ORCHESTRATING HYBRID ENVIRONMENTS: A STIAEM PILOT STUDY ON TEACHER IDENTITY AND ALGORITHMIC ETHICS

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ABSTRACT
The integration of Generative AI (GenAI) into schools mandates a critical reconfiguration of professional roles. This paper presents a pilot study validating a multidimensional survey co-designed within the Erasmus+ STIAEM project (2025-1-IT02-KA220-SCH-000365213). Administered via CAWI to pre-service teachers, the instrument integrates a scale on AI perceptions, items mapped onto the European DigComp framework, and three dilemmatic scenarios exploring methodological deskilling, educational alliance erosion, and the docimological assessment of student AI use. Latent Profile Analysis (LPA) identified three theoretically consistent clusters: optimistic teachers, ambivalent adopters, and traditionalists. Inferences attest to the high sensitivity of these scenarios, revealing a significant correlation between safeguarding the teacher's pedagogical intentionality and preserving relational classroom mediation.

KEYWORDS
AI Literacy; STIAEM; Pilot study; Artificial Intelligence; Pre-service teachers.

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1. Introduction and Theoretical Framework

The integration of Generative Artificial Intelligence (GenAI) drives the co-configuration of hybrid learning spaces, necessitating a profound reconfiguration of methodological and docimological practices within the contemporary school ecosystem (Jayasinghe, 2024). This transition is situated within the regulatory framework outlined by the European AI Act (Regulation EU 2024/1689), international frameworks from UNESCO (Miao & Cukurova, 2024) and the OECD (2024), and the Guidelines issued by the Italian Ministry of Education and Merit (MIM, 2024). To guide this evolution towards a balanced and conscious integration, the international Erasmus+ STIAEM project (*Slow Tech Innovation: AI, Ethics, and New Teaching Methods* - 2025-1-IT02-KA220-SCH-000365213) adopts the perspective of Slow Tech (Patrignani & Whitehouse, 2014), emphasising the demand for "good, clean, and fair" technologies in synergy with Human-in-the-Loop (HITL) governance models (Benedikt et al., 2020; Natarajan et al., 2025; Wu et al., 2022). Within this socio-technical framework, the approach promoted by the consortium focuses on a collaborative dynamic where educational technologies support instructional action without replacing the professional, coexisting with the teacher's design authorship and pedagogical intentionality (Küçükuncular & Ertugan, 2025; Makhmudova et al., 2025; Rind, 2026; Xerri, 2025). At an operational level, the research aims to define institutional policies, structure evidence-based training modules, and set up a physical, interactive Hub conceived as an innovative and inclusive learning environment (Annapureddy et al., 2025; Işık et al., 2024).

Within this socio-technical framework, the construct of AI Literacy is redefined by moving beyond purely functional or technocentric approaches that focus on the mere acquisition of computational or prompting skills. Algorithmic literacy is configured as a complex ecological-affective dimension, where technical

mastery is bound to critical reflexivity and the capacity for relational mediation within school contexts (Topali et al., 2025). This framework is reflected in the prominent multidimensional models of educational research, starting from the threefold articulation of AI as a tool for teaching (*teaching tool*), a content of learning (*teaching content*), and a means for developing ethical frameworks (*learning tool*) (Prilop et al., 2025). This perspective converges both with the ABCE model, which integrates Affective, Behavioural, Cognitive, and Ethical dimensions to move beyond exclusively cognitive metrics of assessment (Ng et al., 2024), and with the CARE-KNOW-DO model, in which ethical awareness (CARE), epistemic knowledge (KNOW), and responsible agency (DO) operate synergistically to foster equity and inclusion by design (*equity by design*) (Bagdonaitė & Dagienė, 2025; Okada et al., 2025). Expanding upon the Intelligent-TPACK framework (i-TPACK; Celik, 2023), literacy emerges as a recursive path wherein ethics and assessment competence guide curricular planning (Aldemir et al., 2025), supporting a necessary professional scepticism vital to preventing dynamics of technological dependency and uncritical subalternity (Alexandron et al., 2026; Lakhe Shrestha et al., 2025; Wu & Chen, 2026).

The transition towards the new paradigms of Agentic AI (*Agentic AI*), characterised by proactive modules equipped with persistent memory and advanced autonomy (Alva & Pandey, 2026), profoundly disrupts the teacher's professional self, evoking a dense and often submerged emotional burden (Bae et al., 2024). Exploring AI Literacy while excluding the emotional sphere constitutes a methodological limitation, as the development of digital competences is heavily conditioned by the construct of *affective readiness*, defined as the teacher's reflective capacity to recognise and regulate their own emotional states when facing disruptive innovation (Prilop et al., 2025).

Consistent with affective integration models, the attitudinal domain is bounded by the tension between algorithmic anxiety, understood as a barrier to innovation, and perceived self-efficacy, seen as a driving factor towards authorship (Işık et al., 2024; Ng et al., 2024). Training pathways focused exclusively on software functionalities increase technical self-efficacy but risk generating an uncritical approach regarding educational risks; conversely, perspective-shifting interventions foster the development of reflective skills and a conscious, responsible orientation towards instructional hybridisation (Huynh et al., 2025; Soleimani et al., 2025).

The renegotiation of professional roles directly impacts the dynamics of cognitive load and the risks of methodological *deskilling*. While the automation of routine tasks and document extraction offer support (*scaffolding*) aimed at easing bureaucratic burdens (Kalasapudi et al., 2026), an uncritical reliance on the algorithm risks compromising the teacher's decision-making autonomy, reducing spaces for reflexivity and generating *data-driven* dynamics of professional alienation (Küçükuncular & Ertugan, 2025; Rind, 2026). The teacher must maintain the role of a critical moderator of algorithmic insights to safeguard the educational alliance and interpersonal mediation (Bagdonaitė & Dagienė, 2025; De Silva et al., 2025). Consequently, it becomes necessary to configure artificial intelligence systems as co-design partners (*co-design partners*) operating under continuous human oversight within transparent instructional architectures (Alioto et al., 2025; Potter et al., 2026).

This pilot study is situated within this methodological framework to test and validate the STIAEM consortium's survey. The psychometric and inferential analysis serves as the empirical prerequisite to identify the teaching staff's latent profiles and evaluate their decision-making responses when faced with

dilemmatic scenarios, providing the necessary evidence to shape institutional policies, guide future training pathways, and direct the pedagogical and spatial setup of the interactive Hub.

2. Research Methodology

The methodological framework of this pilot study adopts a quantitative empirical approach to explore the attitudinal configurations and decision-making postures of teachers facing the introduction of generative artificial intelligence into classroom practices, framing the investigation within the paradigms of experimental pedagogy and educational technologies.

2.1 Pilot Study Objectives and Research Questions

The primary objective of the data collection is to map the heterogeneity of teachers' perceptions and to verify the soundness of a theoretical model of critical hybridisation of teacher agency, moving beyond purely linear or deterministic interpretative logics. On a methodological and psychometric level, the investigation aims to test and validate the survey architecture, evaluating its discriminative effectiveness and statistical soundness on a preliminary sample of teachers prior to its large-scale European expansion. The methodological refinement of the instrument is configured as a research-training device designed to intercept professional postures and emerging training needs of the teaching staff, assuming affective readiness as a constitutive dimension of AI Literacy (Annapureddy et al., 2025; Işık et al., 2024).

To achieve these cognitive goals, the experimental design was guided by four specific research questions:

RQ1: Is it possible to identify distinct phenotypic configurations and latent profiles within the teaching population, determined by the non-linear combination of their perceptions of competence, levels of algorithmic anxiety, and the perceived usefulness of GenAI?

RQ2: How does membership in specific identity latent profiles influence the intensity of resistance expressed by teachers when faced with critical scenarios of pedagogical identity alienation (authorial deskilling), erosion of the educational relationship (relational substitution), and methodological reconfiguration (algorithmic assessment)?

RQ3: Is there an associative relationship and a significant synergy between the concern over losing the "personal touch" in instructional design (SD01) and the fear of degrading interpersonal relational mediation in the classroom (SD02)?

RQ4: Do the distribution across latent profiles and the intensity of resistance expressed in dilemmatic scenarios vary significantly based on structural and institutional positioning factors, specifically regarding the teachers' school level of service (Pre-school/Primary, Lower Secondary, Upper Secondary)?

2.2 Participants and Sample Context

From a methodological standpoint, the pilot study involves pre-service teachers with the specific goal of validating the data collection instrument prior to large-scale international administration. This target group, enrolled in teacher certification pathways and approaching permanent appointment, allows for testing the stability of psychometric scales and the sensitivity of dilemmatic scenarios in capturing the actual variability of postures within the investigated population. The reference population for the pilot study was intercepted during initial training and qualification activities within the specialisation pathways for educational support (TFA) at the University of

Foggia, yielding a total sample size of 385 participants. As structured in Table 1, the analysis of demographic characteristics highlights a clear prevalence of female respondents (80.8%) and an age concentration of 95.3% within the bands between 25 and 54 years. Under the professional profile, the preeminent indicator is the participants' teaching experience, which is heavily skewed towards pre-service or novice teachers, with 80.0% of professionals reporting less than five years of teaching experience. The stratification of the sample based on the current school level of service ensures a cross-level distribution divided among lower secondary school (40.3%), upper secondary school (36.9%), and the aggregated segments of pre-school and primary school (22.9%).

Table 1: *Demographic and professional characteristics of the sample (n = 385), showcasing a high proportion of novice and female teachers to contextualise pilot generalisability bounds.*

Demographic and Professional Variable	**Sub-category**	**Frequency (N)**	**Percentage (%)**
Gender	Woman	311	80.8%
	Man	72	18.7%
	Prefer not to answer	2	0.5%
Age Group	Under 25 years	2	0.5%
	25–34 years	117	30.4%
	35–44 years	134	34.8%
	45–54 years	116	30.1%
	55 years or older	16	4.2%
Current School Level (School Level - G)	Pre-school / Primary	88	22.9%
	Lower Secondary	155	40.3%
	Upper Secondary	142	36.9%
Teaching Experience	Less than 5 years	308	80.0%
	5–15 years	73	19.0%
	16–25 years	4	1.0%

2.3 Research Instrument

The research instrument consists of a multidimensional survey administered via CAWI. As outlined in Table 2, the overall architecture is divided into four functional modules structured to combine validated psychometric scales and complex situational questions. The first module tracks the biographical variables and institutional positioning of the respondents. The second module adapts the Teachers' Perception Scale Towards the Use of Artificial Intelligence Tools in Education (Işık et al., 2024). In the original Turkish validation, the instrument was structured into 37 items across three dimensions. However, psychometric scrutiny of the original validation revealed that the seventh item of the Perceived Usefulness subscale (Item 37 / I21: "Artificial intelligence tools can make students addicted to technology") exhibited severe empirical vulnerabilities, including a marginal factor loading ($\lambda = .304$) and a negligible item-total correlation ($r = .091$), alongside an evident semantic discordance with the construct of instrumental utility. Consequently, during the transcultural adaptation phase for the STIAEM survey, this item was omitted to preserve construct validity, yielding a refined 36-item metric instrument: Perceived Competence (22 items, TCH_COMP_01–22), Classroom Algorithmic Anxiety (8 items, TCH_ANX_23–30), and Perceived Usefulness (6 items, TCH_UTIL_31–36). Evaluated on the current sample ($N = 385$), the 36-item adapted scale demonstrated excellent internal consistency across all subscales: Competence ($\alpha = .93$, $\Omega = .94$), Anxiety ($\alpha = .86$, $\Omega = .87$), and Usefulness ($\alpha = .88$, $\Omega = .89$). Confirmatory Factor Analysis (CFA) using robust maximum likelihood estimation (MLR) corroborated the empirical stability of the three-factor structure ($X^2/df = 1.98$, CFI = .918, TLI = .911, RMSEA = .051 [90% CI .047, .055], SRMR = .054).

The third module explores diffuse digital skills through 8 metric items on a 1–5 scale mapped onto the areas of the European DigComp 3.0 framework.

The fourth module introduces 3 dilemmatic scenarios co-designed within the STIAEM consortium to explore teachers' positioning when faced with pressures towards school automation. Specifically, Scenario SD01 describes a classroom situation where the intensive use of automatically generated lesson plans, despite guaranteeing high standardised quality, risks causing the teacher to perceive a progressive loss of content mastery and methodological-didactic skills; Scenario SD02 presents the introduction of an intelligent tutor active in the home environment which, while increasing student performance, drastically reduces direct requests for help to the teacher, threatening interpersonal mediation and the classroom educational alliance; finally, Scenario SD03 proposes a real docimological dilemma centred on the submission of an excellent assignment where the student declares the intentional use of a generative model for logical architecture and stylistic refinement, in the absence of defined institutional policies. Each scenario provides four textual response options, coded according to an index of increasing pedagogical resistance, treated as a linearly progressive ordinal scale from 1 to 4.

Table 2: *Structural matrix of the survey instrument, mapping items to their respective psychometric scales and co-designed dilemmatic scenarios.*

Module / Item Codes	Construct / Investigated Dimension	Type of Measure	Response Format
TP_01 – TP_08	Demographic and professional profiling	Demographic questions	Multiple choice / Text
TCH_COMP_01 – 22	Perceived AI Competence (Işık et al., 2024)	Validated scale	1–5 Likert scale
TCH_ANX_23 – 30	Classroom Algorithmic Anxiety (Işık et al., 2024)	Validated scale	1–5 Likert scale
TCH_UTIL_31 – 36	Perceived Usefulness of GenAI (Işık et al., 2024)	Validated scale	1–5 Likert scale
DIG_01 – DIG_08	Diffuse digital skills (DigComp 3.0)	Area indicators	1–5 Likert scale
SD01	Authorial deskilling and identity posture	Dilemmatic scenario	Multiple choice
SD02	Substitution of relational mediation	Dilemmatic scenario	Multiple choice
SD03	Educational assessment and model use	Dilemmatic scenario	Multiple choice

2.4 Data Analysis Plan

Statistical analyses were performed within the R computational environment (version 4.5.1), leveraging the functionalities of the *tidyverse*, *psych*, *tidyLPA* (*mclust* engine), and *ggplot2* packages across five sequential phases.



Figure 1: *Methodological workflow illustrating the five sequential phases of data analysis executed within the R environment.*

In the first phase (Pre-processing and scoring), raw headings were normalised via regular expressions; the metric items of the three attitudinal subscales and the DigComp block were aggregated by calculating row means to generate continuous composite indices, while the dilemmatic scenarios were converted into ordered numerical vectors on a 1–4 scale. In the second phase (Latent Profile Modelling), the three continuous composite macro-indices were standardised into Z-scores to eliminate scale differences, and a Latent Profile Analysis (LPA) was conducted by comparatively estimating models with 1 to 4 classes; the selection of the optimal model was guided by the balance between statistical fit indices (Log-Likelihood, AIC, BIC, entropy) and the criteria of theoretical parsimony and numerical consistency of the extracted groups. In the third phase (Inferential analysis on distal outcomes), membership in the optimal latent profile was integrated as a discrete factor into the dataset, and RQ2 was tested using three separate one-way analyses of variance (ANOVA), assuming the scenario scores as dependent variables. In the fourth phase (Cross-dimensional association analysis), to examine RQ3, Spearman's rank correlation test (ρ) was applied between Scenario SD01 and Scenario SD02, managing the ordinal nature of the forced-choice responses. In the fifth phase (Contingency and conditional variance analysis), to answer RQ4, school level was treated as a three-level categorical factor; a Pearson's Chi-square test (χ^2) was performed on the cross-contingency table to verify the independence of

the distribution of teachers across profiles with respect to the school level, complemented by new one-way ANOVA models and Tukey's HSD post-hoc tests to isolate significant mean contrasts across the different school levels.

3. Preliminary Descriptive Analysis of Measures and Scenarios

Preliminary descriptive analyses map the distribution of responses across the entire sample (N = 385) for the investigated constructs. The mean values and dispersion indices associated with the metric scales and situational scenarios are summarised in Table 3, providing the baseline framework of the investigated population.

Mean scores for Perceived Competence range from a minimum of 2.70 (SD = 1.21) to a maximum of 4.01 (SD = 0.90), revealing higher self-efficacy in basic operational management compared to advanced instructional design tasks. The Algorithmic Anxiety subscale records item means between 2.05 (SD = 1.12) and 3.27 (SD = 0.97), while Perceived Usefulness ranges between 2.89 (SD = 1.03) and 3.59 (SD = 0.92). Indicators linked to the diffuse digital skills of the DigComp 3.0 framework reveal a homogeneous distribution, with area means ranging between 2.65 (SD = 1.14) and 3.48 (SD = 0.91).

Regarding the dilemmatic scenarios operationalised as Situational Judgment Tests, the intensity of pedagogical resistance is distributed in a differentiated manner: Scenario SD01 records a mean of 2.22 (SD = 0.82), Scenario SD02 shows the highest central tendency value at 2.63 (SD = 0.71), and Scenario SD03 stands at 2.32 (SD = 0.84).

Table 3: *Overall descriptive framework of constructs and situational scenarios in the total sample (N = 385).*

Investigated Dimension / Variable	Type of Measure	Mean Range (M)	Std. Dev. Range (SD)
Perceived AI Competence	Metric 1–5 Likert scale	2.70 – 4.01	0.90 – 1.21
Classroom Algorithmic Anxiety	Metric 1–5 Likert scale	2.05 – 3.27	0.97 – 1.12
Perceived Usefulness of GenAI	Metric 1–5 Likert scale	2.89 – 3.59	0.92 – 1.03
Diffuse digital skills (DigComp 3.0)	Area indicators 1–5	2.65 – 3.48	0.91 – 1.14
Scenario SD01: Identity Alienation	Ordinal dilemma 1–4	2.22	0.82
Scenario SD02: Educational Alliance	Ordinal dilemma 1–4	2.63	0.71
Scenario SD03: Methodological Reconf.	Ordinal dilemma 1–4	2.32	0.84

3.1 Latent Profile Modelling (LPA)

The comparative estimation of hierarchical models from 1 to 4 latent classes evaluated unobserved attitudinal heterogeneity across the standardized composite indices (Z-scores) of Perceived Competence, Algorithmic Anxiety, and Perceived Usefulness. As shown in Table 4, although information criteria (AIC and BIC) continued to decrease through the 4-class solution, relying solely on minimum penalisation indices in moderate-to-large samples carries an acute risk of statistical over-extraction.The selection of the optimal solution was determined by balancing statistical diagnostics, classification precision, and theoretical parsimony. Model 4 was rejected because it isolated an over-fitted, spurious micro-cluster comprising only 2.8% of the sample (n = 11), failing to

satisfy the conventional 5% minimum prevalence threshold required for inferential stability. Conversely, the 3-profile solution (Model 3) displayed strong classification accuracy (Entropy = .821), robust posterior probabilities (> .88), and theoretically interpretable groupings without numerical fragmentation. In light of the exploratory pilot nature of the study, Model 3 was retained as the most robust heuristic representation of teacher phenotypes. The extraction of Model 3 delineates three distinct professional postures, whose standardized centroid values correspond to the trajectories shown in Figure 2: Profile 1: Tech-Optimistic Teacher (n = 243, 63.1%): Characterized by positive self-efficacy (Z_{COMP} = +0.42) and high perceived utility (Z_{UTIL} = +0.38), combined with low algorithmic anxiety (Z_{ANX} = -0.48). Profile 2: Anxious Adopter (n = 111, 28.8%): Defined by an acute structural dissociation: despite recognizing the instructional value of GenAI (Z_{UTIL} = +0.24) and possessing average self-efficacy (Z_{COMP} = +0.06), they report the highest algorithmic anxiety across the entire sample (Z_{ANX} = +0.91).Profile 3: Traditionalist (n = 31, 8.1%): Characterized by markedly negative competence scores (Z_{COMP} = -1.24) and low perceived usefulness (Z_{UTIL} = -1.48), coupled with moderate defensive apprehension (Z_{ANX} = +0.32).

***Table 4**: Fit indices, diagnostic classification metrics, and class proportions for competing latent profile models (transposed vertical layout).*

Model	**Evaluated Metric / Parameter**	**Value / Diagnostic Output**
Model 1 (1 Class)	LogLik / Parameters (k)	-1637.4 / 6
	AIC / BIC	3287.4 / 3310.9
	Entropy / BLRT (p)	-- / --
	Class Prevalence	Class 1: 385 (100%)
	Status	Rejected
Model 2 (2 Classes)	LogLik / Parameters (k)	-1573.0 / 10
	AIC / BIC	3165.9 / 3205.3
	Entropy / BLRT (p)	.784 / < .001
	Class Prevalence	Class 1: 279 (72.5%), Class 2: 106 (27.5%)
	Status	Rejected
Model 3 (3 Classes)	LogLik / Parameters (k)	-1522.7 / 14
	AIC / BIC	3073.4 / 3128.7
	Entropy / BLRT (p)	.821 / < .001
	Class Prevalence	Profile 1: 243 (63.1%), Profile 2: 111 (28.8%), Profile 3: 31 (8.1%)
	Status	Selected
Model 4 (4 Classes)	LogLik / Parameters (k)	-1480.4 / 18
	AIC / BIC	2996.8 / 3067.9
	Entropy / BLRT (p)	.791 / .012
	Class Prevalence	Class 1: 228 (59.2%), Class 2: 101 (26.2%), Class 3: 45 (11.7%), Class 4: 11 (2.8%)
	Status	Rejected (Micro-class < 5%)

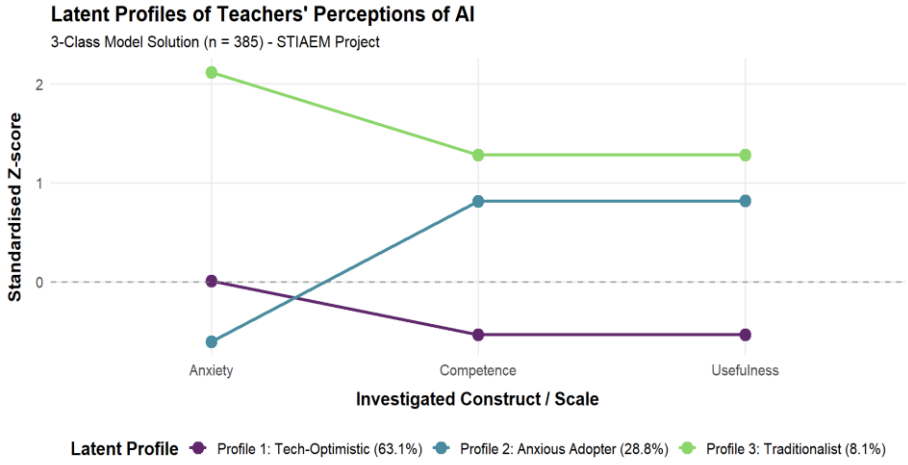


Figure 2: *Graphical representation of the three extracted latent teacher profiles based on standardised Z-scores.*

3.2 Inferential Analysis of Dilemmatic Scenarios and Examination of Linear Associations

One-way ANOVA models reveal highly significant statistical differences across profiles for all three investigated dilemmas (Table 5), confirming the systematic impact of latent profiles on teachers' operational positioning in the face of automation pressures. The effect is robust in Scenario SD01, which focuses on the risk of authorial deskilling, $F(2, 382) = 9.53$, $p < .001$; in Scenario SD02, centred on the defence of interpersonal mediation against relational substitution, $F(2, 382) = 8.99$, $p < .001$; and remains significant in Scenario SD03, concerning the critical posture towards automated grading, $F(2, 382) = 5.13$, $p = .006$, with the sharpest mean contrasts consistently located between Profile 1 and Profile 3.

The examination of cross-dimensional associative relationships using Spearman's rank correlation coefficient reveals a positive, moderate, and highly significant correlation between Scenario SD01 and Scenario SD02 ($\rho =$

0.333, $p < .001$), validating the ecological covariation between the safeguarding of the teacher's design authorship and the protection of the classroom educational alliance.

Table 5: *Summary of one-way ANOVAs testing the significant effect of latent identity profiles on distal dilemmatic outcomes.*

Scenario (Distal Outcome)	**Source of Variation**	**df**	**SS**	**MS**	**F-value**	**Significance (p)**
SD01: Identity Alienation	Latent Profile	2	12.15	6.075	9.530	< .001
	Residuals	382	243.52	0.637		
SD02: Educational Alliance	Latent Profile	2	8.69	4.344	8.987	< .001
	Residuals	382	184.67	0.483		
SD03: Methodological Reconf.	Latent Profile	2	7.05	3.525	5.133	= .006
	Residuals	382	262.29	0.687		

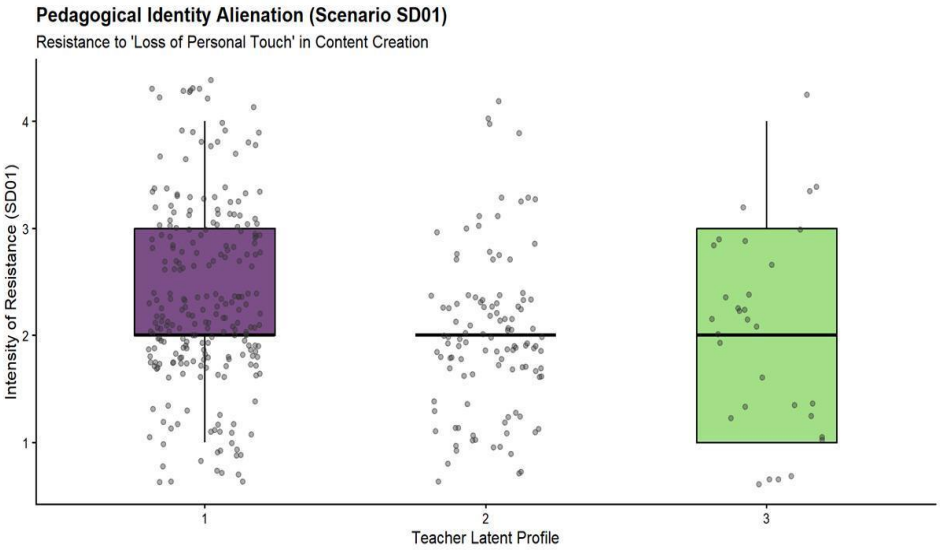


Figure 3: *Boxplot tracking pedagogical resistance scores for Scenario SD01 across the three latent profiles.*

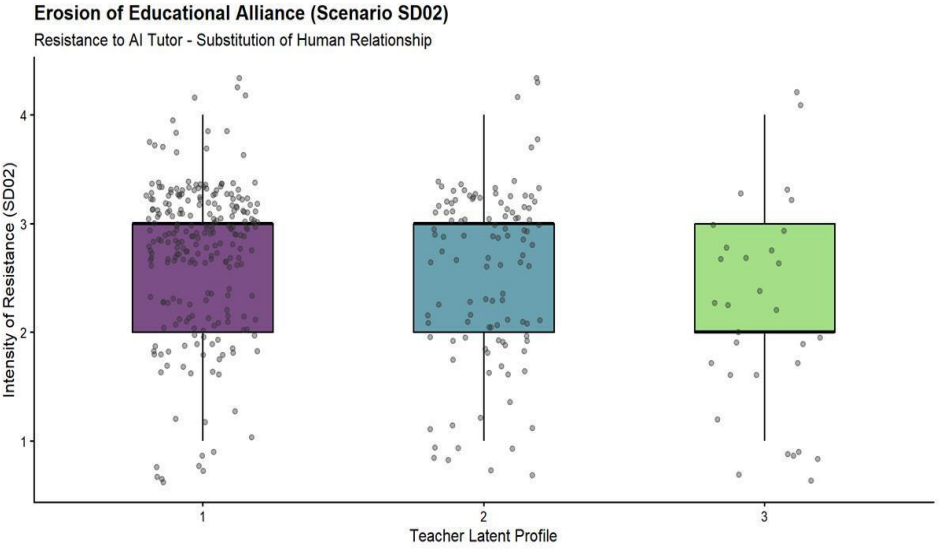


Figure 4: *Boxplot mapping the distribution of relational mediation protection scores (SD02) by latent profile.*

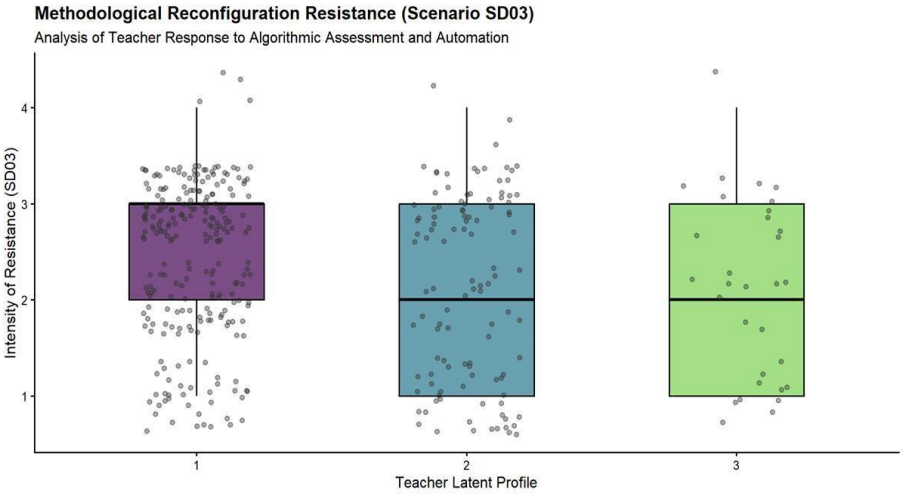


Figure 5: *Boxplot illustrating teachers' docimological positioning (SD03) stratified by latent profile.*

3.3 Contingency Analysis and Variance Conditioned by School Level

Pearson's Chi-square test performed on Table 6 confirms the statistical independence between the school level of service and membership in the latent clusters, $\chi^2(4) = 4.12$, $p = .390$, attesting to the distributional homogeneity of identity postures with respect to the organisational specificities of the work context.

Table 6: *Cross-tabulation mapping latent profile distribution across school levels for the independence Chi-square test.*

Current School Level (G)	Profile 1 (Tech-Optimistic)	Profile 2 (Anxious Adopter)	Profile 3 (Traditionalist)	Total by Level
Pre-school / Primary	55	26	7	88
Lower Secondary	101	38	16	155
Upper Secondary	87	47	8	142
Total validated sample	243	111	31	385

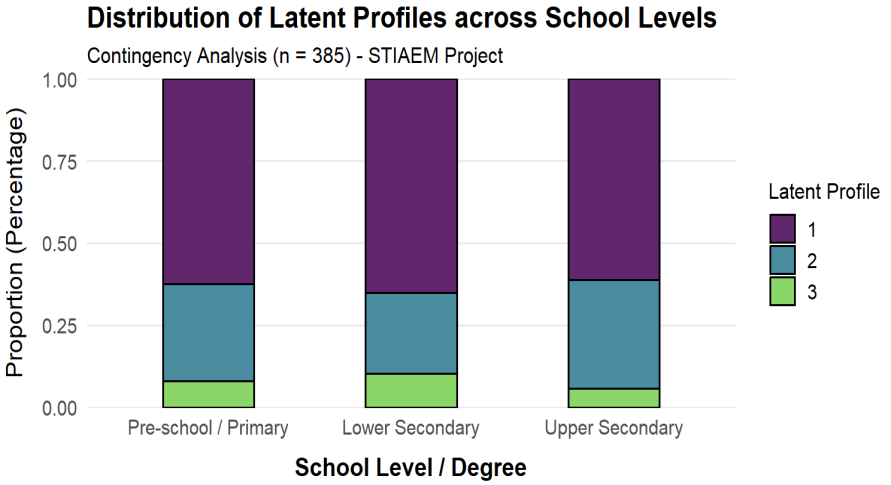


Figure 6. *Percentage-based stacked bar chart displaying latent profile distribution across school levels.*

One-way ANOVA models conditioned by school level (Table 7) indicate an absence of systematic variations for Perceived Competence ($p = .214$), Perceived Usefulness ($p = .869$), and Scenario SD02 ($p = .365$). Conversely, the school level exerts a direct and significant impact on the levels of Algorithmic Anxiety: $F(2, 382) = 4.22$, $p = .015$.

Tukey's HSD post-hoc test isolates the source of this variance in the sharp contrast between lower secondary school and upper secondary school (diff = -0.229, $p_{adj} = .026$), highlighting a specific affective vulnerability and emotional apprehension among lower secondary school teachers compared to their upper secondary colleagues, while the comparison between upper secondary and primary school exhibits a marginal trend (diff = -0.238, $p = .055$).

Table 7: *Summary of conditional ANOVAs testing the effect of institutional school level on attitudinal variables.*

Investigated Variable	df	SS	MS	F-value	Significance (p)
Perceived Competence	2, 382	1.43	0.713	1.546	.214
Algorithmic Anxiety	2, 382	4.85	2.423	4.222	.0154
Perceived Usefulness	2, 382	0.17	0.085	0.140	.869
Scenario SD02: Educational alliance	2, 382	1.02	0.509	1.010	.365

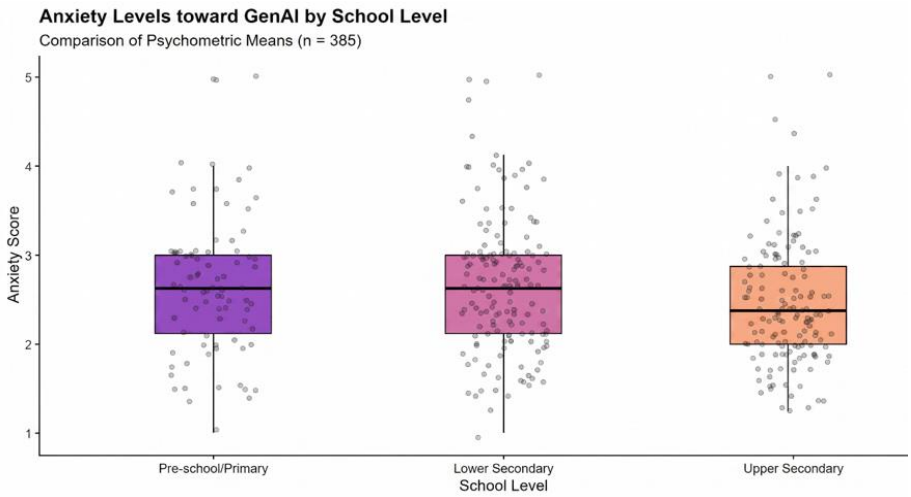


Figure 7: *Boxplot with jittered raw data illustrating the significant variation of algorithmic anxiety across school levels.*

4. Discussion

The empirical findings of the pilot study confirm the psychometric reliability of the survey and the sensitivity of the three dilemmatic scenarios (SD01, SD02, SD03) in capturing the actual variability of teachers' postures without social desirability bias. Latent Profile Analysis (LPA) reveals the intrinsically multidimensional nature of algorithmic literacy, highlighting a clear divide

between the majority cluster of optimistic teachers (63.1%, N = 243), who are inclined towards a functional orchestration of GenAI, and the profile of ambivalent adopters (28.8%, N = 111). This latter group, characterised by high algorithmic anxiety despite recognising the tool's use-value, reveals a submerged technological malaise that demands reflective support interventions and feedback literacy, moving beyond the logic of purely procedural or mechanical training.

On an inferential level, the ANOVA outcomes demonstrate that these identity postures directly condition teachers' ethical and docimological responses. To understand the variability of these responses and provide transparency to the data matrix, the analysis integrated the automatic numerical conversion based on the alphabetical order of the response options (A = 1, B = 2, C = 3, D = 4). Within this metric, the critical and ecological centre of gravity of Slow Tech is positioned on the intermediate and safeguarding scores of the scale. Specifically, the orientation stabilises at a value of 2 for the design scenario SD01 (Option B: confining AI to draft preparation to protect the teacher's decision-making autonomy), at a value of 3 for the relational scenario SD02 (Option C: deliberately limiting the use of the software to protect classroom social mediation), and at a value of 3 for the assessment scenario SD03 (Option C: requiring the manual re-execution of the assignment to verify the student's actual metacognitive processes). The docimological transition traced in scenario SD03 thus corresponds to the ANOVAs by offering a clear empirical anchor: it highlights the rift between the bureaucratic penalisation of the output construed as plagiarism (value of 4) and the shift of the evaluative axis towards the germane cognitive load activated by the subject.

Within this framework, the most disruptive finding is the significance of the Spearman correlation between the design scenario SD01 and the relational

scenario SD02 ($\rho = 0.333$, $p < .001$). Since in both dilemmas the responses grounded in critical awareness occupy the control positions of the statistical coding, the positive correlation mathematically attests that the protection of pedagogical intentionality and the safeguarding of the interpersonal educational alliance are two structurally interconnected ecological dimensions. The teaching staff senses that the depletion of design autonomy translates immediately into an erosion of classroom relational mediation. This evidence downscales cybernetic *human-in-the-loop* frameworks, frequently reduced to mere ex-post formal control, to mandate a conscious progression wherein technology operates exclusively as a subsidiary reflective partner, validating the necessity of the Slow Tech paradigm within the school ecosystem.

5. Concluding considerations and future perspectives

As a pilot study aimed at validating the survey instrument, the analysis does not intend to establish definitive lines of action, but rather offers an initial exploratory outline of the potential implications that the subsequent large-scale international survey will allow to consolidate. For instance, the trend that emerged from the *Tukey HSD post-hoc* test (RQ4), which detects higher levels of algorithmic anxiety in lower secondary school teachers compared to upper secondary school, suggests the opportunity to move past standardised (*one-size-fits-all*) training strategies in the future. Preliminary findings indicate that intervention plans may need to integrate reflective support pathways capable of addressing the apprehension linked to the destructuring of content carried out by generative models and to *feedback literacy*.

On an operational level, the preliminary validation of the pilot exemplifies how future global data will guide the setup criteria for the physical STIAEM Hub, prefiguring an environment capable of modulating itself based on the

heterogeneity of the identified latent profiles. Initial findings show the utility of providing both advanced *prompt design* stations to leverage the optimistic component of the sample (63.1%) and reflective counselling areas designed to mitigate the *technological distress* of the ambivalent audience (28.8%). The affective vulnerability intercepted in middle schools ($p = .026$) and the link between pedagogical intentionality and educational alliance ($\rho = 0.333$) found among pre-service teachers also offer a preview of how the Hub can exclude dynamics of isolated human-machine interaction. Looking ahead, the definitive data from the international survey will allow the Hub to be permanently structured as a space for in-presence collaborative practices, where the assistive use of *GenAI* is aimed at easing the bureaucratic burden, restoring professional time to the educational relationship (Janloy et al., 2025; Kalasapudi et al., 2026; Ramaiah et al., 2026).

Despite the robustness of the extracted models, this contribution must be interpreted in light of specific methodological limitations inherent to the exploratory nature of a pilot study. The investigated sample exhibits a strong gender polarisation (80.8% female presence) and is markedly unbalanced in favour of novice pre-service teachers with less than five years of service (80.0% of the total population). Consequently, the generalisability of the findings and the extension of cross-grade contingency indexes require caution and further field investigations. Furthermore, both the psychometric refinement of the 36-item perception scale and the 3-profile latent taxonomy reflect the preliminary scope of this investigation. While internal consistency, factor adequacy, and classification entropy supported the stability of the model within the current sample ($N = 385$), ongoing administrations across the five STIAEM partner

countries will provide broader cross-cultural datasets to test strict measurement invariance and confirm latent profile configurations on in-service cohorts.

Moving from these considerations, the future research trajectories of the STIAEM international consortium will develop along two priority directions. The first involves the large-scale administration of the validated survey within the school systems of the partner countries (Italy, Spain, Greece, Turkey, and Lithuania), activating cross-national comparative analyses to map how different macro-institutional and regulatory contexts shape teachers' professional identity and critical action in the era of artificial intelligence. Precisely in view of this global extension, the consortium will make a precise methodological optimisation choice, moving from the alphabetical ordinal coding (1-4) applied in the pilot to a rigorous binary coding (0-1). While the four-point scale was indispensable in this exploratory phase to map the heterogeneity of latent profiles and test the sensitivity of the items, international quantification requires a drastic reduction of statistical noise in cross-country comparisons. In the official survey, the value of 1 will be restrictively and exclusively assigned only to response options that reflect the critical posture of the *Slow Tech* paradigm: specifically, the choice to confine *GenAI* to drafting raw materials (SD01, option B), the orientation towards a strictly limited use of the software to preserve classroom mediation (SD02, option C), and the docimological decision to require the re-execution of the task without technological support to safeguard the student's cognitive autonomy (SD03, option C). All remaining responses, whether skewed towards automated delegation or anchored in rigid rejection, will be collapsed into the value of 0, allowing for an accurate measurement of the exact adherence rate of the European teaching body to the principles of digital ecology. The second

direction will focus on the longitudinal and quasi-experimental monitoring of the pedagogical effects deriving from the activation of the project Hub, transforming it into a permanent scientific infrastructure where the community of practice can test the effectiveness of training modules oriented towards a responsible mindset, the co-design of open educational resources (*OER*) accurately catalogued through metadata, and the concrete operationalisation of collaborative practices, ensuring that the digital evolution of schools remains a process guided by human intentionality and the irreplaceable centrality of the educational relationship.

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