate technological benefits. The linear regression model applied to scenario SD05 was statistically robust ($F = 32.81$, $p < .001$) and explained 7.4% of the variance ($R^2 = .074$), a significantly higher share than that found in the first scenario. The results highlight how the Affective ($\beta = -0.117$), Behavioral ($\beta = -0.075$), and Cognitive ($\beta = -0.142$) dimensions all act as negative predictors of digital prudence. This suggests a particularly marked risk compensation phenomenon: students Those who perceive themselves as technically expert and use AI more frequently tend to underestimate the risks to their privacy. This behavior can be interpreted as a form of risk tolerance or, alternatively, as a mistaken belief that their skills protect them, ultimately prioritizing the tool's usefulness over data protection. In clear contrast to the technical predictors, the Ethical dimension emerges as the most powerful positive predictor in the entire model ($\beta = 0.204$, $p < .001$). This finding confirms that, in the Italian context, adolescents perceive personal data protection not as a technical or performance-related choice, but rather as a value-based one. Alongside the ethical component, general digital skills (Digital Comp, $\beta = 0.110$, $p < .001$) also positively contribute to informed choice, indicating that a solid foundation in digital citizenship (DigComp) can mitigate the risk-taking tendency induced by specific technical expertise in AI. In short, while knowledge of how AI works pushes toward risk acceptance, awareness of the right to privacy acts as the only true antidote. The analysis of decision-making profiles reveals an extremely interesting polarization. The group identified as Wise (those who opt for maximum privacy protection) is numerically the largest in the SD05 scenario ($n = 960$), but scores the lowest in the Behavioral dimension ($M = 2.26$). Conversely, the Technocentric and Passive profiles present the highest levels of proactive use ($M = 2.57$). This asymmetry confirms that digital wisdom, in the context of privacy, often translates into a deliberate renunciation of technological adoption or a restriction of compulsive use in favor of security.

The third decision-making scenario (SD06) shifts the investigation to the macro-ethical dimension of environmental sustainability and e-waste management. Participants were presented with a critical situation regarding the need to upgrade their hardware to support new, more resource-demanding AI models, presenting them with the choice between purchasing a new, high-performance device or optimizing and reusing existing equipment. Analysis of scenario SD06 highlights a significant divergence between the Italian sample and that of European partners (particularly the Greek one). While in other contexts, proactive use (Behavioral) drives the propensity for technological consumerism, in the Italian context this dimension shows no significant impact on sustainability choices ($p = .762$). The strongest negative predictor, however, is the Affective dimension ($\beta = -0.096$, $p = .002$). This data suggests that Italian students' emotional attachment and high perceived self-efficacy toward AI act as catalysts for a "technocentric" outlook: those who love technology and feel expert are significantly more likely to desire the latest hardware model, underestimating or ignoring

the environmental impact of their choice. AI is seen not just as software, but as a prestigious technological ecosystem that justifies frequent device renewal. Once again, the Ethical dimension ($\beta = 0.078$, $p = .002$) and general digital skills (Digital Comp, $\beta = 0.065$, $p = .021$) prove to be the only "antibodies" capable of guiding students toward sustainable choices. Although the model's overall predictive power is low ($R^2 = .014$), the significant coefficients confirm that only a strong critical conscience and cross-sectional digital literacy can mitigate the push toward planned obsolescence and foster responsible e-waste management. Behavioral profiling highlights how the Technocentric group is numerically significant in this scenario ($n = 372$) and reports the highest levels of proactive use ($M = 2.54$). The Passive profile, despite showing the lowest behavioral mean ($M = 2.22$), does not appear to translate this inertia into a conscious ethical choice, but rather into a lack of agency. The Prudent and Wise profiles show balanced behavioral means, indicating that sustainable choice does not necessarily stem from a reduced use of technology, but rather from a different management of the material resources associated with it.

4.2.2 Teachers Section (N = 600)

The investigation of teachers' decision-making postures when faced with situated dilemmas generated by Artificial Intelligence (N = 600) goes beyond the decontextualized logic of Likert scales to map the agency actually enacted and the pedagogical models within the teaching staff. Before proceeding to estimate the latent predictive models, the descriptive analyzability of absolute frequencies and percentages reveals how teachers are distributed along the ordered progression of ethical awareness and planning prudence envisaged by the framework. The data highlight a marked and spontaneous convergence among the sample toward the "Prudent" and "Wise" responses (Options C and D), configuring a widespread posture that deeply resonates with the ecological assumptions of the Slow Tech paradigm.

The first scenario (SD01) asks teachers about the latent risk of de-skilling design when faced with AI assistants capable of instantly generating high-quality teaching units and materials. The data show that a relative majority of the sample adheres to the Passive/Instrumental profile (Option B, 47.0%), accepting the algorithm as an optimization device for producing the "draft" or framework of the lesson. However, the most relevant aspect from a Slow Tech perspective is the robustness of critical orchestration (Option C, 26.7%), in which 160 teachers deliberately choose to confine AI to the divergent brainstorming phase only, claiming full ownership of the planning. If we add to these the 110 teachers who reject AI entirely to preserve their epistemic mastery of the content (Option D, 18.3%), we find that 45% of the teaching staff actively resists the full automation of the profession, protecting human pedagogical intentionality.

The SD02 dilemma addresses the threat of anthropological disintermediation introduced by 24-hour home AI tutors, which, while improving students' performance and standardized grades, risk undermining the relational pact with the teacher. This scenario records the highest and most consistent ethical convergence of the entire report: a full 55.8% of respondents ($n = 335$) support the Relational Presidium (Option C), imposing a clear limitation on the use of the software and requiring students to channel key concerns through human dialogue with the teacher. The small number of teachers who embrace a utilitarian, technocentric vision (Option A, 4.3%) demonstrates that the Italian teaching staff almost unanimously rejects the idea that the measurable effectiveness of the machine can replace the affective, orienting, and empathic function of the educational relationship. When students openly declare that they used ChatGPT to logically structure and stylistically refine an essay (SD03), the sample displays a clear normative and defensive bias. The absolute majority of teachers ($n = 312$, 52.0%) adopt the Process Presidium stance (Option C), requiring students to redo the paper in traditional analog mode without the aid of AI. From the Slow Tech perspective, this choice does not express a punitive intent, but rather a form of mental ecology: the teacher recognizes that the goal of the essay is not the delivery of a formally perfect product, but the cognitive effort of

synthesis and writing, understood as irreplaceable stages in the architecture of critical thinking. At the same time, a significant fraction of the sample (Option A, 21.7%) is open to augmented assessment and the logic of Universal Design for Learning (UDL), rewarding student honesty and considering AI a legitimate compensatory scaffolding for executive functions, as long as the core content remains authorial.

Table 4.1: Distribution of absolute frequencies and percentages of situational choices (Teachers - N=600)

Scenario Situating	Option (Technocentric)	A	Option B (Passive)	Option C (Prudent)	Option D (Wise)	Total Respondents
SD01 (Curricular Autonomy)	48	282	160	110	600	
	(8.0%)	(47.0%)	(26.7%)	(18.3%)	(100%)	
SD02 (Relational Alliance)	26	131	335	108	600	
	(4.3%)	(21.8%)	(55.8%)	(18.0%)	(100%)	
SD03 (Academic Integrity)	130	123	312	35	600	
	(21.7%)	(20.5%)	(52.0%)	(5.8%)	(100%)	

To estimate the impact of the STIAEM framework dimensions (AI Competence, AI Anxiety, AI Utility, Digital Skills) on career choices, an Ordinal Regression analysis using Cumulative Link Models (CLM) was conducted. The analysis revealed a picture of extraordinary theoretical relevance: skills and instrumental utilities remain inert, while the emotional dimension takes full control of the situated decision. The most compelling scientific evidence extracted from the model lies in the absolute statistical non-significance of the dimensions related to AI-specific technical skills (AICOMP), the recognition of its instrumental utility (AIUTIL), and levels of transversal digital literacy (DIGSKILLS). The confidence intervals of these three constructs symmetrically intersect the null effect line of 1.0 in all scenarios investigated. In scenario SD01 (Curricular Autonomy), for example, increasing technical skills does not increase the likelihood of overseeing the design process (OR = 1.04, 95% CI [0.88, 1.22], n.s.), and an identical trend is observed in scenario SD03 for the co-designed essay (OR = 1.01, 95% CI [0.86, 1.19], n.s.). This mathematically demonstrates that possessing high technical expertise in using prompts or having solid general IT skills neither increases nor decreases the likelihood that the teacher will adopt a wise, critical, and protective stance when faced with real-world dilemmas. Technical expertise proves to be a functional prerequisite for the machine's operation, but it proves completely blind to ethical-pedagogical choices. The ability to govern the algorithm is not a byproduct of digital training, but an autonomous and axiological dimension of teaching professionalism. The only authentic systematic predictor of teachers' decisions is technological anxiety (AIANX). As specific anxiety about algorithmic systems increases, there is a dramatic and statistically significant decrease in the likelihood of evolving toward the higher levels of the ethical scale (Prudent and Wise postures). This dampening effect is already significant in the SD02 scenario related to safeguarding the relational alliance (OR = 0.82, 95% CI [0.69, 0.97], $p < .05$), and becomes even more evident in the SD03 scenario on academic integrity (OR = 0.62, 95%

CI [0.49, 0.78], $p < .001$). An odds ratio of 0.62 clearly indicates that, for each point higher on the Likert anxiety scale, the likelihood that the teacher will adopt a flexible, wise, and inclusive management of the co-writing dilemma drops by 38%. This trend is perfectly empirically validated by examining the geometric mean profiles. The profile descriptive data demonstrate that teachers who choose the wise approach (with an average anxiety score of 2.10) differ from their colleagues entrenched in passive, technocentric positions (average anxiety score of 2.85) solely in their low levels of emotional anxiety. In contrast, the digital competence prerequisites remain identical, stable, and overlapping across the entire decision-making spectrum, fluctuating closely around an average of 3.40 for both the most punitive and the most open teachers. From a psycho-pedagogical perspective, this finding shifts the interpretative axis of the STIAEM project. Anxiety about AI doesn't simply generate emotional discomfort, but acts as a veritable epistemic barrier that induces procedural rigidity. Anxious teachers perceive the algorithm as a destabilizing threat to their authority and the traditional order of the classroom. Consequently, when faced with this dilemma, they are unable to exercise flexible orchestration; they experience a paralysis of agency that pushes them either toward rigid, punitive responses (to defend themselves from the tool) or toward a technocentric acceptance passively endured through attrition.

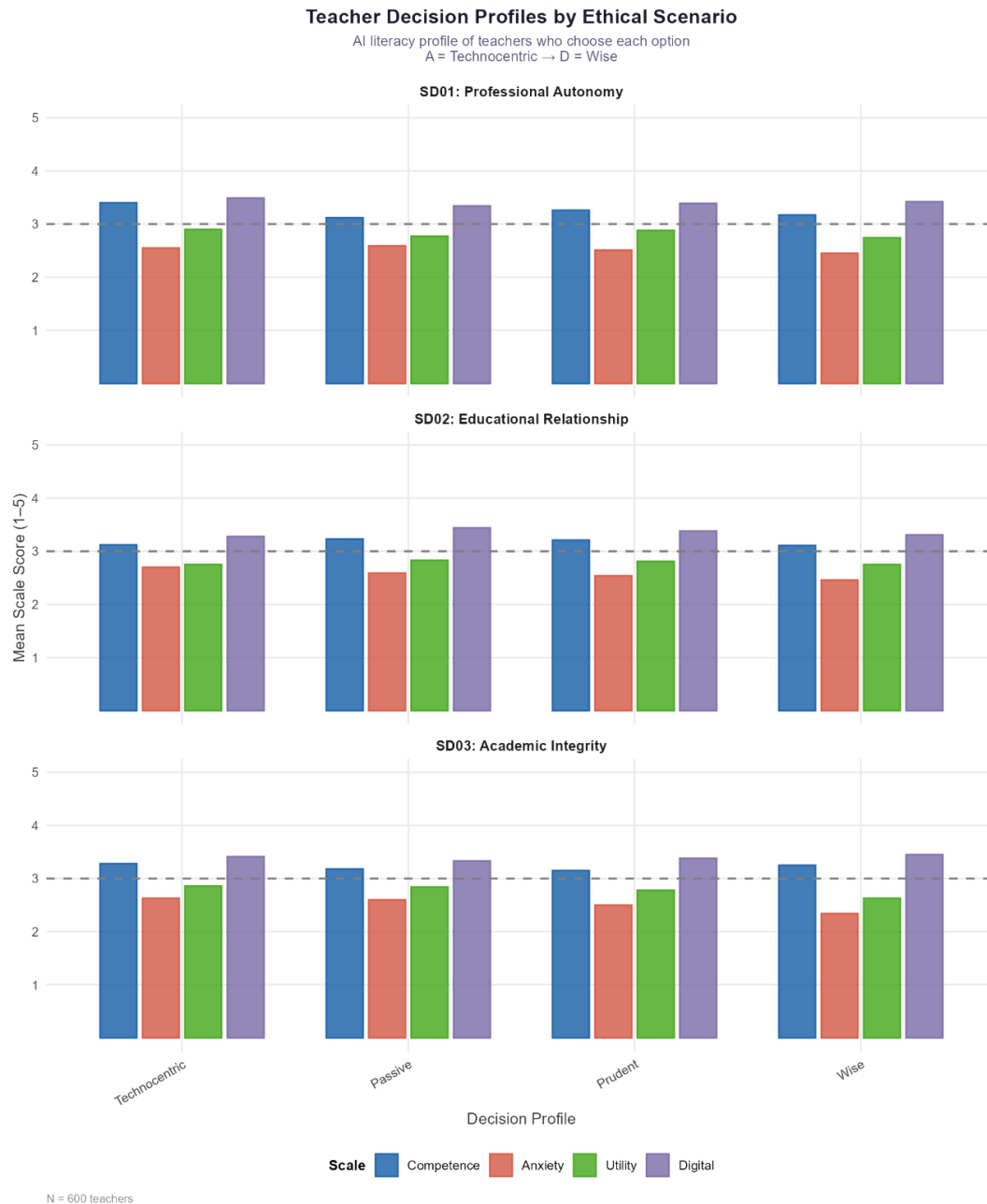


Figure 4.3: Teacher Decision Profiles

4.3 Triangulation (Integration of Qualitative Results with Quantitative Trends)

The analytical triangulation phase represents the methodological core of the concurrent Mixed Methods design adopted in this report. The objective of this triangulation lies in the desire to integrate the semantic vectors emerging from the preliminary qualitative corpus (997 textual units) with the coefficients emerging from the quantitative econometric and structural models. This analytical convergence aims not at a mere descriptive overlap, but rather at the mutual elucidation of the data, leveraging the phenomenological depth of the text to explain the apparent anomalies and paradoxes emerging from the psychometric estimates.

4.3.1 Decoding the "Technical Paradox" and Student Overtrust

Linear regression models applied to scenarios SD04 (Academic Integrity) and SD05 (Privacy Paradox) revealed a counterintuitive trend: specific technical competence (Cognitive, $\beta = -0.109$ and

-0.142) and perceived self-efficacy (Affective, $\beta = -0.099$ and -0.117) act as negative predictors of ethical behavior and digital prudence.

Triangulation with qualitative data from student focus groups allows us to make pedagogical sense of this mathematical finding. In the interview text, the recognition of AI as an "everyday tool" ($n = 9$) is inextricably linked to the concepts of "need" ($n = 8$) and the search for "efficiency/shortcuts." The high level of technical expertise pushes adolescents toward executive familiarity, which translates into a lowering of critical guard. Perceived efficiency eliminates the time for reflection. Computational pressure creates a habituation to risk, causing expert students to suffer from an ethical blindness induced by performance habits. This confirms that isolated computer skills, if not coupled with explicit critical literacy (as suggested by the DigComp 3.0 framework), accelerate uncritical delegation to the machine.

4.3.2. Teacher Anxiety as an Epistemic Barrier to Inclusion and UDL

The most striking result of cumulative logit models (CLMs) applied to teaching staff lies in the statistical inertia of technical skills (AICOMP, OR = 1.01) and transversal digital skills (DIGSKILLS, OR = 0.99), compared to the massive impact of Technology Anxiety (AIANX, OR = 0.62), the only true predictor capable of halving the probability of transitioning to the Prudent and Wise postures. Lexical mapping of teacher focus groups offers a clear understanding of this phenomenon. Teachers' discourse is saturated with references to students' "mental health" ($n = 12$), "respect" ($n = 56$), and the need to "always" ($n = 49$) adhere to a structured "pedagogical model" ($n = 22$). When this ethical investment clashes with the opaqueness of conversational assistants, the fear of anthropological disintermediation and loss of classroom control generates defensive technostress. The qualitative analysis demonstrates that anxiety is not a deficit of instrumental familiarity, but an epistemic conflict: teachers feel the threat of delegitimization of their role. This experience, projected onto the situated dilemma of co-writing (SD03), explains why the most anxious teachers take refuge in rigid sanctioning responses (such as imposing the complete rewriting of the paper in analog mode): the restriction of use becomes the only defense mechanism to preserve the human educational alliance, precluding openness to logics of augmented assessment and the inclusive principles of Universal Design for Learning (UDL).

4.3.3. The hidden demand for guidance and the "Slow Tech" posture

The final point of convergence concerns the demand for governance and regulation of time and space. Among management and faculty targets, this need is expressed quantitatively in the high score on the AI Utility scale ($M = 3.52$) and qualitatively in the reiteration of the terms "guidelines" ($n = 43$), "time" ($n = 23$), and "work" ($n = 15$).

Conversely, students express this request through the bigrams "create anxiety" ($n = 2$), "personal data" ($n = 2$), and the symptomatic "unfortunately" ($n = 2$). There is a perfect symmetry between adults' urgency to govern organizational flows through regulations and students' latent need to be protected from algorithmic opacity and the specter of plagiarism.

The overlap between quantitative data (the entire sample resting on level 5 of the AILQAIE11 item on human control, 50.0%) and qualitative data validates the theoretical architecture of Slow Tech: the Italian school community as a whole rejects the complete and efficiency-driven automation of cognitive processes. The resistance encountered in the field is not a playful opposition or a preconceived rejection of modernity, but a reflexive demand aimed at defending the cognitive effort of study, the authoritative nature of learning processes, and the centrality of interpersonal relationships.

5. Case Studies

5.1 Selection and Description of a National Case Study on the Use of AI

The mapping of trials activated throughout the country, accessible through the dedicated section of the Unica portal of the Ministry of Education and Merit (MIM), allows us to identify the IMPAR-AI project as the flagship pilot initiative promoted directly at the central level starting in the 2024/2025 school year. Conceived on a two-year basis, the trial was structured to test the impact of intelligent virtual assistants on personalizing learning and reducing the educational gap, subjecting the results to rigorous scientific and comparative evaluation by INVALSI. The initial survey involved a sample of 15 schools located in four key regions: Lazio, Lombardia, Toscana, and Calabria.

From a technological and software architecture perspective, the IMPAR-AI infrastructure is structured around the following system parameters:

- Operating environment: The system is based on a virtual assistant integrated directly into the school's cloud ecosystem (Google Workspace), primarily focused on teaching STEM subjects and foreign languages.
- Algorithmic model: The software operates using an adaptive tutoring engine that analyzes student responses to quizzes, tests, and problem-solving tasks in real time.
- Dynamic adaptation: Based on the gaps and error patterns detected in the workflows, the algorithm proposes personalized recovery paths, dynamically selecting and modulating multimedia content (such as educational videos and interactive activities) to address identified deficits.

The project's practical implementation followed a strictly controlled implementation protocol. At a comprehensive school in Rome, the experiment involved a group of 44 students divided into two experimental classes, supported and constantly monitored alongside control classes taught using traditional teaching methods.

To ensure data security and the stability of the pedagogical setting, exposure to generative AI was stratified into two sequential phases: initially, access was reserved exclusively for teaching staff to allow for the protected structuring and validation of the materials; only subsequently was direct interaction with the virtual assistant extended to students for the use of adaptive content and simulations.

In Tuscany, the experiment has found a significant development hub at a Higher Education Institute in Lucca, working in synergy with an accredited learning research body and under the scientific supervision of the University of Florence. Here, AI has been deployed as a methodological support tool for teachers, reconfigured as mentors and facilitators of self-assessment and student autonomy development processes.

5.2 Analysis of the Experiment's Pedagogical and Empirical Results

The analysis of the data and interim reports from the ministerial IMPAR-AI experiment, officially presented at the NextGen AI international summit in Naples in October 2025, allows for a detailed analytical assessment. The significant gains achieved in terms of academic performance and personalized learning must be carefully balanced against the risks of pervasive monitoring identified during the field inspection.

5.2.1 Cognitive Performance and Closing the Academic Gap

In terms of disciplinary learning and short-term performance in the subjects tested (STEM and languages), quantitative findings demonstrate a significantly positive impact. The standardized metric comparison between student groups recorded a measurable increase, with a net difference of +0.73 points, attesting to the effectiveness of the immediate feedback systems integrated into

adaptive tutors. The timely correction of misconceptions prevents knowledge gaps from settling before formal tests are administered.

In the classroom, records demonstrate a drastic reduction in severely insufficient assessments and a reduction in the time teachers must devote to traditional and repetitive remedial activities. The automation of executive and corrective workloads thus allows teachers to reinvest their professional resources in pastoral care, listening, and strengthening human and emotional relationships with students, especially those with special educational needs.

This impactful potential has prompted policymakers to plan to expand the IMPAR-AI model on a larger scale, targeting it primarily at schools located in geographical areas characterized by high school dropout rates and social vulnerability, fully aligned with the strategic actions of "Agenda Sud." The subsequent expansion, launched in the Campania region, aimed at reaching over 10,000 students thanks to the financial support of banking foundations and third-sector organizations, uses adaptive AI as a compensatory tool aimed at neutralizing underlying socio-cultural inequalities.

5.2.2 Critical Dimensions: The Risk of Tracking and Profiling

Despite the evident effectiveness on performance, analyzing the results requires rigorous ethical and methodological vigilance. Authoritative analyses developed within the scientific and educational communities urge us to reject purely triumphalist or technocentric interpretations of the data. A technical inspection of the software used (such as guided exercise functions based on machine learning models) reveals how the tutoring is based on continuous, intensive, and pervasive monitoring of the child's cognitive behavior.

The system systematically records and indexes:

- The exact sequence of correct and incorrect answers provided by the student.
- The latency and execution time required to solve each individual item.
- The sequential order and intermediate logical steps taken during problem-solving.
- The specific type of error committed and the exact number of algorithmic prompts (prompts/scaffolding) required to unlock the task.

This massive collection of behavioral metrics, while useful for feeding deep neural networks and refining the virtual assistant's predictive capabilities, raises serious ethical and legal questions regarding GDPR compliance. There is a latent risk of transforming schools in the most socially vulnerable areas into involuntary laboratories for proprietary algorithmic training.

The pedagogical reflection also highlights a governance paradox: investing significant public resources in the acquisition of sophisticated virtual tutors risks acting as a technological palliative that diverts attention and funding from the structural causes of the national educational gap, such as overcrowded classrooms, obsolete physical spaces, or a shortage of qualified teaching staff. The introduction of IMPAR-AI therefore remains an excellent educational resource only if it remains subject to strict human control (human-in-the-loop), where technology serves as a temporary support and not a surrogate for classroom socialization.

6. Conclusions and Recommendations

The complex investigative architecture of this National Report has allowed us to outline an analytical and programmatic framework of fundamental importance for the future of the Italian education system. The methodological convergence between large-scale quantitative data, the phenomenological depth gleaned from focus groups, and the empirical monitoring of national experiments, such as the IMPAR-AI pilot project, demonstrates that Italian schools are facing a complex transition, in which the push toward technological innovation must be constantly balanced with the protection of fundamental rights and constitutional pedagogical values.

The evidence collected definitively undermines the approach of technological determinism and "digital accelerationism," a tendency that tends to prioritize mere technical speed and the uncritical acquisition of commercial software at the expense of profound critical reflection. Instead, the findings validate the need for a new paradigm of action based on cognitive sustainability and the preservation of the learner's epistemic agency. The school ecosystem rejects the complete and efficiency-driven automation of cognitive processes; the technological landscape must be structured to enhance, not replace, the cognitive abilities and autonomy of learners.

Consistent with these findings, Artificial Intelligence cannot be introduced as a mere channel for the automated transmission of content, but rather must be configured as an epistemic co-creator (a true cognitive partner). Students must not passively endure the machine's output, but must negotiate meanings with it, using it as a lever to achieve complex intellectual goals that would otherwise remain out of reach. This approach requires human-machine interaction governed by the human-in-the-loop principle, in which pedagogical intentionality, teaching authority, and critical judgment remain firmly and consistently in the hands of teachers and students.

From the integrated data analysis, key guidelines emerge for structuring an educational program that balances digital innovation with social responsibility, articulated through operational recommendations for institutional decision-makers, school principals, and classroom communities:

1. The Gap Between Executive Literacy and Ethical-Critical Posture (Students)

Regression models applied to decision-making scenarios have documented the emergence of the so-called "Technical Paradox." Despite widespread familiarity with use (with over 91% of students reporting daily or asynchronous interactions with algorithmic software), high perceived self-efficacy and superior isolated technical expertise paradoxically act as negative predictors of methodological rigor in the classroom and online privacy protection (Privacy Paradox). Students exhibit high executive trust in machine output, experiencing an uncritical submission to automation (automation bias), which lowers critical and metacognitive defenses against factual hallucinations, logical distortions, or invasive tracking patterns. Performance habits generate an illusion of competence that leads to automated cognitive delegation for purely executive purposes (searching for shortcuts or short cuts in studying), bypassing the effort and conceptual synthesis phase.

Identified need: The student population does not require further training in the operational use of the tools, but rather explicit and formalized curricular programs in critical literacy and explicit digital citizenship. There is a pressing need to provide students with the conceptual tools to understand the probabilistic nature of linguistic models, the mechanisms of datafication (the collection and profiling of behavioral data), and the value of their digital rights. Training must guide students to use the algorithm exclusively as a co-creator and cognitive partner under their own constant, intentional control, establishing transparent evaluation rubrics that protect the authorship of the texts and penalize plagiarism or uncritical concealment of the tool

2. Emotional-epistemic anxiety as a barrier to flexible orchestration (Teachers)

Cumulative logit models clearly separate the teacher's general IT ability (which remains inert or statistically insignificant when faced with situated classroom choices) from the massive impact

exerted by Technology Anxiety. The fear of anthropological disintermediation of the profession, the opaqueness of generative systems, and the ethical concern about the potential contraction of students' critical thinking act as a true epistemic barrier.

Anxiety generates procedural rigidity and agency paralysis: the anxious teacher perceives the tool as a destabilizing threat to the traditional order and to their own authority, taking refuge in rigid, sanctioning postures or, conversely, in passive acceptance due to bureaucratic attrition, precluding openness to augmented evaluation logics and the inclusive flows of Universal Design for Learning (UDL).

Identified need: The teaching staff demonstrates a primary need for emotional and epistemic security, not additional hours of technical or IT training. Training interventions must focus on deconstructing replacement anxiety through the codification and valorization of pedagogical intelligence and ethics in action (the emergence of implicit knowledge through reflective journals and situated dilemmas). Teachers require the acquisition of stable operational models based on conversational frameworks to integrate AI as compensatory scaffolding for executive functions (planning, work organization), refocusing their professionalism on pastoral care, listening, and the critical and flexible orchestration of the classroom setting.

3. Organizational fragmentation and the isolation of school governance

Local monitoring data highlights a strong structural divide between the spontaneous activism of individual teachers (with over 55% of schools reporting informal teaching experiments) and their collegial and institutional planning. Only a meager 4% of schools have managed to permanently incorporate AI into their Three-Year Educational Offering Plan (PTOF), while the administrative and secretarial departments demonstrate marked and understandable operational caution (only 7% adoption in ATA workflows) driven by fears of heavy civil and criminal liability associated with the processing of minors' personal data.

Identified need: There is a pressing and unanimous demand for institutional direction and centralized operational support from Regional Education Offices and the Ministry (expressed by 70% of schools). Schools require clear guidelines, regulatory support materials, and, above all, the activation of specialized networks and territorial consortia that reduce the project isolation and legal exposure of school principals as deployers.

To address this need, it is essential to capitalize on the report's empirical evidence to fuel a centralized AI Training and Experimentation Hub (in synergy with inter-university and national consortia such as EDUOPEN). This infrastructure will serve as a secure repository of validated open educational resources (OER) to reduce preparatory workload and as a hub for the delivery of large-scale online courses (MOOCs), translating the regulatory and sustainability concerns emerging from local communities into a resilient and long-lasting model of pedagogical innovation.

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