



STIAEM

Slow Tech Innovation

AI, Ethics and
New Teaching Methods

NATIONAL REPORT GREECE



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



İSTANBUL - ESENLER
İLÇE MİLLİ EĞİTİM MÜDÜRLÜĞÜ



1474



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PROJECT STIAEM INFORMATION

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Preface

This National Report provides a systematic, large-scale mapping of Artificial Intelligence within the Greek secondary education system. Developed under the international Erasmus+ STIAEM consortium (Slow Tech Innovation: AI, Ethics, and New Teaching Methods), this research directly supports the European Commission's Digital Education Action Plan (2021–2027) by delivering robust evidence on AI literacy and ethical practices to guide the responsible digital transformation of schools. Rejecting technological determinism and market-driven acceleration, the study aligns with Erasmus+ goals by framing AI in education through the "Slow Tech" paradigm and human-in-the-loop pedagogy. This approach emphasizes human agency and critical reflection, viewing AI literacy not merely as technical skill with generative software, but as a multidimensional competence encompassing cognitive, behavioral, and ethical dimensions. It positions ethical literacy as a prerequisite for active, democratic citizenship, ensuring educators and students can govern emerging technologies rather than passively surrendering to automation.

Methodologically, the study combines quantitative precision with qualitative depth, using inferential statistics and qualitative focus groups to analyze a sample of 350 secondary education students and 71 secondary education teachers. To explore actual ethical reasoning, the research utilizes Situational Judgment Tests (SJTs) based on three global challenges: autonomy versus automation, digital privacy and the educational relationship, and civic and ecological responsibility (such as algorithmic bias and carbon footprints).

The empirical mapping of Artificial Intelligence within the Greek secondary education system reveals a tension between superficial technological adoption and genuine ethical comprehension across both teachers and students. Quantitatively, both cohorts report comparable baselines of moderate AI competence and digital literacy, yet qualitative insights uncover a more fragile reality where technological confidence often masks an illusion of knowledge. For teachers, anxiety is driven by the actual mode of AI adoption; teachers practicing innovative, active AI integration in their teaching materials are the ones that report the lowest technostress and the highest perceived utility, whereas educators relegated to basic administrative tasks face significant stress and an overwhelming professional burden due to a lack of systemic training. While teachers widely praise AI for optimizing workflows and saving up to 90% of instructional preparation time, they strictly reject the automated delegation of pedagogically sensitive tasks like grading, advocating instead for rigid human-in-the-loop safeguards to protect the educational relationship. On the student side, regular users exhibit a pragmatic dependency on AI, frequently leveraging it as a shortcut for homework or copy-pasting content without deeply understanding the underlying logic, which they confess threatens independent critical thinking. Demographically, male students score higher in both affective and behavioural dimensions. Also, while students view AI as a supportive, non-judgmental companion and teachers value its productivity gains, both groups actively demand a unified, school-wide policy to eliminate fragmented expectations and establish a structured, ethically grounded pedagogical framework for digital behavior.

Ultimately, this report serves as a methodological compass aligned with the European AI Act's principles of human oversight, transparency, and risk awareness. The gathered evidence will form the empirical foundation for the STIAEM project to design, implement, and evaluate new teacher training programs and pedagogical interventions, establishing a sustainable, human-centered model for AI integration in European classrooms.

1.Introduction and Methodology

1.1 Objectives of the national report

The primary purpose of this National Report is to provide a comprehensive mapping of the current educational landscape in Greece regarding the integration and impact of Artificial Intelligence (AI). This report serves as a baseline for the development of the project s pedagogical framework. Within this frame, the main specific objectives are:

- to analyze the national regulatory landscape and to examine the current Greek legal framework and policy initiatives (including Law 4961/2022 and Ministry of Education s directives) governing the ethical and pedagogical/functional use of AI in schools.
- to evaluate teachers' and students' perceptions and readiness and ethical concerns toward AI.
- to assess digital competencies and to determine the current level of AI literacy and technical abilities among the target groups to identify specific training gaps.

1.2 Description of the sample (Demographics and numerical data of teachers and students)

A convenience sampling strategy was employed, addressing to the school networks of the project partners. The quantitative phase of the study involved a total of 71 secondary school teachers (ISCED levels 2 and 3) and 350 students aged between 11 and 20. In addition, qualitative data were collected through focus groups, involving 5 secondary school teachers and 5 secondary school students. More specifically, the participating sample is the following:

The mixed approach has the advantage of allowing depth and bringing into surface individualized approaches and experiences that cannot be identified and depicted only with the quantitative approach. More specifically the sample has the following demographic characteristics:

Frequencies and percentages were calculated in both samples for the main background variables. In the case of the teachers sample, the variables considered were gender, age, teaching experience, the educational level at which they teach, specialty, and relationship with technology. For the students sample, gender, age, frequency of AI tool use, and perceptions of AI use in academic tasks were analysed.

b.1 Teachers

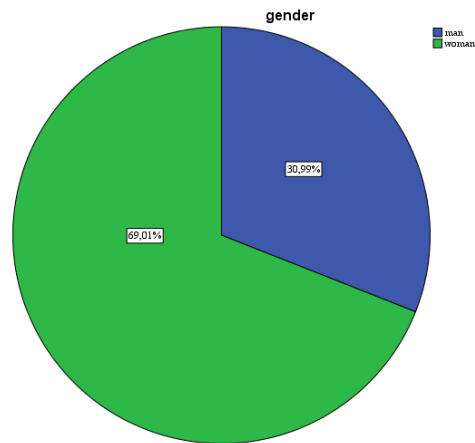
Gender

In the sample of teachers there is 31% men (N=22) and 69% women (N=49). Total sample is 71 Greek teachers of secondary education (table 1).

Table 1: Gender frequencies for teachers

Gender	N	%	Cumulative %
Man	22	31,0	31,0
Woman	49	69,0	100,0
Total	71	100,0	

Figure 1. Gender distribution of the Greek teachers' sample (N=71)

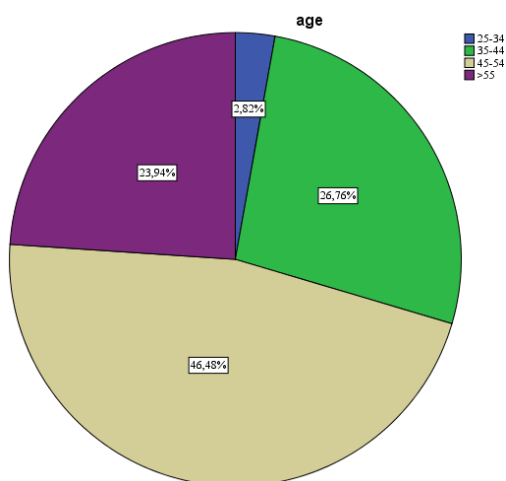


Regarding age, 2.8% (N=2) of the teachers belong to the age group from 25 to 34 years old, 26.8% (N=19) of the teachers belong to the age group from 35 to 44 years old, 46.5% (N=33) of the teachers belong to the age group from 45 to 54 years old and the rest 23.9% (N=17) are older than 55 years old (table 2).

Table 2: Age frequencies for teachers

Age	N	%	Cumulative %
25-34	2	2,8	2,8
35-44	19	26,8	29,6
45-54	33	46,5	76,1
>55	17	23,9	100,0
Total	71	100,0	

Figure 2. Age distribution of the Greek teachers' sample (N=71)

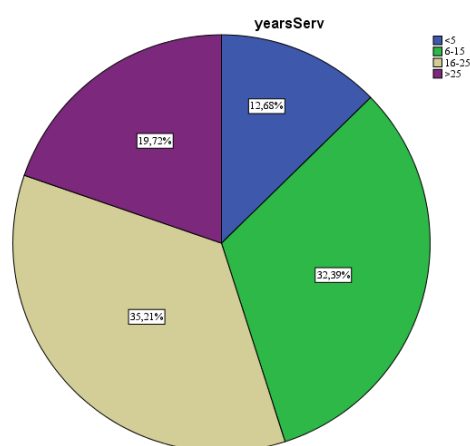


Regarding years of service, 12.7% of the sample (N=9) have less than five years of service, 32.4% (N=23) have 6 - 15 years of service, 35.2% (N=25) have 16 - 25 years of service and 19.7% (N=14) have more than 25 years of service (table 3).

Table 3: Years of service s frequencies for teachers

Years of service	N	%	Cumulative %
<5	9	12,7	12,7
6-15	23	32,4	45,1
16-25	25	35,2	80,3
>25	14	19,7	100,0
Total	71	100,0	

Figure 3. Teaching experience distribution of the Greek teachers' sample (N=71)

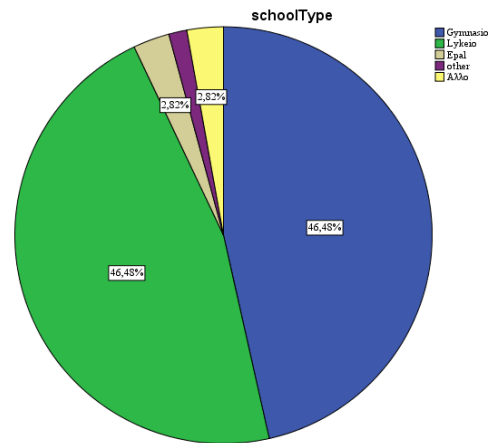


Regarding school type, 46.5% (N=33) of the sample teach in middle school (Middle school or ISCED2), 46.5% (N=33) teach in high school (High school or ISCED3), 2.8% (N=2) work in vocational high schools and 4.2% (N=3) work in other types that were not specified (table 4).

Table 4: School type frequencies for teachers

School type	N	%	Cumulative %
ISCED 2	33	46,5	46,5
ISCED 3	33	46,5	93,0
Vocational	2	2,8	95,8
Other	3	4,2	100
Total	71	100,0	

Figure 4. School type distribution of the Greek teachers' sample (N=71)

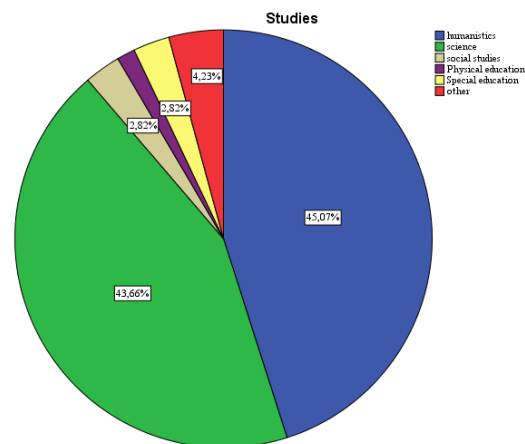


Regarding their studies or their scientific field, 45.1% (N=32) of the teachers come from humanistic science background, 43.7% (N=31) from STEM with these two polls accounting for the majority of the sample. 2.8% (N=2) are from social studies, and 2.8% (N=2) from physical education. Only 1.4% (N=1) is from physical education, and the remaining 4.2% (N=3) are from other fields (Table 5).

Table 5: Studies frequencies for teachers

Studies	N	%	Cumulative %
Humanistics	32	45,1	45,1
Science	31	43,7	88,7
Social studies	2	2,8	91,5
Special Education	2	2,8	98,6
Physical Education	1	1,4	100,0
Remaining fields	3	4,2	95,8
Total	71	100,0	

Figure 5; Studies distribution of the Greek teachers' sample (N=71)

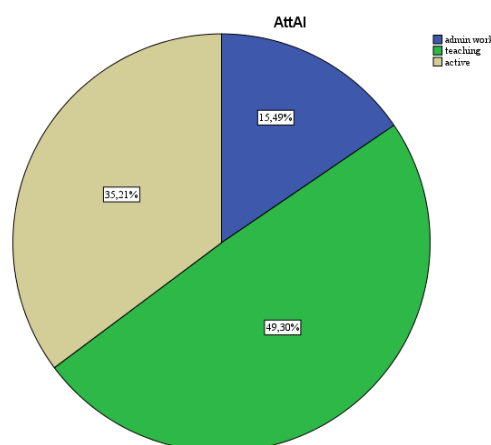


Regarding their general reported preferred AI use, only 15.5% (N=11) use AI solely for administrative work, 49.3% (N=35) explore AI as an assistant to prepare their teaching contents and 35.2% (N=25) explore AI as an active integration teaching tool (table 6).

Table 6: AI use frequencies for teachers

Subgroups	N	%	Cumulative %
Administrative work	11	15,5	15,5
Teaching preparation	35	49,3	64,8
Active integration	25	35,2	100,0
Total	71	100,0	

Figure 6: Use of AI distribution of the Greek teachers' sample (N=71)



Description of students' sample

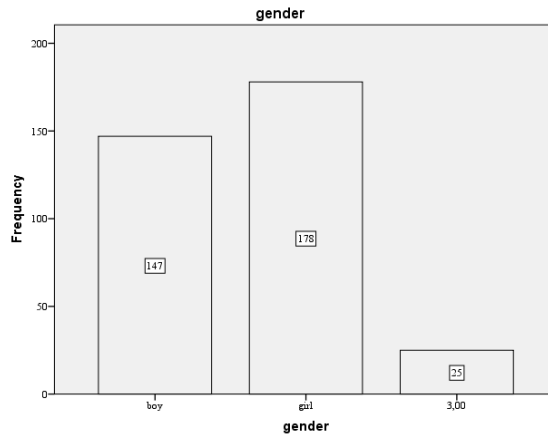
Gender

The questionnaire was sent to all schools of secondary education, for the region of Dodecanese, South Aegean, Greece. The sample is 350 students that responded to the questionnaire. Approximately 42.0% (N = 147) of the students are boys, while 50.9% (N = 178) are girls. A smaller proportion, 7.1% (N = 25), did not wish to report a gender (table 7).

Table 7: Frequencies based on gender for students

Gender based groups	N	%	Cumulative %
Boy	147	42,0	42,0
Girl	178	50,9	92,9
I don't want to say	25	7,1	100,0
Total	350	100,0	

Figure 7: Gender distribution of the Greek students' sample (N=350)

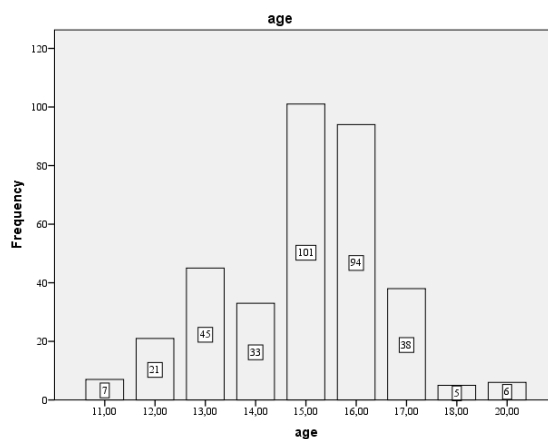


Regarding age, students' sample was predominantly composed of mid-adolescents. The largest age groups were 15-year-olds (28.9%, N = 101) and 16-year-olds (26.9%, N = 94). This was followed by 13-year-olds (12.9%, N = 45) and 17-year-olds (10.9%, N = 38). Smaller proportions included 14-year-olds (9.4%, N = 33) and 12-year-olds (6.0%, N = 21). The youngest participants were 11 years old (2.0%, N = 7), while 18-year-olds (1.4%, N = 5) and 20-year-olds (1.7%, N = 6) represented only a minimal share of the sample (table 8).

Table 8: Frequencies based on age for students

Age based groups	N	%	Cumulative %
11	7	2,0	2,0
12	21	6,0	8,0
13	45	12,9	20,9
14	33	9,4	30,3
15	101	28,9	59,1
16	94	26,9	86,0
17	38	10,9	96,9
18	5	1,4	98,3
20	6	1,7	100,0
Total	350	100,0	

Figure 8: Age distribution of the Greek students' sample (N=350)

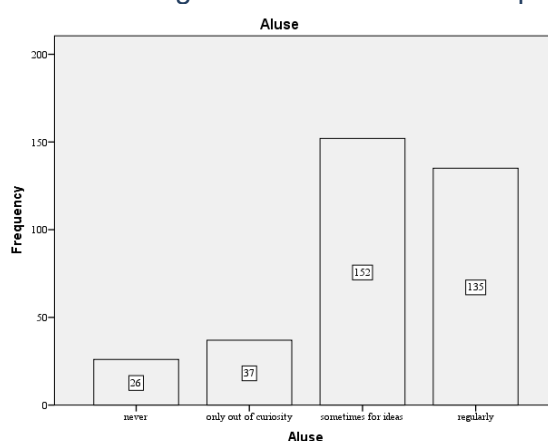


In terms of students' preferred AI usage, the majority reported moderate to frequent engagement. Specifically, 43.4% (N = 152) indicated that they use AI sometimes for ideas, and 38.6% (N = 135) reported using it regularly. In contrast, 10.6% (N = 37) stated that they use AI only out of curiosity, while a small proportion, 7.4% (N = 26), reported never using AI (table 9).

Table 9: Frequencies based on AI use

Ai use based groups	N	%	Cumulative %
Never	26	7,4	7,4
only out of curiosity	37	10,6	18,0
sometimes for ideas	152	43,4	61,4
Regularly	135	38,6	100,0
Total	350	100,0	

Figure 9: Ai use among the Greek students' sample (N=350)

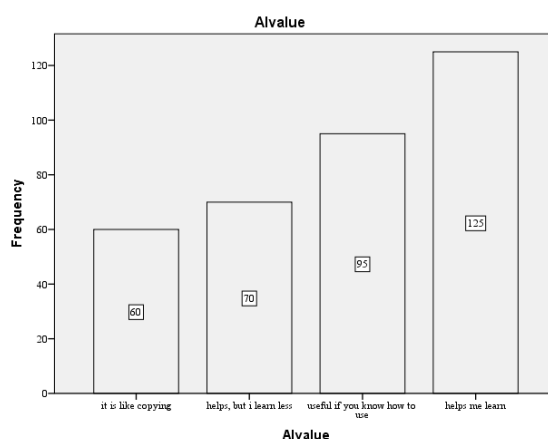


Regarding their preferred AI use, students' perceptions of AI were generally positive. The largest proportion, 35.7% (N = 125), reported that AI helps them learn, followed by 27.1% (N = 95) who considered it useful if one knows how to use it. Conversely, 20.0% (N = 70) believed that AI helps but leads to less learning, while 17.1% (N = 60) perceived it as equivalent to copying (table 10).

Table 10: Frequencies based on AI attitudes

AI attitudes	N	%	Cumulative %
it is like copying	60	17,1	17,1
helps, but i learn less	70	20,0	37,1
useful if you know how to use	95	27,1	64,3
helps me learn	125	35,7	100,0
Total	350	100,0	

Figure 10: Views on AI and homework among the Greek students' sample (N=350)



1.3 Data collection tools (Surveys, semi-structured interview protocols)

Data was gathered through two questionnaires (one for teachers and one for students) specially developed by STIAEM scientific team, based on two instruments: Isik et al (2024) for teachers, focusing on five core dimensions, AI competence, AI anxiety, AI usefulness, General digital literacy and Ng et al (2024) for students, focusing on four core dimensions, Affective, Behavioural, Cognitive and Ethical. For both samples, three scenarios of ethical dilemma and decision making were included, asking them their preferred course of action on given theoretically grasped and presented scenario. The data were subsequently processed through standardised procedures, including descriptive statistics (means, standard deviations, frequencies), and inferential analyses (e.g., ANOVA, t-tests, and regression models).

The qualitative phase was designed to offer further light and more specific angles to the quantitative findings. It included focus groups with 5 secondary school teachers and 5 secondary school students. In addition, qualitative instruments comprised semi-structured interview protocols and Situational Judgement Tests (SJTs), which presented real-life ethical dilemmas (e.g., efficiency vs. equity, personalization vs. privacy, autonomy vs. assistance) in order to capture participants' decision-making processes and ethics in action. Finally, a triangulation process was conducted to integrate quantitative trends with qualitative insights, providing a more comprehensive and nuanced understanding of the integration of Artificial Intelligence in educational contexts.

2. National context of AI in education

2.1 current policies, regulations and ministerial guidelines

Artificial Intelligence (AI) integration in schools in Greece.

The rapid integration of Artificial Intelligence (AI) into pedagogical frameworks aims to foster high-performing digital education systems across EU. The present Greek national report evaluates the current landscape of AI within the Greek educational system, mapping the transition from official policies and centrally designed initiatives to teachers' stand and outlook towards AI. It is important to initially state that Greece has a national plan for AI that includes a section about education and a law that allows the use of AI in school settings (European Schoolnet, 11/12/2025). The report is structured to provide an overview on the topic of AI in Greek Education, through the following thematic pillars:

- Legislative Framework:** An examination of the regulatory environment governing AI use in general.
- Ministry of education Initiatives:** A review of projects by the Ministry of Education, Religious Affairs, and Sports that aim to regulate AI use in education and to align with EU policies.

- The Institute of Educational Policy (IEP):** An analysis of the training approached and professional development material designed for Greek primary and secondary education teachers.

- Universities seminars for teachers:** An overview of university-led seminars and higher education's role in bridging the gap between AI expansion and the need for practical teaching methodologies.

- Academic studies:** A synthesis of recent journal articles and empirical data regarding Greek teachers' attitudes, perceptions, and perceived barriers toward AI adoption.

2.1.1. Legislative Framework

Law 2639/2026

The regulatory framework established by Gazette B 2639/12.05.2026 introduces a comprehensive set of guidelines for the integration of Artificial Intelligence within Greek secondary education, prioritizing safety, transparency, and ethical responsibility. The primary objective is to support the work of teachers and enhance the learning process while ensuring full compliance with European and national data protection laws, such as the GDPR. A fundamental principle of this legislation is that participation is strictly voluntary; neither teachers nor students are penalized for choosing not to engage with AI tools, and their evaluation remains unaffected by such decisions.

At the heart of this initiative is a human-in-the-loop approach, where AI serves as an assistive technology rather than a replacement for human judgment. All AI-generated outputs must be supervised and evaluated by trained educational personnel to prevent risks associated with algorithmic bias, misinformation, and the unauthorized substitution of personal effort. To protect the rights of the school community, the law explicitly prohibits fully automated decision-making regarding student grading or teacher performance, and it forbids the creation of individual profiles based on AI usage data.

Technical implementation is centered on security and data minimization. Access to AI systems is managed through the Panhellenic School Network (PSD), ensuring that users are properly authenticated in a secure environment. Only essential information, such as names and institutional emails, is processed, and systems must adhere to strict principles of data protection by design. On a local level, each school unit utilizing these technologies appoints an AI Coordinator. This designated teacher manages consent forms, organizes collaborative digital workspaces, and ensures that the technical use of AI aligns with the safety standards dictated by the Ministry of Education, which acts as the primary Data Controller.

Regarding academic integrity, the framework distinguishes between supervised learning and independent work. The use of AI is generally prohibited during exams and tests unless a teacher provides explicit permission for a controlled educational activity. For assignments and projects, students are encouraged to use AI responsibly and transparently, but they cannot submit work created entirely or significantly by an AI system. The final product must remain the result of the student's personal effort and reflect their own understanding of the subject matter. Teachers are tasked with guiding students toward a critical awareness of these tools, ensuring they are used to foster creativity rather than bypass the learning process.

Finally, the regulation sets clear red lines to prevent digital abuse. It strictly prohibits the creation or distribution of deepfakes—manipulated audiovisual content—without explicit consent. It also bans the generation of fraudulent bibliographic references or fake data, often referred to as AI hallucinations. By establishing these boundaries and focusing on digital literacy, the framework aims to familiarize the educational community with emerging technologies while safeguarding the ethical and social dimensions of the classroom.

Law 4961/2022

Law 4961/2022 establishes the institutional governance architecture for Artificial Intelligence and Cybersecurity in Greece, aligning with the National Strategy for AI. This law previews the following bodies:

Coordinating Committee: A body chaired by the Minister of Digital Governance. Its mandate encompasses strategic steering to ensure the iterative refinement of the National Strategy while safeguarding fundamental rights.

Supervisory Committee: Serving as the executive arm of the Coordinating Committee, this body monitors the implementation of measures and coordinates the various public and private stakeholders involved.

AI Observatory: A data-driven body under the General Secretariat for Digital Governance. It is responsible for collecting data, mapping AI activities in Greece (including educational programs and best practices), and publishing bi-annual progress reports based on key performance indicators.

Law 5237/2025

While Law 5237/2025 (Gazette A 176/13.10.2025) primarily focuses on the Establishment of Vocational Training Academies, it functions as the legislative vehicle for integrating the EU AI Act into the Greek vocational and secondary education sectors. Law 5237/2025 serves as a regulatory bridge, mandating that all digital interventions within the Greek Vocational Education and Training (VET) system strictly adhere to Regulation (EU) 2024/1689 (the AI Act), ensuring that educational AI tools align with standards for transparency, algorithmic safety, and the protection of fundamental rights. The framework emphasizes the protection of personal data and technical robustness and specific provisions are made for the interoperability of AI-enhanced platforms and the implementation of organizational measures to secure participants' data. AI tools and electronic applications must ensure effective access for users with disabilities, aligning with universal design principles in digital education.

Critically, the legislation stipulates mandatory professional development for teachers to foster AI Literacy and pedagogical readiness, authorizing the Ministry of Education to define and certify the technical specifications of AI applications used in schools, in strict accordance with Regulation (EU) 2024/1689.

Law 5128/2024

Law 5128/2024 institutionalizes the Digital School (Ψηφιακό Σχολείο-<https://digitalschool.gov.gr>) as a central pillar of the national educational strategy and as a flagship initiative for hybrid pedagogical models. It specifically provides the legal basis for a hybrid educational model that leverages AI to enhance accessibility and personalized learning.

More specifically the web platform of Ψηφιακό Σχολείο (Digital School) is a national educational web platform developed by the Greek Ministry of Education, Religious Affairs and Sports to support teaching, learning, and collaboration within the Greek school system. It brings together a wide range of digital tools, services, and educational resources in a single online environment, aiming to modernize education and facilitate both in-person and distance learning. Through this platform, students, teachers, and schools can access digital educational material, participate in online lessons, collaborate in learning communities, and engage in innovative educational activities.

In addition, the platform hosts specialized educational services that support interactive learning and collaboration. For example, LAMS (Learning Activity Management System) allows teachers to design and manage structured sequences of learning activities, while Eduspace offers opportunities for professional development through seminars, as well as participation in educational competitions and initiatives. Teachers and students can also participate in online communities through educational blogs and collaborative spaces that promote communication, sharing of teaching practices, and the development of digital literacy.

The platform further encourages student creativity and participation through Schoolpress, an environment where schools can create electronic magazines and newspapers, allowing students to publish articles and collaborate on digital publications. It also supports civic engagement through initiatives related to active citizenship, encouraging students to participate in projects that promote social awareness and democratic values.

Another important section of the platform is Aesop (Αἴσωπος), a repository of digital teaching scenarios designed by teachers, which provides structured lesson plans and innovative pedagogical approaches. The platform also includes resources related to school evaluation and the sharing of good practices, helping schools improve their educational processes through reflection and collaboration.

Beyond general teaching resources, the Digital School platform places significant emphasis on inclusive education. It offers educational software for preschool education, resources for students with special educational needs, and support material for refugee students who are integrating into the Greek educational system. Additionally, it provides guidance and resources for teachers on inclusive education, promoting teaching approaches that ensure equal participation and learning opportunities for all students.

Overall, the Digital School functions as a comprehensive digital ecosystem for Greek education, combining teaching resources, communication tools, collaborative environments, and inclusive educational support. By integrating these services into a unified platform, it aims to enhance the

quality of education, promote digital transformation in schools, and provide equitable access to learning opportunities for all members of the educational community.

The Law also initiates Digital Tutor (Ψηφιακό Φροντιστήριο - <https://streaming.digitalschool.gov.gr>) which is a flagship initiative offering synchronous and asynchronous support to secondary education students. More specifically, the platform of the Digital Tutor is a service, which provides structured online educational support and access to supplementary learning material. The platform also integrates tele-education through Webex, enabling synchronous online lessons and virtual classrooms when distance learning is required. Another important feature that functions in combination with the Digital Tutor is the Digital Repository of Graded Difficulty Exercises, a pool of exam questions and assessment material that helps teachers design evaluations while supporting transparent and standardized assessment practices across schools.

Since this report is about AI integration in Greek educational map, it is very meaningful to refer to the EduAI initiative which is an upcoming, planned upgrade of the national Digital Tutor platform, aiming to integrate artificial intelligence technologies into the provision of this supplementary educational support for secondary school students. The ongoing project seeks to transform the existing platform from a repository of recorded instructional material into a comprehensive interactive learning environment. At the core of the system is the development of an AI-driven module capable of generating personalized exercises and adaptive learning pathways tailored to the individual knowledge level, learning progress, and preferences of each student. Through the use of intelligent algorithms, the system is expected to analyse student responses, detect common misconceptions and knowledge gaps, and dynamically adjust the difficulty and type of tasks presented to the learner. In this way, EduAI is designed to function as a national AI tutoring system that enhances student engagement and supports deeper understanding by providing targeted feedback and individualized learning support within the framework of the public digital education ecosystem. But this initiative is also described in the next section that refers to Ministry of Education AI relevant initiatives.

Last, the same Law mandates the development of digital content that incorporates AI tools to assist in the remediation of learning gaps and the support of students with disabilities. Recently was announced by the Ministry of Education that AI will be utilized in the platform of Digital Tutor to analyze student performance and most significantly to provide adaptive learning paths.

Ministr. Decision 10267/2026/ B 227/22.01.2026

The ministerial decision 10267/ΕΞ/2026 (Government Gazette B 227/22.01.2026) recognizes that many challenges are identified in the digital transformation of Education Institutions, as there is a lack of a unified digital operating environment and horizontally interoperable administrative Information Systems. Furthermore, the decision states that the integration of Artificial Intelligence (AI) and Machine Learning (ML) within research services, administration, and the delivery of both on-site and distance education remains at a very nascent stage.

2.1.2. Initiatives of Ministry of Education referring to AI

Ministry of Education project, called EDUCONTACT (under construction)

The Ministry of Education, is launching EDUCONTACT, an integrated, multi-channel citizen support system powered by Artificial Intelligence (AI). The project aims to modernize communication between the educational community and the Ministry through a 24/7 automated infrastructure. Regarding its key functional pillars the system is an AI-Driven Support, thus with the use of an AI Assistant the system will be providing automated responses in multiple languages and intelligent request routing (Intelligent Routing) to specialized personnel. The system aims the transition from fragmented, manual procedures (physical protocol and standard telephony) to a centralized digital hub is expected to significantly reduce administrative workload, enhance transparency through real-time ticket tracking, and decrease the operational workload of Ministry staff.

Regarding more specific technical details, the above system integrates AI Agents (Virtual Assistants) capable of handling natural language queries via text (chat, email, WhatsApp) and voice, thus employing multichannel interaction. AI is employed for Intelligent Routing, where complex queries are automatically redirected to the appropriate administrative department (back-office) if the AI Agent

cannot provide an immediate answer. Regarding knowledge Management and Analytics the system will use a smart knowledge base with advanced technologies like Vector Search and semantic analysis to categorize content and provide accurate, context-aware responses to students, parents, and teachers. There are also AI-Driven Analytics, since an advanced reporting system utilizes AI to visualize data in real-time dashboards, allowing the administration to monitor performance trends (KPIs) and predict future service needs. Regarding the operational and technical standards and the generative AI Capabilities, the framework incorporates agent-assist functions, assisting public servants in automating responses and enriching the national educational knowledge base.

It must be noted that the project is developed within the Microsoft Azure ecosystem, ensuring high standards of data security (GDPR compliance) and technical interoperability with existing governmental infrastructures.

Ministry of education, Strategic Integration of Artificial Intelligence in School Education: The eTwinning Ecosystem (2023–2025) (source: <https://www.minedu.gov.gr/dimofili/61594-21-05-25-draseis-etwinning-gia-tin-proothisi-tis-texnitis-noimosynis-stin-ekpaidefsi>)

The National Support Organization for eTwinning in Greece has developed a comprehensive multi-channel strategy aimed at embedding AI within collaborative educational projects. This framework transitions from theoretical awareness to practical classroom application through:

Long-term Vocational Training: Since 2023, a rigorous 200-hour professional development course titled Pedagogical Utilization of AI in eTwinning Projects and Teaching has been implemented. The program has seen exponential growth, training over 7,000 teachers (2,685 in 2023-24 and 4,459 in 2024-25), focusing on content generation, automated assessment, and the ethical dimensions of algorithmic governance.

On-site Seminars and Collaborative Design: In May 2024, a multilateral seminar in Patras hosted secondary teachers from 13 countries. The primary objective was the collaborative design of eTwinning projects that inherently incorporate AI tools to facilitate cross-border student cooperation. Currently, the eTwinning initiative expands its digital reach through specialized open-access platforms using a new Massive Open Online Course (MOOC) titled Leveraging AI in Education and eTwinning Programs which introduces four critical thematic pillars: Ethics and Data Privacy, Generative Chatbots, Multi-modal Content Creation, and Instructional Design.

The effectiveness of the interventions is monitored through standardized European evaluation tools, such as the European Commission's Selfie4Teachers self-reflection tool, where data indicates a measurable increase in the digital competencies of participating teachers.

The majority of participants report high levels of efficacy, noting that AI-driven training significantly enhances their ability to create adaptive learning environments. The eTwinning ecosystem is evolving toward a research-oriented model. Future initiatives aim to:

Establish direct links between school-level actions and AI research projects.

Support Adaptive and Collaborative Learning Environments (ACLE), where AI acts as a facilitator for personalized student trajectories.

Foster a Community of Practice that ensures the responsible and visionary adoption of emerging technologies in the European pedagogical space.

AI based digital tutoring -Ψηφιακό φροντιστήριο (from Ministry of Education)(source: <https://streaming.digitalschool.gov.gr/>)

The Greek Ministry of Education has recently initiated the development of an advanced Artificial Intelligence-based Personalized Exercise System within the national Digital Tutor Platform (EduAI). The project represents a significant investment in the digital transformation of public education. The initiative aims to upgrade the existing Digital Tutor environment from a repository of educational videos into a comprehensive, interactive learning ecosystem that supports personalized learning pathways for students. The new system, titled AI based digital tutoring, or EduAI, will employ AI technologies to generate adaptive and personalized learning activities and tailored feedback to students, supporting their learning process. Through AI-driven mechanisms, the platform will dynamically adjust exercises according to each student's knowledge level, learning progress, and

individual educational needs. This adaptive functionality is expected to enhance student engagement and support deeper understanding of curricular content by transforming passive consumption of learning material into active and responsive learning experiences. According to the Ministry's design framework, the system will function as a national AI-based learning platform capable of performing several pedagogically relevant tasks. These include understanding the instructional content of lessons, generating questions aligned with pedagogical objectives, identifying common student misconceptions and typical errors, and evaluating the quality of students' reasoning and analytical responses. Furthermore, the platform will continuously adapt to students' cognitive levels and learning trajectories, allowing it to detect knowledge gaps at an early stage and provide targeted practice opportunities. Importantly, the initiative is not conceived merely as a digital practice tool. Rather, it represents a strategic integration of AI into the core infrastructure of public education, designed to operate within a controlled and pedagogically grounded framework. The system seeks to support teachers, students, and parents by providing meaningful learning analytics and feedback mechanisms that enhance the transparency and effectiveness of the learning process. The development of this system is also motivated by a critical assessment of the current Digital Tutoring platform. Although the existing platform provides a substantial collection of instructional videos, the Ministry acknowledges that its functionality remains largely unidirectional. Students are primarily limited to viewing educational content without opportunities for interactive engagement or structured practice. Currently, the platform lacks several essential pedagogical features, including mechanisms for assessing students' comprehension, tools for systematic practice, and immediate feedback on learning progress. As a result, a significant gap exists between passive content consumption and active learning engagement. This limitation has broader implications for the educational ecosystem. Students are often unable to determine whether they have adequately understood the material, teachers lack sufficient digital tools to identify individual learning difficulties, and parents have limited visibility regarding their children's actual academic progress. The introduction of the AI-supported exercise system therefore aims to address these challenges by creating a more data-informed, personalized, and interactive learning environment within the Greek public education system.

2.1.3. GUIDE from Institute of Educational Policies (IEP) https://www.iep.edu.gr/wp-content/uploads/2025/09/2024-07-17_1721062001478.pdf

Institute of Educational Policies uploaded in their website the Translation of the Unesco guide Digital Transformation and Innovation in Primary and Secondary Education: Strategic Implementation of AI and Digital Infrastructure (2024–2026)

Teachers' training from ITE (Institution of Technology and Research which operates under the Ministry of Development) titled experience AI (Source: <https://www.nationalcoalition.gov.gr/training-offer/experience-ai-ekpaideytiko-programma-technitis-n/> & <https://www.experience-ai.gr/>)

The Experience AI course series is an educational initiative designed to provide innovative teaching resources on Artificial Intelligence (AI) and Machine Learning (ML) for secondary education teachers and their students. The programme was developed by the Raspberry Pi Foundation in collaboration with Google DeepMind and is offered in Greece through the Foundation for Research and Technology – Hellas (FORTH).

The programme aims to support teachers in introducing students to the fundamental concepts of Artificial Intelligence, a rapidly evolving technological field that increasingly influences modern society and the future labour market. Through a structured set of training activities and pedagogical resources, the programme equips teachers with the knowledge and tools necessary to help young learners develop AI literacy and critical understanding of intelligent technologies.

The educational materials focus on AI applications relevant to young people's everyday experiences, thereby making abstract computational concepts more accessible and engaging. Importantly, the programme has been designed to be interdisciplinary, allowing teachers from a wide range of subject areas to integrate AI-related topics into their teaching practices.

The Experience AI programme is delivered to teachers through three professional development seminars, which aim to strengthen teachers' knowledge of Artificial Intelligence and Machine Learning

while also presenting practical classroom activities. During the seminars, participants explore a variety of ready-to-use teaching resources, including lesson plans, presentation slides, worksheets, and instructional videos. In this way, the programme provides teachers with a comprehensive toolkit for delivering introductory AI and machine learning lessons within secondary school classrooms.

Structure of the Training Programme

The professional development programme consists of three training seminars, each focusing on specific thematic areas of AI education.

Seminar 1 (Part A) introduces the foundational concepts of Artificial Intelligence and explores topics such as: What is Artificial Intelligence? How computers learn from data?

Understanding bias in AI systems and the societal implications of algorithmic bias

Seminar 2 (Part B) expands on these concepts by examining more advanced topics, including:

Decision trees and basic machine learning models, Problem-solving through machine learning approaches, Safety and ethical considerations in AI development and deployment, Career pathways in the field of Artificial Intelligence

Seminar 3 (Part C) introduces emerging developments and interdisciplinary applications of AI, including:

Large Language Models (LLMs) and generative AI technologies, The relationship between ecosystems and AI, with examples drawn from biology

Teachers who participate in the programme receive a certificate of attendance, provided that they complete at least two of the three training seminars. The certification recognises their professional development in AI education and their readiness to introduce foundational AI concepts into secondary school teaching.

Teachers' webinar, Institute of Educational Policies (IEP) <https://www.iep.edu.gr/techniti-noimosyni-neoi-orizontes-sti-didaskalia-kai-sti-mathisi/>

The Hellenic Republic's Ministry of Education, Religious Affairs, and Sports, through the Regional Directorate for Primary and Secondary Education of Epirus, is hosting an online training seminar titled Artificial Intelligence: New Horizons in Teaching and Learning. This academic program, scheduled from February to April 2026, features a series of specialized sessions conducted by university professors, researchers, and educational experts.

The curriculum begins with an exploration of Artificial Intelligence in school education, focusing on international experience and contemporary challenges. Subsequent sessions delve into the pedagogical and ethical frameworks required for developing educational chatbots and the practical application of AI tools in designing active citizenship initiatives.

The program further examines the intersection of AI, cognitive science, and human-centric education, addressing the critical pedagogical question of what occurs in the classroom when technological tools precede instructional methodology. The seminar concludes with an extended roundtable discussion regarding the concerns, future perspectives, and broader implications of AI in the learning environment. Participants include members of the academic community, regional educational consultants, school principals, and primary and secondary teachers.

2.1.4. Universities seminars

Teachers' seminar in AI, University of Patras (<https://kedivim.upatras.gr/cooperatedcourse/techniti-noimosyni-generative-ai/>)

the first university-level certification programme on the pedagogical use of Artificial Intelligence in the classroom has been launched, with the ambitious objective of training up to 50,000 teachers across Greece.

The programme is designed as a fully online and asynchronous professional development course, allowing participants to complete the training flexibly while continuing their professional responsibilities. In addition, the certification provides maximum official credit points within the national teacher evaluation and recruitment framework, making it particularly relevant for teachers seeking appointments, promotions, or professional advancement within the education system.

The programme is addressed to a wide range of education professionals and graduates, including teachers of all subject areas in primary and secondary education, in both public and private schools, adult education trainers and teachers working in Second Chance Schools, professionals involved in

formal and non-formal education structures, graduates from a broad spectrum of academic disciplines, including science, humanities, education, and social sciences, individuals interested in exploring the broader scientific field of Artificial Intelligence applications in education

By addressing such a diverse audience, the programme aims to foster a broad culture of AI literacy within the educational ecosystem, supporting both classroom practitioners and educational leaders. The primary objective of the programme is to equip participants with the knowledge, skills, and pedagogical competencies necessary to understand and apply Artificial Intelligence technologies in educational contexts. By the end of the course, participants are expected to develop a solid conceptual foundation in the principles of AI and to gain practical experience in applying AI-based tools to teaching and learning processes. The programme also aims to cultivate the attitudes, professional dispositions, and ethical awareness required for the responsible use of AI technologies in educational environments.

Through the training activities, teachers become familiar with a broad range of digital tools and applications that can support instructional design, assessment, student engagement, and personalised learning.

The programme has a nine-month duration, corresponding to approximately 420 hours of study, and is structured into 17 thematic modules. These modules include multiple subtopics and introduce participants to more than thirty AI tools and educational applications relevant to contemporary teaching practices. The curriculum combines theoretical foundations with practical training in the pedagogical use of AI. Core thematic areas include:

Fundamentals of Artificial Intelligence and its historical development, Applications of AI in education, including personalised learning systems, Introduction to ChatGPT Edu and generative AI tools for teaching, Exploration of educational AI tools such as Knewton for adaptive learning and systems for automated lesson plan generation, Digital tools supporting instructional design, including Unit Plan Generators and Science Lab Generators, The use of AI in distance and online education, accompanied by demonstrations of emerging educational technologies, Ethical and responsible uses of AI in academic work, including plagiarism detection and academic integrity tools such as Turnitin, Critical analysis of the impact of AI technologies on educational ethics, teaching quality, educational management, and digital learning environments.

The programme also emphasises practical pedagogical applications, introducing participants to tools that support classroom activities, including platforms for image generation, visual learning, language learning, and automated feedback systems. Examples include AI-assisted image generation and editing tools such as Clipdrop, educational applications such as Photomath, Duolingo, and Grammarly, instructional design tools such as Magic School AI.

Participants also examine and compare leading conversational AI systems, including ChatGPT, Claude, and Google Gemini, with the aim of understanding their pedagogical affordances and limitations.

Finally, the programme addresses advanced topics related to AI in education, including:

AI algorithms used in learning environments, analysis and evaluation of student learning behaviours using AI tools, automated generation of multi-step assignments and learning tasks, ethical case studies concerning AI use in educational and professional contexts, potential risks and ethical concerns associated with AI technologies in education.

Through this comprehensive curriculum, the programme seeks to support the development of digitally competent teachers capable of integrating AI tools in pedagogically meaningful, ethically responsible, and critically informed ways.

In the same direction there is a big number of offered webinars and seminars for teachers in the topic of AI, namely from University of Ioannina (https://educenter.dit.uoi.gr/?page_id=601), from the Panhellenic School Network (<https://www.sch.gr/diadiktyako-epimorfotiko-seminario-gia-ekpaideftikous-psifiakes-deksiotites-gia-tin-protovathmia-kai-defterovathmia-ekpaidefsi-ypodomes-kai-ypiresies-tou-ekt-gia-tin-ekpaideftiki-koinotita/>) and many others, private and public educational organizations.

2.2 Digital infrastructure and technological readiness of Experimental Schools

AI in schools (pilot program with 20 participating schools)

(Source: <https://openai.com/global-affairs/openai-for-greece/> <https://edugpt.sch.gr/features.php>)

Greece's curricula embed AI in the subjects of Informatics, in Skills Labs/Digital Skills Training and in Artificial Intelligence in School Education the critical reflection on technology and society (European Schoolnet, 2025). Within this frame, the pilot programme 'Artificial Intelligence in Schools' is an interactive educational initiative designed for upper secondary school teachers and students. Its primary objective is to empower participants with the knowledge, skills, and practical tools necessary for the responsible, creative, and pedagogically meaningful use of Generative Artificial Intelligence (GenAI) in both teaching and learning processes.

The programme is implemented by the Ministry of Education, Religious Affairs and Sports, with the support of the Onassis Foundation, in collaboration with the educational organisation The Tipping Point in Education. Participation in the programme, including the professional development activities provided, is free of charge for teachers and participating schools, ensuring equitable access to innovation in education.

Greece is among the first countries internationally to pilot the integration of ChatGPT Edu, a secure generative AI platform specifically designed for educational environments. The initiative begins with a pilot implementation in twenty selected secondary schools, where teachers and students will experiment with AI-supported learning in a structured and supervised framework.

The programme responds to a contemporary educational reality: students already interact with generative AI tools in their everyday digital environments. Rather than ignoring or restricting this development, the initiative aims to guide students toward ethical, reflective, and pedagogically beneficial uses of artificial intelligence. In this sense, the programme aligns with international discussions on AI literacy and responsible digital citizenship, recognizing the importance of preparing learners to critically engage with emerging technologies.

A central feature of the programme is its teacher-centred approach. Teachers are positioned as agents of pedagogical innovation, receiving targeted training that enables them to introduce AI tools into classroom practices gradually and safely. Through live training sessions, practical workshops, and extensive support materials, teachers learn how to use ChatGPT Edu, design custom AI-based learning tools (Custom GPTs), and create learning activities that promote critical thinking, creativity, collaboration, and problem-solving skills.

From a pedagogical perspective, the programme also emphasises the ethical and social dimensions of artificial intelligence in education. Particular attention is given to issues such as:

- protection of personal data
- digital safety and cybersecurity
- safeguarding the mental well-being of minors
- intellectual property and copyright
- prevention of plagiarism and academic misconduct

This holistic approach reflects the need for responsible AI governance in educational contexts, ensuring that technological innovation is accompanied by ethical awareness and appropriate safeguards.

To achieve its objectives, the programme is structured into four sequential stages, each designed to progressively integrate AI into teaching and learning practices.

Stage 0 – GenAI Ambassadors (September–October 2025): At the initial stage, each participating school selects one or two teachers who volunteer to serve as GenAI Ambassadors. These teachers receive specialised training and act as reference points and facilitators for AI-related initiatives within their school communities.

An introductory two-hour session provides an overview of the programme, clarifies the responsibilities of the GenAI Ambassadors, and introduces the technical specifications and educational features of the ChatGPT Edu platform.

Stage 1 – Teacher Preparation and Empowerment (October–November 2025): During this phase, teachers participate in structured professional development activities aimed at building their AI literacy and pedagogical confidence in using generative AI tools.

The first training session focuses on the fundamental principles of ChatGPT Edu and responsible AI use in education. Teachers also receive a comprehensive guide containing best practices, pedagogical examples, and asynchronous video modules to support self-directed learning. A second training session provides discipline-specific guidance, enabling teachers to explore how AI tools can support different subject areas. Participants learn how to design Custom GPTs and adapt AI tools to specific teaching workflows and classroom needs.

Stage 2 – Integrating AI into Teaching Practice (December 2025 – February 2026): In this stage, teachers begin to experiment with AI-supported learning activities in the classroom. They receive ongoing pedagogical support and practical examples to help them incorporate AI tools effectively and responsibly into their instructional practices. A third training session focuses on the design of AI-supported learning activities, presenting practical case studies and pedagogical strategies for integrating ChatGPT Edu into classroom teaching. Supporting materials are also provided for students, including activity templates and structured learning resources.

Stage 3 – Student-Centred Learning and Exploration with AI (March–June 2026): The final stage focuses on student engagement and exploration. Students are granted controlled access to AI tools for individual assignments and project-based learning activities. These activities utilise specialised Custom GPT tools, designed and supervised by teachers to ensure that the learning environment remains safe, structured, and pedagogically effective. A fourth training session supports teachers in redesigning learning activities that incorporate individual student use of AI. The emphasis is placed on improving learning outcomes, fostering critical thinking, and encouraging students to produce original and meaningful academic work. Teachers receive additional resources, including examples and templates for designing AI-supported assignments and project-based learning activities.

Participation in the programme is entirely voluntary for both teachers and students. Teachers who wish to participate express their interest through their school principal and complete a consent form regarding the processing of personal data.

The potential direct access of students to the ChatGPT Edu platform during Stage 3 will be carefully evaluated during the implementation phase. The programme's further development and refinement will take place in consultation with the governing committees of Model and Experimental Schools, ensuring alignment with national educational priorities and institutional governance frameworks.

3. Data Standardization and quantitative analysis

3.1 Data Pre-processing (Alignment with the Master Codebook, variable harmonization via ISCED)
https://ec.europa.eu/assets/eac/education/tools/iscedf/codes_en.htm

For both the teachers' and students' samples, the datasets were standardized in accordance with the Master Codebook. Variable names were reviewed to ensure they were suitable for quantitative analysis. Likewise, sociodemographic and educational variables were harmonized, incorporating references based on the ISCED classification.

3.1.2 Variable harmonization and scale preparation

The questionnaire was structured into several thematic sections, each corresponding to a specific dimension of the study. These sections typically included areas such as demographic information and a. self-reported competences on AI, b. anxiety regarding AI use, c. perceived benefits of AI use, d. issues of ethical topics regarding AI, and e. scenario-based AI use preferences. Each section grouped together multiple related items designed to measure a broader underlying construct. To enable the inferential analysis, each section was transformed into a composite variable. This was achieved by aggregating the individual item responses within each section—through calculating the mean or sum of the items. For teachers' sample:

Reliability analysis - teachers

For the items of COMPETENCIES The scale demonstrated excellent internal consistency, with a Cronbach's alpha of .97 ($\alpha = .966$). The scale included 22 items (table 11).

Table 11: Cronbach a for competencies

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,966	,966	22

The second ANX subscale (with reversed coding for ANX30) demonstrated good internal consistency, with a Cronbach's alpha of .87 across 8 items, after item ANX30 was reversely recoded to match the verbalization of the rest items (table 12).

Table 12: Cronbach a for anxiety

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,873	,875	8

The UTILITY subscale demonstrated good internal consistency, with a Cronbach's alpha of .83 across 6 items (table 13).

Table 13: Cronbach a for utility

Cronbach's alpha	Cronbach's alpha Based on Standardized Items	N of Items
,832	,832	6

The DIGITAL LITERACY scale demonstrated good internal consistency, with a Cronbach's alpha of .77 across 6 items (table 14).

Table 14: Cronbach a for digital literacy

Cronbach's alpha	N of Items
,778	6

After establishing adequate internal consistency and reliability (via Cronbach's alpha), each multi-item scale was transformed into a composite variables (mean of scale's items) to represent the underlying construct in subsequent analyses. The sufficiently high Cronbach's alpha of scales indicated that the items share substantial common variance and can be treated as indicators of a single latent construct. Under these conditions, aggregating items into a composite score provided a more reliable estimate of the construct than any individual item, as random measurement error is attenuated through averaging. Also, constructing composite variables facilitates data reduction by collapsing multiple observed indicators into a single summary measure. This reduces model complexity, mitigates issues related to multicollinearity among highly correlated items, and preserves statistical power by limiting the number of predictors in subsequent analyses. In addition, composites enhance interpretability, allowing constructs to be represented parsimoniously without sacrificing substantive meaning. The composite variables that appeared are COMPETENCIES, ANXIETY, UTILITY and DIGITAL LITERACY.

For students sample:

CFA

Inferential analysis commenced with factorial analysis to evaluate the construct validity of the instrument and to facilitate data reduction in accordance with the hypothesized ABCE model. Sampling adequacy and factorability of the correlation matrix were assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett s test of sphericity. The KMO value was .930, which is considered excellent. Bartlett s test of sphericity was also statistically significant, $\chi^2(990) = 7307.34$, $p < .001$. This finding confirms that and the data are highly suitable for factor analysis (table 15).

Table 15: KMO and Bartlett s Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.930
Bartlett s Test of Sphericity		Approx. Chi-Square 7307,342
		Df 990
		Sig. ,000

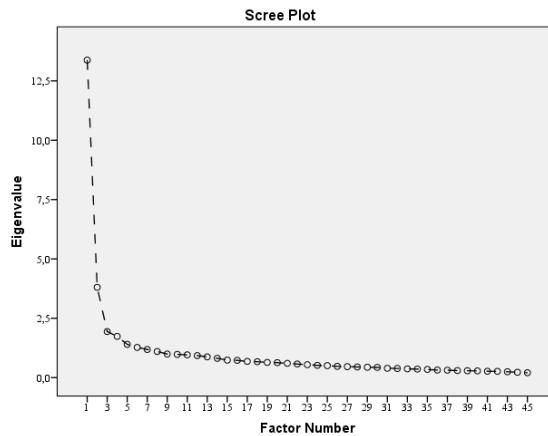
The initial eigenvalues indicate that five factors exceeded the conventional Kaiser criterion (eigenvalue > 1), jointly accounting for 49.46% of the total variance prior to extraction. The first factor accounted for a substantial proportion of variance (29.72%), suggesting a strong general dimension underlying the data. Following extraction using the maximum likelihood method, the five-factor solution explained 43.33% of the total variance. The reduction in explained variance from the initial solution reflects the elimination of unique and error variance components. After rotation, the variance explained was more evenly distributed across factors, enhancing interpretability. Specifically, the rotated solution shows that the first four factors account for 10.72%, 10.04%, 8.89%, and 8.51% of the variance, respectively, while the fifth factor contributes 5.17%. The cumulative variance explained by the rotated solution remains at 43.33% (table 16).

Table16: Variance explained

Total Variance Explained									
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13,374	29,721	29,721	12,805	28,455	28,455	4,825	10,721	10,721
2	3,805	8,456	38,177	3,282	7,293	35,748	4,518	10,039	20,760
3	1,938	4,307	42,484	1,359	3,019	38,767	3,999	8,887	29,648
4	1,738	3,862	46,346	1,192	2,650	41,416	3,830	8,512	38,160
5	1,401	3,113	49,460	,862	1,916	43,333	2,328	5,173	43,333
Extraction Method: Maximum Likelihood.									

The visual inspection of the scree plot aligns with the five factors solution.

Figure: 11 : Scree plot for factorial analysis



The factorial analysis largely supported the intended theoretical structure of the ABCE model, with only minor deviations. The items corresponding to the behavioural dimension loaded most strongly, forming a well-defined factor. However, the final two items exhibited only marginally acceptable loadings (.43 and .48, respectively). Depending on the strictness of the loading threshold adopted, these items may be considered for exclusion. The ethical dimension emerged as the second factor and demonstrated a clear and robust structure, with all items loading strongly and without evidence of cross-loadings. Similarly, the affective dimension formed a distinct and interpretable factor, free from cross-loadings; however, three items were excluded due to insufficient loadings. The safety dimension constituted the fourth factor and was also well-defined, with satisfactory loadings and no cross-loading issues.

A notable issue identified by the CFA concerns the cognitive dimension in the Greek student version of the questionnaire. Specifically, the items intended to capture this construct did not coalesce into a single latent factor, indicating a lack of unidimensionality. This may be attributable to several factors, including potential translation effects, cultural differences in the conceptualization of cognitive aspects of the construct, or heterogeneity in item content leading to multidimensionality. It is also possible that respondents interpreted the items in a more differentiated manner, thereby weakening the shared variance necessary for factor formation.

Despite the absence of a coherent factor structure for the cognitive dimension, internal consistency analysis yielded an acceptable Cronbach's alpha coefficient. In light of this, and given the theoretical importance of the cognitive component within the ABCE framework, the dimension will be retained and treated as a composite scale. The use of Cronbach's alpha is justified here as an index of the overall reliability of the items, even in the absence of strict unidimensionality, particularly when supported by strong theoretical grounding. This approach allows for the preservation of construct coverage while acknowledging the limitations revealed by the CFA (table 17).

Table 17: Factors loadings

ITEMS	BEH	ETHICAL
BEH AILQ_EN02	0,69	
BEHAVAILQ_SI01	0,654	
BEHAVAILQ_SI03	0,652	
BEH AILQ_EN01	0,604	
BEHAVAILQ_BI03	0,485	
BEHAVAILQ_SI02	0,439	
		ETHICAL
		L
ETHICAL_AILQ_AIE05		0,736
ETHICAL_AILQ_AIE10		0,736

ETHICAL_AILQ_AIE 12	0,655		
ETHICAL_AILQ_AIE 08	0,642		
ETHICAL_AILQ_AIE 02	0,642		
ETHICAL_AILQ_AIE 07	0,574		
ETHICAL_AILQ_AIE 11	0,515		
ETHICAL_AILQ_AIE 13	0,5		
		AFFECTIVE	
AFFECTIVE_CL03	0,701		
AFFECTIVE_SE02	0,693		
AFFECTIVE_SE01	0,61		
AFFECTIVE_SE04	0,553		
AFFECTIVE_CL01	0,456		
AFFECTIVE_IM02	0,214		
AFFECTIVE_IM04	0,182		
AFFECTIVE_IM03	0,032		
		SAFETY	
DIG_SAF45	0,608		
DIG_SAF42	0,602		
DIG_SAF41	0,586		
DIG_SAF43	0,566		
DIG_SAF44	0,538		
DIGCRE	0,521		
		COGNITIVE	
COGN_AILQ_EC01	0,196		
COGN_AILQ_EC03	0,097		
COGN_AILQ_EC04	0,135		
COGN_AILQ_KU01	0,049		
COGN_AILQ_KU02	0,174		
COGN_AILQ_KU05	0,080		

Reliability for students' scales

All extracted scales are above the threshold of acceptable Cronbach's alpha values (table 18).

Table 18: Cronbach a for scales

SCALE	N of Items	Cronbach's alpha
AFFECTIVE	10	.856
BEHAVIOURAL	8	.836
COGNITIVE	6	.772
ETHICAL	8	.858
SAFETY	12	.861
DIGITAL LITERACY & DECISION MAKING	6	.778

3.2 Descriptive Analysis (Frequencies, means, standard deviations for AI Literacy and Ethical Awareness)

3.2.1. Frequencies of the main background variables

Frequencies and percentages were calculated in both samples for the main background variables. In the case of the teachers sample, the variables considered were gender, age, teaching experience, the educational level at which they teach, specialty, and relationship with technology. For the students sample, gender, age, frequency of AI tool use, and perceptions of AI use in academic tasks were analysed. Tables 19 and 20 present the results for teachers and students, respectively. The teachers sample shows a predominance of women and a concentration of participants in the 45–54 age group. The majority of teachers teach in ISCED 2 and ISCED 3 types of school, with percentages among the two equally balanced.. Most teachers reported using technology regularly to prepare their teaching, and Humanities and STEM were the most represented specialty area, with similar percentages (table 19).

Table 19. Demographic of the Greek teachers sample

Variable	Category	N	%
Gender	Male	22	31.0
	Female	49	69.0
Age group	Prefer not to say	0	0.0
	Under 25 years	0	0.0
	25-34 years	2	2.8
	35-44 years	19	26.8
	45-54 years	33	46.5
Teaching experience	55 years or older	17	23.9
	Less than 5 years	9	12.7
	6-15 years	23	32.4
	16-25 years	25	35.2
	More than 25 years	14	19.7
Education level taught	Upper secondary education (ISCED 3)	33	46.5
	Compulsory secondary education (ISCED 2)	33	46.5
	Vocational education and training (ISCED 3)	2	2.8
	Other	3	4.2
Specialty	Special education / attention to diversity	2	2.8
	Social sciences	2	2.8
	Physical education	1	1.4
	Humanities and arts	32	45.1
	STEM	31	43.7

	Other (Remaining fields)	3	4.2
Relation with technology	Active integration	25	35.2
	Teaching preparation	35	49.3
	Administrative work	11	15.5

Figure 12: Main background characteristics of the Greek teachers' sample

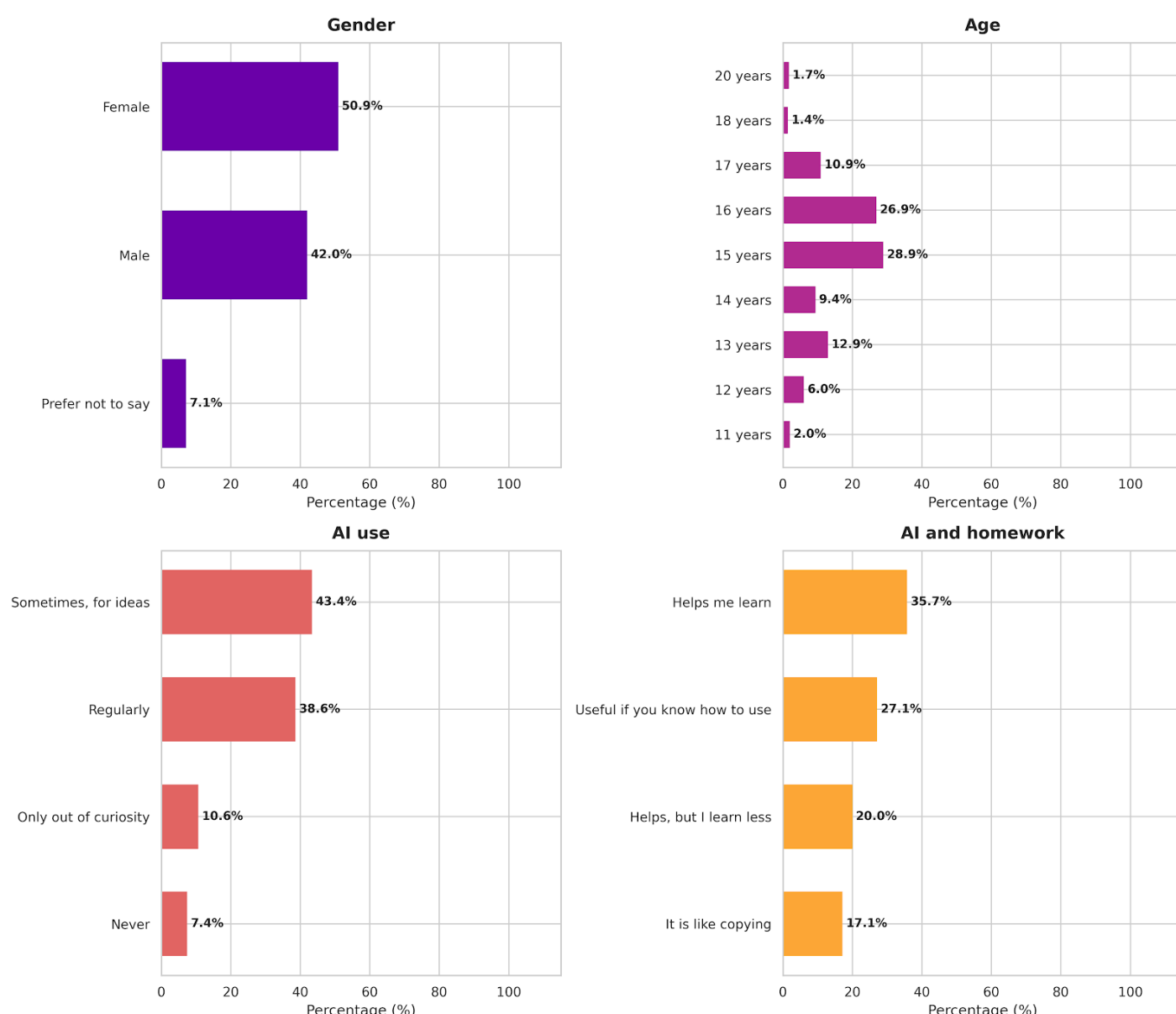


The students' sample also shows a slight female majority, as well as a notable presence of 15- and 16-year-old students. Most students reported using AI at least sometimes, mainly to obtain ideas, and a notable percentage uses it regularly. Most believe that AI helps them learn or that AI is useful if you know how to use it (table 20).

Table 20. Main background characteristics of the Greek students' sample

Variable	Category	n	%
Gender	Male	147	42.0
	Female	178	50.9
	Prefer not to say	25	7.1
Age	11 years	7	2.0
	12 years	21	6.0
	13 years	45	12.9
	14 years	33	9.4
	15 years	101	28.9
	16 years	94	26.9
	17 years	38	10.9
	18 years	5	1.4
AI use	20 years	6	1.7
	Never	26	7.4
	Sometimes, for ideas	152	43.4
	Regularly	135	38.6
	Only out of curiosity	37	10.6
AI and homework	It is like copying	60	17.1
	Useful if you know how to use	95	27.1
	Helps me learn	125	35.7
	Helps, but I learn less	70	20.0

Figure 13: Main background characteristics of the Greek students' sample



3.2.2. Means and standard deviations for AI Literacy and Ethical Awareness

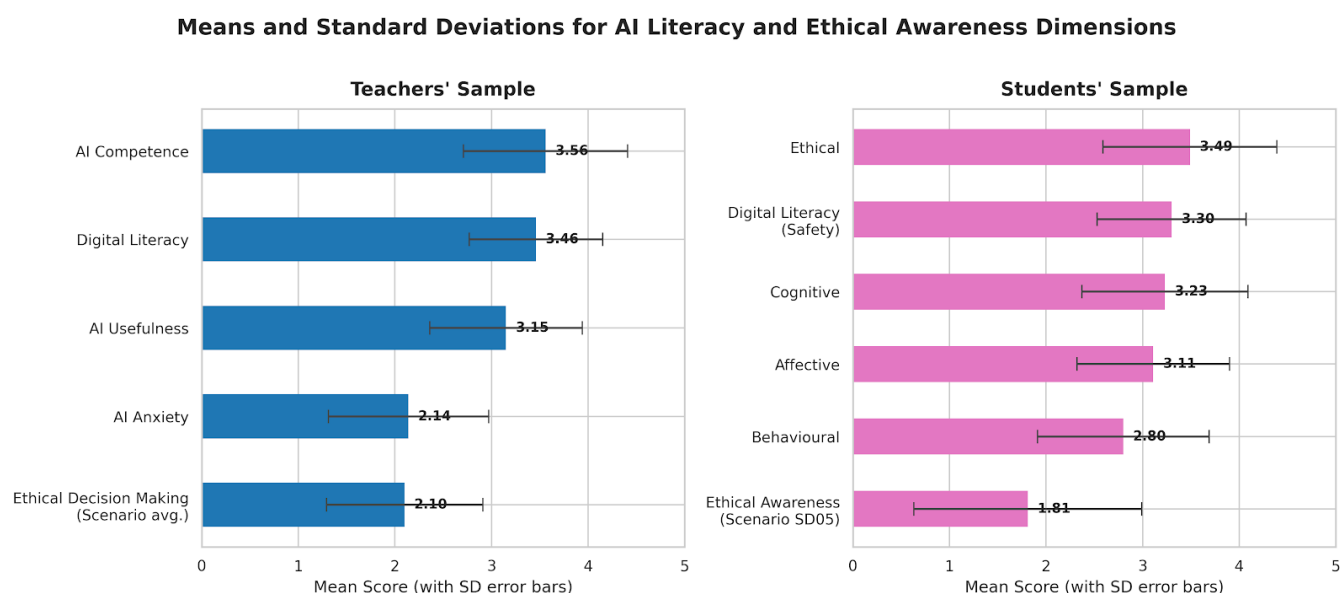
Means and standard deviations were calculated for the main dimensions in both the teachers and students samples. In the teachers sample, the descriptive statistics were organized around the dimensions of AI Competence, AI Anxiety, AI Usefulness, Digital Literacy, and Ethical Decision Making. In the students sample, the dimensions considered were Affective, Behavioural, Cognitive, Ethical, Digital Literacy, and Ethical Awareness. As shown in Table 21, the highest mean scores in the teachers sample correspond to AI Competence ($M = 3.56$, $SD = 0.85$), Digital Literacy ($M = 3.46$, $SD = 0.69$) and AI Usefulness ($M = 3.15$, $SD = 0.79$), and whereas AI Anxiety shows a lower mean score ($M = 2.14$, $SD = 0.83$). In turn, Ethical Decision Making shows a mean score of 2.10 ($SD = 0.81$) on a recoded scale ranging from 0 to 3.

In the students sample, the dimension with the highest mean score is Ethical ($M = 3.49$, $SD = 0.90$), followed by Digital Literacy ($M = 3.30$, $SD = 0.77$), Cognitive ($M = 3.23$, $SD = 0.86$), and Affective ($M = 3.11$, $SD = 0.70$). The lowest scores are observed in Behavioural ($M = 2.80$, $SD = 0.89$) and Ethical Awareness ($M = 1.81$, $SD = 1.18$), the latter also calculated on a recoded 0–3 scale (Table 21).

Table 21. Means and standard deviations for AI literacy and ethical awareness dimensions

Sample	Dimension	N	Mean	SD
Teachers	AI Competence	71	3.56	0.85
	AI Anxiety	71	2.14	0.83
	AI Usefulness	71	3.15	0.79
	Digital Literacy	71	3.46	0.69
	Ethical Decision Making (Scenario avg.)	71	2.10	0.81
Students	Affective	350	3.11	0.79
	Behavioural	350	2.80	0.89
	Cognitive	350	3.23	0.86
	Ethical	350	3.49	0.90
	Digital Literacy (Safety)	350	3.30	0.77
	Ethical Awareness	350	1.81	1.18

Figure 14: Means and standard deviations



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

3.3.1. Pearson correlations

Pearson correlations were calculated to examine the relationship between the main AI literacy dimensions and the ethical outcome variables in both samples. In the teachers sample, the

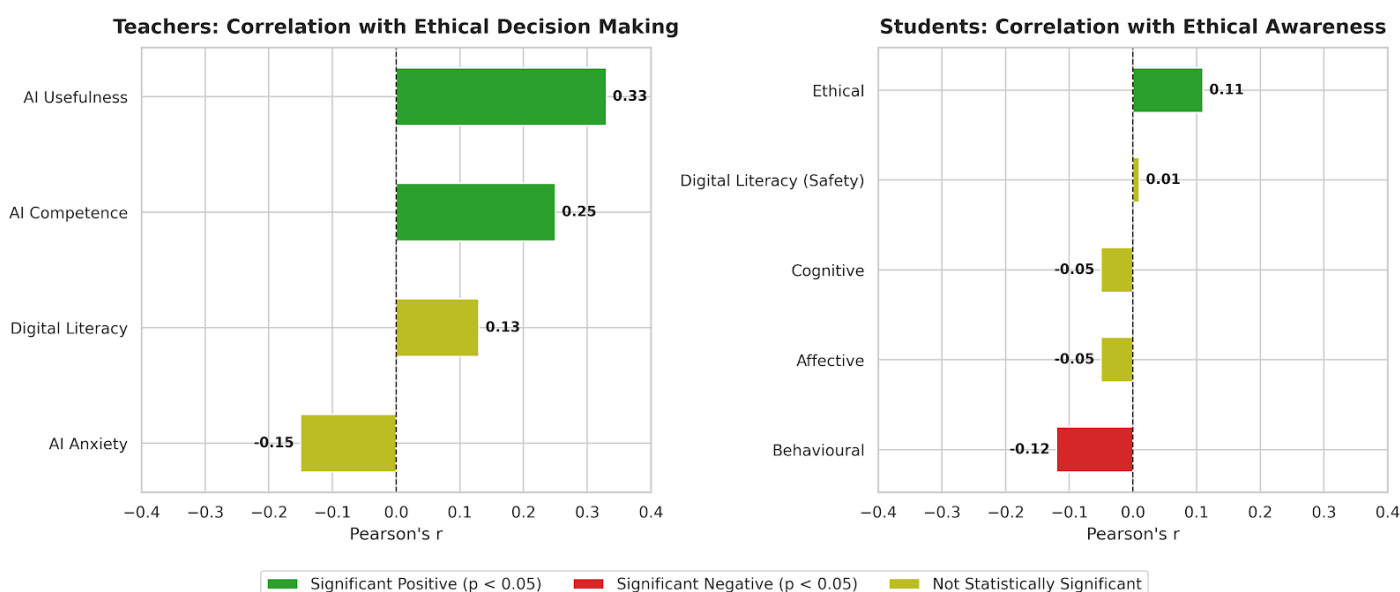
associations between AI Competence, AI Anxiety, AI Usefulness, and Digital Literacy and Ethical Decision Making were analysed. In the students sample, the relationships between the Affective, Behavioural, Cognitive, Ethical, and Digital Literacy dimensions and Ethical Awareness were examined. As shown in Table 22, in the teachers sample the correlations with Ethical Decision Making were rather weak. Significant positive associations were observed for AI Competence ($r = 0.25$, $p = 0.039$) and AI Usefulness ($r = 0.33$, $p = 0.005$). The remaining correlations were insignificant ($p > .05$).

In the students sample, all associations were weak. Significant but weak was the negative correlation with behavioural dimension ($r = -0.12$, $p = 0.049$) and significant but weak was the positive correlation with ethical dimension ($r = 0.11$, $p = 0.049$). Remaining correlations did not reach statistical significance ($p > .05$)

Table 22. Pearson correlations between the main dimensions and the ethical outcome variables

Sample	Dependent variables	Variables	Pearson r	P
Teachers	Ethical Decision Making (2nd Scenario)	AI Competence	0.25*	0.039
		AI Anxiety	-0.15	>0.05
		AI Usefulness	0.33*	0.005
		Digital Literacy	0.13	>0.05
Students	Ethical Awareness (Scenario SD05)	Affective	-0.05	>0.05
		Behavioural	-0.12*	0.049
		Cognitive	-0.05	>0.05
		Ethical	0.11*	0.049
		Digital Literacy (Safety)	0.01	>0.05

Figure 15: Correlations



3.3.2. Multiple linear regression models

Multiple linear regression models were estimated to examine the extent to which the main AI literacy dimensions predicted the ethical outcome variables in both samples. In the teachers sample, the dependent variable was Ethical Decision Making, whereas in the students sample the outcome variable was Ethical Awareness. As reported in Table 23, in the teachers sample the overall model was not statistically significant, $F(4, 66) = 2.019$, $p = 0.102$, and explained a small proportion of the variance ($R^2 = 0.109$; adjusted $R^2 = 0.055$). From the predictors only AI usefulness was significant ($B = 0.334$, $p = 0.048$). In the students sample, the regression model was statistically significant, $F(5, 344) = 3.844$, $p = 0.002$, although its explanatory power was weak ($R^2 = 0.053$; adjusted $R^2 = 0.039$). In this case, the Affective ($B = 0.274$, $p = 0.048$) and Behavioural ($B = -0.371$, $p = 0.002$) dimensions predicted the dependent variable of the model and the rest were not significant.

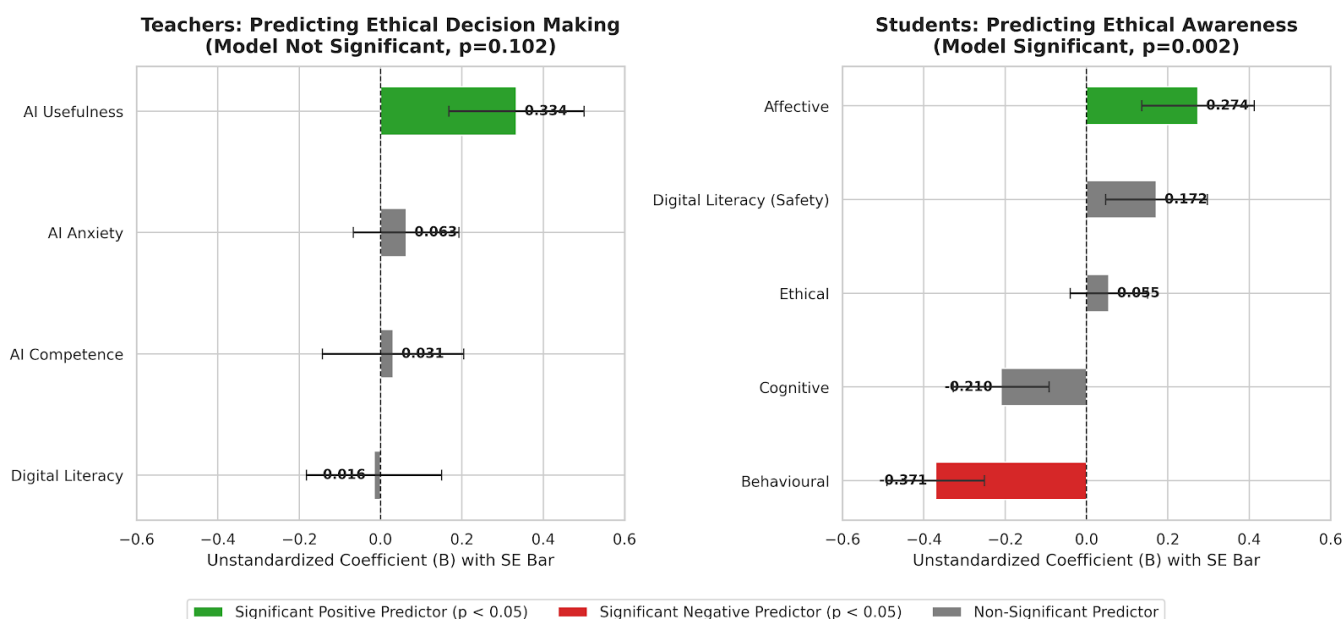
Table 23. Multiple linear regression models

Sample	Outcome variable	Predictor	B	SE	t	p
Teachers	Ethical Decision Making (2nd Scenario)	AI Competence	0.031	0.174	0.179	0.858
		AI Anxiety	0.063	0.130	0.482	0.631
		AI Usefulness	0.334	0.166	2.013	0.048
		Digital Literacy	-0.016	0.166	-0.097	0.923
Students	Ethical Awareness (Scenario SD06)	Affective	0.274	0.138	1.984	0.048
		Behavioural	-0.371	0.120	-3.098	0.002
		Cognitive	-0.210	0.118	-1.785	0.075
		Ethical	0.055	0.095	0.577	0.564
		Digital Literacy (Safety)	0.172	0.125	1.377	0.170

Note. Teachers: $R^2=0.109$, adjusted $R^2=0.055$, $F(4,66)=2.019$, $p=0.102$.

Students : $R^2=0.053$, adjusted $R^2=0.039$, $F(5,344)=3.844$, $p=0.002$.

Figure 16: Regressions



3.3.3. Group comparisons: t-test and ANOVA

Group comparison tests were conducted using t-tests and ANOVA in order to explore possible differences in the main dimensions according to background variables. In the teachers sample, the t-test was applied by gender, while ANOVA was conducted according to age, teaching experience, educational level, and specialty. In the students sample, the t-test was used for gender comparisons, whereas ANOVA was performed according to age, frequency of AI use, and perceptions of AI use in schoolwork.

In the teachers sample, there were not any significant differences based on gender, or age, or years of service. Type of school differentiated teachers regarding digital literacy with teachers working in vocational schools scoring higher. But the small number of members in this subgroup means we have to approach this finding with caution. Use of AI was a strong control variable with the ones with active AI use, scoring higher in AI competence, AI usefulness and digital literacy and lower in AI anxiety.

Table 24 Summary of significant group comparisons in the teachers' sample

Grouping variable	Dependent variable	Test	Statistic (F/t)	P
Gender	AI Competence	T test	-1,242	,225
	AI Anxiety		1,307	,202
	AI Usefulness		,277	,783
	Digital Literacy		1,424	,159
	Ethical decision making		,367	,715
Age	AI Competence	anova	2,421	,074
	AI Anxiety		1,507	,221
	AI Usefulness		1,904	,137
	Digital Literacy		2,115	,107

	Ethical decision making		.609	,611
Years of service	AI Competence	anova	2,286	,087
	AI Anxiety		,244	,865
	AI Usefulness		,651	,585
	Digital Literacy		2,293	,086
	Ethical decision making		,181	,909
Type of school	AI Competence	anova	2,704	,074
	AI Anxiety		1,311	,276
	AI Usefulness		2,568	,084
	Digital Literacy		4,489	,015
	Ethical decision making		,051	,950
Studies	AI Competence	anova	,415	,743
	AI Anxiety		1,944	,131
	AI Usefulness		,872	,460
	Digital Literacy		2,638	,057
	Ethical decision making		,837	,478
Use of AI	AI Competence	anova	20,877	,000
	AI Anxiety		4,891	,010
	AI Usefulness		8,171	,001
	Digital Literacy		5,118	,009
	Ethical decision making		,347	,708

By contrast, several statistically significant differences were identified in the students sample, as summarized in Table 25. In the gender comparisons, significant differences were found in Affective, Behavioural, Cognitive and safety, with boys scoring higher. Age only differentiated students on ethical awareness with students of 18 years old scoring higher than all other age groups. AI use and AI homework opinion differentiated students in all variables making it a very strong control variable. The ones who use AI regularly and the ones that believe AI helps them learn, scored higher in most dimensions.

Table 25. Summary of significant group comparisons in the students samples

Grouping variable	Dependent variable	Test	Statistic (F/t)	P
Gender	Affective	ANO VA	7.131	0.001
	Behavioural	ANO VA	8.548	< .001
	Cognitive	ANO VA	3.899	0.021
	Ethical	ANO VA	4.265	0,161
	Safety	ANO VA	1,837	,015
Age	Affective	ANO VA	1,175	,313
	Behavioural	ANO VA	,988	,445
	Cognitive	ANO VA	,944	,480
	Ethical	ANO VA	,761	,637
	Safety	ANO VA	3,030	,003
AI Use	Affective	ANO VA	6,363	,000
	Behavioural	ANO VA	3,925	,009
	Cognitive	ANO VA	2,886	,036
	Ethical	ANO VA	5,948	,001
	Safety	ANO VA	2,263	,081
AI Homework Opinion	Affective	ANO VA	4.427	0.005
	Behavioural	ANO VA	3.447	0.017
	Cognitive	ANO VA	5.398	0.001
	Ethical	ANO VA	2.872	0.036
	Safety	ANO VA	1,642	,179

Findings of the research hypothesis follow for both, teachers and students samples in two different tables.

Table 26: Research hypothesis and findings

RESEARCH HYPOTHESIS	FINDING
H1 Competence is positively associated with ethical decision making	Partially Supported Perceived competence had a significant positive correlation with ethical decision-making in the second scenario ($r_s = .25$, $p = .039$) and the third

	scenario ($r_s = .24$, $p = .043$). However, it showed no significant correlation with the first scenario.
H2 Perceived usefulness is positively associated with ethical decision making	Partially Supported Perceived utility is positively demonstrated a moderate, statistically significant positive correlation with the second scenario ($r_s = .33$, $p = .005$). There were no statistically significant correlations found between utility and the first or third scenarios.
H3 Digital Literacy is positively associated with ethical decision making	Rejected
H4 Anxiety is negatively associated with ethical decision making	Partially Supported Technology-related anxiety showed a significant negative association with ethical decision-making, but only in the third scenario ($r_s = -.26$, $p = .031$). This indicates that lower anxiety is associated with higher scores on the third ethical scenario. However, this relationship did not hold true for the first or second scenarios, where no significant correlation was found.
H5 The set of the four IV can predict the teachers decision making	Rejected for all 3 scenarios.
H6 Mean scores across the variables differ significantly according to gender	Rejected
H7 Mean scores across the variables differ significantly according to age	Rejected
H8 Mean scores across the variables differ significantly according to years of service	Rejected
H9 Mean scores across the variables differ significantly according to school type	Partly accepted the analysis revealed a statistically significant main effect for Digital Literacy based on school type: teaching in a vocational or alternative setting was associated with significantly higher digital literacy compared to traditional middle and high school settings
H10 Mean scores across the variables differ significantly according to studies	Rejected
H11 Mean scores across the variables differ significantly according to AI use	Accepted Unlike previous demographic variables, the primary reported use of AI—categorized as administrative work, teaching preparation, and active integration—yielded highly statistically significant main effects across almost all measured dimensions: Competence: The analysis revealed a highly significant main effect. Teachers using AI strictly for administrative work reported the lowest competence. Furthermore, the active integration group scored significantly higher than the teaching preparation group.

	Digital Literacy: Teachers with active AI use demonstrated significantly higher digital literacy than both the teaching preparation group and the administrative group. Perceived Utility: Teachers restricted to administrative use perceived significantly less utility compared to those using it for teaching preparation and active integration. Anxiety: A significant main effect was found. Teachers using AI solely for administrative work experienced the highest anxiety. First Scenario (AI Assistant): A significant main effect was observed. The administrative group scored significantly lower than both the teaching preparation group and the active integration group.
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Next table demonstrate hypotheses findings for the students sample.

Table 27: Research hypothesis and findings (students sample)

RESEARCH HYPOTHESIS	FINDING
H1 Affective is positively associated with ethical decision making	Rejected
H2 Behavioural is positively associated with ethical decision making	Partly accepted (negative small correlations with 2nd and 3d scenario)
H3 Cognitive is positively associated with ethical decision making	Partly accepted (negative small correlations with 3d scenario)
H4 Ethical is positively associated with ethical decision making	Partly accepted (positive small correlations with 2d scenario)
H5 Safety is positively associated with ethical decision making	Partly accepted (positive strong correlations with 3d scenario)
H5 The set of the five core dimensions can predict the students decision making in the three scenario	Partly accepted (regressions predicted 2nd and 3d scenaria)
H6 Mean scores across the variables differ significantly according to gender	Partly accepted (boys scored significantly higher than girls in the Affective dimension ($p = .001$), the Behavioural dimension ($p < .001$), the Cognitive dimension ($p = .020$), and the Safety dimension ($p = .011$) than girls.)
H7 Mean scores across the variables differ significantly according to age	Limited acceptance (the 20-year-old students scored significantly lower in the Ethical dimension compared to the 16-year-olds ($p = .012$), the 17-year-olds ($p = .020$), and the 18-year-olds ($p = .019$).)
H8 Mean scores across the variables differ significantly according to AI use	Partly accepted (for 2n and 3d scenario, and all dimensions except safety)
H9 Mean scores across the variables differ significantly according to AI value	Partly accepted (for all dimensions except safety, but none of the three scenaria)

4. Qualitative Analysis and Dilemma Scenarios (SJT)

4.1 Thematic analysis and content coding of focus groups/interviews

Due to time constraints and the extensive amount of quantitative data that had to be previously collected and analysed, the qualitative phase of the study was limited to a small exploratory sample. Interview recordings were collected from:

- 5 secondary school teachers
- 5 secondary school students

Tables 28 and 29 that follow, offer basic demographics for teachers and students interviewees that participated in the qualitative section.

Table 28 Description of teachers that were interviewed

TEACHERS	Age	Field	Years of service	Gender
1	65	Sociology	34	Male
2	48	Language	21	Female
3	37	Informatics	9	Male
4	44	Mathematics	14	Male
5	50	Language	22	Female

Table 29: Description of students that were interviewed

STUDENTS	Age	Field	Gender
1	17	Humanities	Female
2	18	Science	Male
3	18	Informatics	Male
4	19	Humanities	Female
5	17	Health	Male

A pilot qualitative analysis was conducted with the interviews of secondary school teachers in order to identify preliminary themes, perceptions, and emerging concerns regarding the use of AI in education. However, the current qualitative sample is still limited and should not be considered representative at national level. Therefore, before extending the analysis to the remaining participant groups, it is recommended to enlarge the sample in order to ensure greater validity, reliability, and robustness of the findings included in the National Report.

4.2 Dilemma Scenarios Analysis

The qualitative analysis followed these phases:

- First, a list was drawn up with the recurring concepts of the answers.
- Next, the frequency levels of each concept were identified.
- After this, the most iterative concepts were regrouped into codes and subcodes.
- Finally, frequencies and percentages were analysed.

The freeware mermaid.js was used for the transformation of themes tables into graphs.

Thematic Analysis and Content Coding of Focus Groups/Interviews

4.2.1 teacher section

The distribution shows a relatively even weighting across thematic clusters, with recurrent mid-high frequency codes (AF = 5; 6.6%) appearing across barriers, benefits, and ethical AI, indicating a structurally symmetrical perception of AI in education as both enabling and constraining. Pedagogical concerns linked to integrity, validity of content, and systemic limitations co-occur with parallel emphasis on efficiency, engagement, and inclusivity, suggesting a dual framing of AI as both an instructional augmentation tool and a source of epistemic disruption. Lower-frequency cognitive and mental health codes indicate secondary salience but persistent awareness of risks such as cognitive offloading, reduced attentional control, dependency, and social withdrawal, pointing to emerging but not dominant concern for learner autonomy and wellbeing. Ethical AI codes concentrate on transparency, intellectual property, bias mitigation, and human oversight, aligning with European higher education discourses on responsible innovation and governance. Overall, the pattern reflects a balanced but pedagogy-centred interpretive structure in which AI is positioned within higher education as simultaneously a driver of instructional efficiency and a generator of epistemic, ethical, and cognitive tensions (table 30).

Table 30. Thematic analysis of teachers.

Codes	Subthemes	AF	AF%
barriers / fears	Decreased pedagogical Integrity	5	6.6%
	Risk of non valid content	5	6.6%
	Professional & Systemic Barriers	4	5.3%
	Human-Centric & Ethical Concerns	3	3.9%
Ai benefits	Instructional Efficiency (eg Accelerated Content Production)	5	6.6%
	Enhanced Student Engagement	5	6.6%
	Personalized & Inclusive Learning	4	5.3%
	Professional & Pedagogical Shift	3	3.9%
ai drawbacks	Cognitive & Intellectual Atrophy	4	5.3%
	Illusion of Knowledge	3	3.9%
risks to mental health for students	Social Isolation	2	2.6%
	Addiction & Behavioral Issues	5	6.6%
Risks to cognitive health for students	Cognitive Entrapment	1	1.3%
	Decision-Making Impairment	1	1.3%
	Dehumanization of Learning	3	3.9%
	Decreased attention & Concentration	2	2.6%
what is ethical ai	Intellectual Property & Citation	5	6.6%
	Data Anonymity	3	3.9%
	Pedagogical Ethics	5	6.6%
	Human-in-the-Loop	4	5.3%
	Bias & Hallucination Awareness	4	5.3%
TOTALS		76	100%

It is methodologically important to note that the summary tracking in Table 30 reflects distinct conceptual code occurrences, whereas the subsequent detailed analytical tables (Tables 31–38) map the granular frequency of specific statements and thematic sub-nodes. Because an individual participant may express multiple concurrent concepts or cross-cutting arguments within a single response, the cumulative code counts in the thematic breakdowns naturally exhibit a higher density than the absolute participant-level clusters.

More analytically, table (31) categorizes teachers' concerns regarding the integration of AI into education into four overarching themes: Pedagogical integrity, epistemic and technical risks, professional and systemic barriers, and human-centric and ethical concerns. Each theme highlights

distinct subthemes—such as academic dishonesty, AI hallucinations, institutional neglect, and the potential dehumanization of education—supported by specific qualitative extracts from the teachers. According to the frequency metrics provided, the primary pressures driving this educational anxiety center around plagiarism and loss of students' critical thinking and AI hallucinations (the generation of technically erroneous information), both of which appear most frequently across the data set.

Table 31: What are the main barriers or fears (e.g., fear of replacement, lack of skills) that you encounter in the adoption of AI in your school?

Main Theme	Subthemes	Extract	Frequency
1. Pedagogical Integrity	Academic Dishonesty	it's no longer just about students copying some detail from another student... now they can generate entire essays... with minimal effort.	2
	Crisis of Assessment	Am I evaluating the student's understanding, or the machine's output? It challenges the very idea of assessment. And this is very disheartening	2
	Cognitive De-skilling	students have simply stopped trying to develop their own voice or critical thinking... effort became an optional thing.	3
2. Epistemic & Technical Risks	AI Hallucinations	AI often improvises—what is technically referred to as AI hallucination—so it is easy for it to lead you toward erroneous conclusions.	3
	Erosion of Truth	We are heading toward a reality where erroneous claims are becoming slowly legitimized... I'm afraid that this will take us to many mistakes that will gradually will be treated as correct information	2
	Verification Burden	It requires a higher level of critical thinking to detect inaccuracies... need to constantly verify and filter.	2
3. Professional & Systemic Barriers	The Digital Divide	we are being split into two different categories of teachers... AI-literate group... and everyone else.	1
	Institutional Neglect	the state simply drops these tools on us and tells us to figure it out on our own, without providing any real, systemic training.	1
	Workload & Burnout	We are already burnt out, and now there is this constant,	2

		unbearable pressure to reinvent the wheel.	
4. Human-Centric & Ethical Concerns	Dehumanization of Education	The fear here is... about the potential loss of the human dimension in education... relationships, empathy, mentorship.	2
	Teacher Displacement	fear of promoting AI in a way that could eventually replace teachers... reduce the role of human teachers.	1
	Ecological & Societal Impact	environmental cost of operating AI data centers... technological shift that could have unpredictable consequences for society.	2

The visualization follows to facilitate the reading of table's data.

Figure 17: Barriers and fear

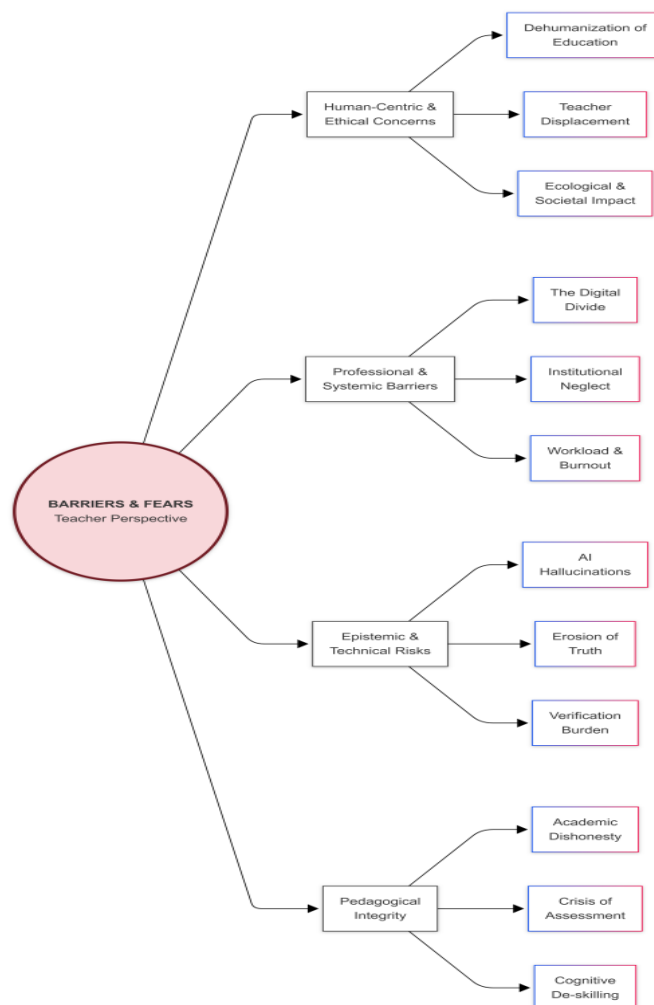


Table 32 outlines the perceived benefits and opportunities of integrating AI into the classroom, organizing teachers positive insights into four core themes: instructional efficiency, enhanced student

engagement, personalized and inclusive learning, and professional and pedagogical shift. the data highlights a transition toward more dynamic classrooms, where AI serves as a catalyst for creative contextualization, differentiated instruction, and linguistic equity—such as adapting materials into foreign students' native languages. Based on the frequency data, the most significant advantages recognized by teachers are accelerated content production (the rapid creation of lesson materials) followed closely by gamification and differentiated instruction, emphasizing that AI's greatest immediate value lies in drastically reducing preparation time while simultaneously allowing teachers to tailor engaging experiences to diverse student needs.

Table 32: in which specific areas do you believe AI can offer the greatest opportunities to improve teaching quality?

Main Theme	Subtheme	Extract	Frequency
1. Instructional Efficiency	Accelerated Content Production	easy and fast production of material. It once took up the entire afternoon; now, it is just a few minutes away	4
	Bureaucratic Relief	reduction of the bureaucratic workload. Tasks such as document formatting, drafting instructions... can be streamlined	2
	Resource Synthesis	feed the AI three different academic articles and ask for a bulleted synthesis and a set of tiered materials	1
2. Enhanced Student Engagement	Gamification & Interaction	transform a dry history lesson into a digital Choose Your Own Adventure game... kids are thrilled.	3
	Creative Contextualization	ask AI for modern-day analogies... as if a past event were happening now... children adore these parallels.	2
	Visual & Accessible Content	present content in more engaging and catchy ways... simplifying complex concepts, generating visual aids.	2
3. Personalized & Inclusive Learning	Differentiated Instruction	create customized materials... every student (or at least groups of students) has materials close to their needs.	3
	Linguistic Equity	instantly adapt information into the native languages of my students who understand limited Greek... ensures equity.	1
	Autonomous Pathways	develop exercises that provide feedback to students, allowing them to improve without constant teacher intervention.	1
4. Professional & Pedagogical Shift	Shift to Facilitator Role	moves us from the role of a lecturer... to the role of a facilitator who helps children understand the process.	1
	Focus on High-Level Skills	students can spend their energy on high-level tasks—such as ethical analysis, critical questioning, creative reframing.	1

	Teacher Well-being	This found time now goes exactly where it should: toward self-care, which leaves me more rested and productive.	1
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Figure 18: advantages

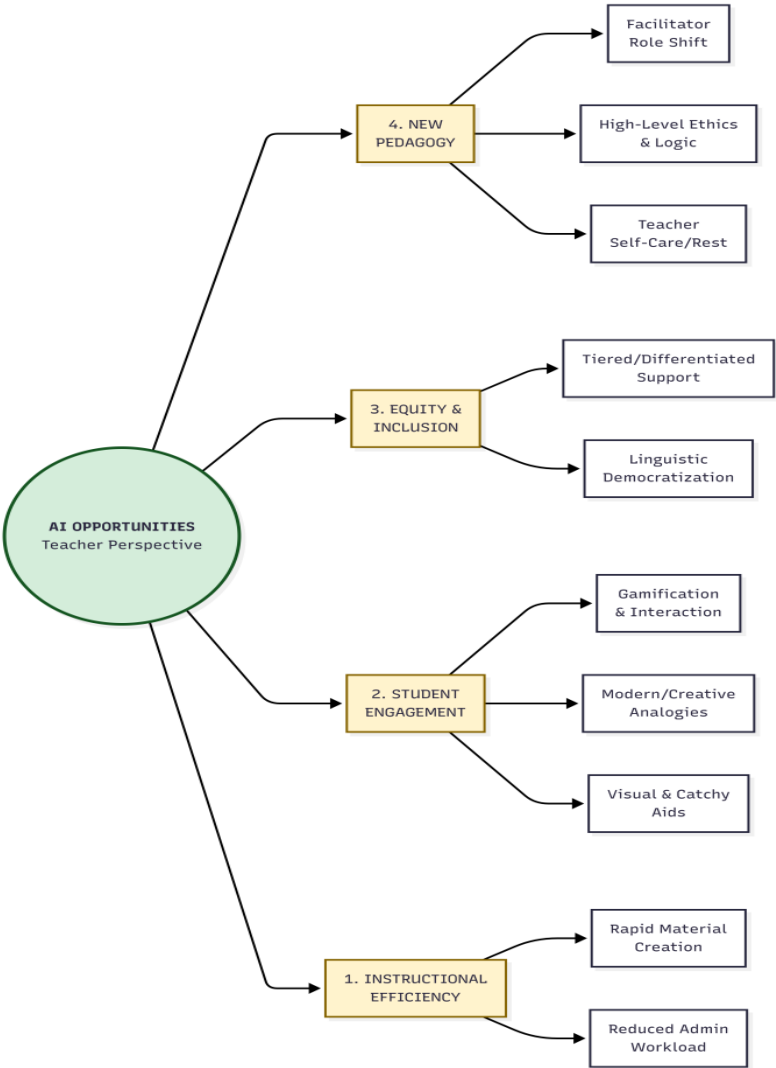


Table 33 maps out the psychological, social, and developmental risks teachers associate with AI usage, clustering them into four critical themes: cognitive and intellectual atrophy, emotional and psychological fragility, social and relational erosion, and agency and ethics. The extracts capture a deep anxiety about how machine interaction alters human development, highlighting subthemes like decreased frustration tolerance, digital anthropomorphism (treating ai as a human friend), and intellectual detachment. according to the frequency metrics, the most acute concern is cognitive laziness—the weakening of deep learning neural pathways due to effortless information retrieval—followed closely by the illusion of knowledge, a general dehumanization of the learning experience, and a fragile emotional state where students quickly abandon'tasks because they cannot tolerate the struggle of a natural, imperfect creative process.

Table 33: Considering the Slow Tech approach (which prioritizes human well-being over technological acceleration), what risks do you see in the daily use of AI for students' mental and cognitive health?

Main Theme	Subtheme	Extract	Frequency
1. Cognitive & Intellectual Atrophy	Cognitive Laziness	The reduction in the effort required to retrieve information... weakens the neural connections associated with deep learning.	5
	Illusion of Knowledge	students often confuse an AI-generated answer with their own understanding... creates a gap in self-awareness.	3
	Attention & Concentration	deterioration of the attention span... today's children are unable to focus on anything for long.	2
2. Emotional & Psychological Fragility	Decreased Frustration Tolerance	eliminates the incredibly useful stage of struggle ... making them more prone to anxiety when facing problems AI cannot solve.	3
	Inadequacy & Fatalism	Students compare their own imperfect creative process with the flawless... output of the machine... leading to abandonment.	2
	Addiction & Behavioral Issues	Children behave with AI like substance abusers... acting like addicts seeking their fix.	1
	Digital Anthropomorphism	tendency of children to view AI as an invisible human friend... turn there for company, conversation, advice, and secrets.	2
3. Social & Relational Erosion	Dehumanization of Learning	If students increasingly interact with machines rather than people, learning may lose its relational and emotional dimension.	3
	Social Isolation	they prefer staying at home, hunched over an electronic device... blurring the lines between reality and virtual reality.	2
	Intellectual Detachment	students feel less personal responsibility for the content... I didn't write it, the AI said it, so it must be right.	2
4. Agency & Ethics	Cognitive Entrapment/Bias	limits the students' cognitive flexibility... they recycle and confirm their own biases and prejudices.	1
	Decision-Making Impairment	excessive use of tools that think for the student can hinder the development of the prefrontal cortex... center for decision-making.	1

Figure 19: disadvantages for students

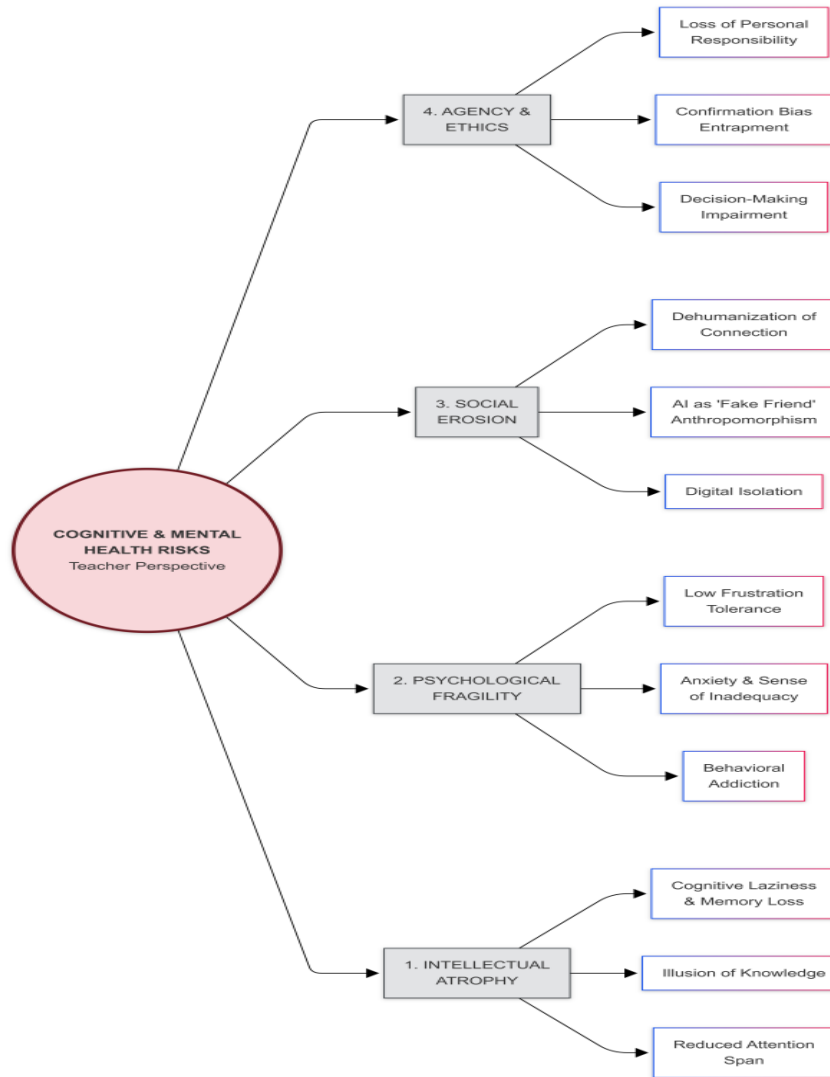


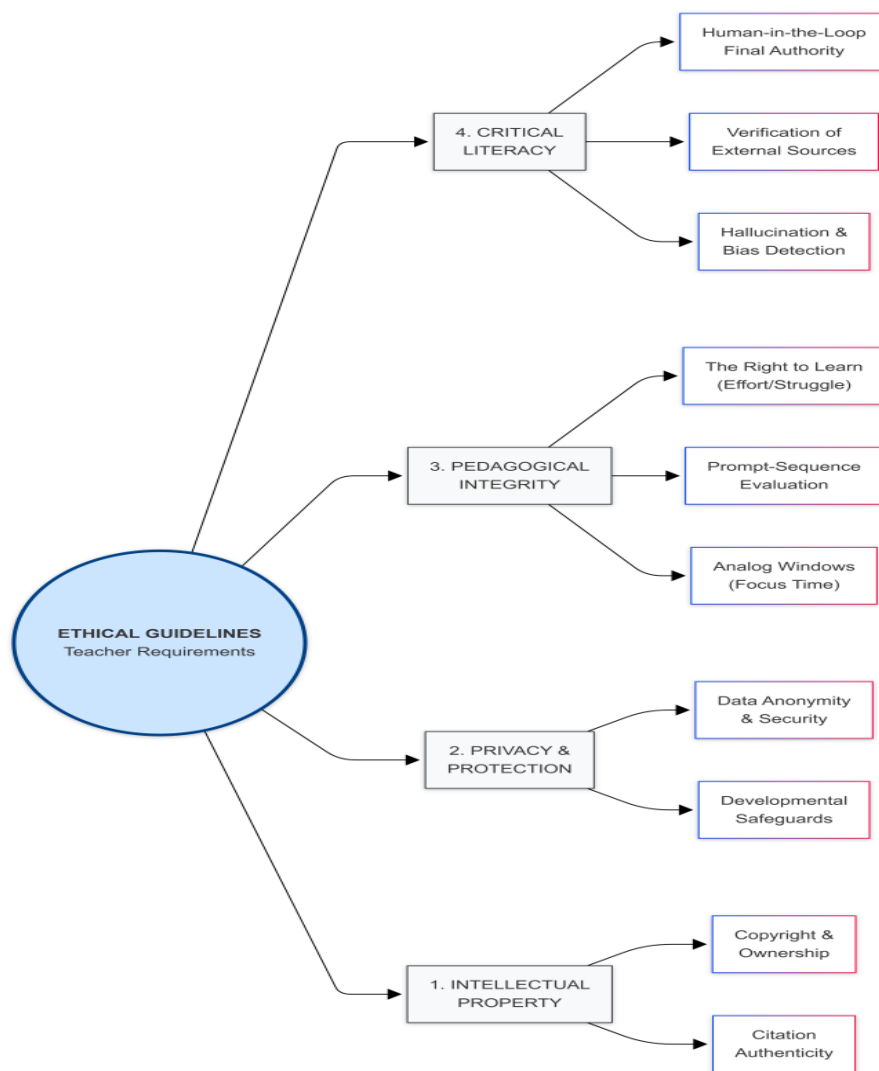
Table 34 organizes the ethical guidelines and regulatory frameworks teachers believe are necessary for AI integration into four primary themes: intellectual property and citation, privacy and safety safeguards, pedagogical ethics, and critical literacy and oversight. The data underscores a strong demand for structure, emphasizing subthemes like process-oriented evaluation, data anonymity, and the creation of Analog Windows to preserve focused, offline learning spaces. The frequency data reveals that the single highest priority for teachers is maintaining a Human-in-the-Loop approach, where human judgment remains the ultimate controller of AI outputs, supported closely by a rigorous verification mindset, a demand for explicit copyright/authorship clarity, and a protective defense of the student's sacred right to learn over effortless shortcut prompt generation.

Table 34: Do you feel the need for clearer guidelines for ethical use? If so, on which specific aspects?

Main Theme	Subtheme	Extract	Frequency
1. Intellectual Property & Citation	Authorship & Copyright	clarity around copyright and ownership... what content can be used, adapted, or shared.	3
	Verification of Sources	AI generates many non-existent bibliographic references... correct intellectual owner not cited.	2

2. Privacy & Safety Safeguards	Data Anonymity	ensure that no personal or sensitive information is shared... rules should define what is safe to input.	2
	Protection of Minors	safeguards for minors, ensuring that the content they access through AI is appropriate [and] safe.	1
3. Pedagogical Ethics	The Right to Learn	Who will protect the children's sacred right to learning... if [it] is replaced by a single prompt?	3
	Process-Oriented Evaluation	teachers must ask students about the entire succession of prompts: what did they ask, in what order, and why?	2
	Analog Preservation	hours where technology stays outside the door... Analog Windows ... forced to focus deeply.	1
4. Critical Literacy & Oversight	Human-in-the-Loop	AI must not replace human judgment... the human factor, human judgment... must be the controller.	4
	Verification Mindset	Nothing that comes out of AI should be considered final ... you sit down, read it, find where the machine made a mistake.	3
	Bias Hallucination & Awareness	understand that AI is not an infallible being... much of [the online data] may be wrong.	2

Figure: ethical guidelines



Dilemma Scenarios Analysis (Efficiency vs. Equity, Personalization vs. Privacy, Autonomy vs. Assistance)

Teachers -FIRST SCENARIO

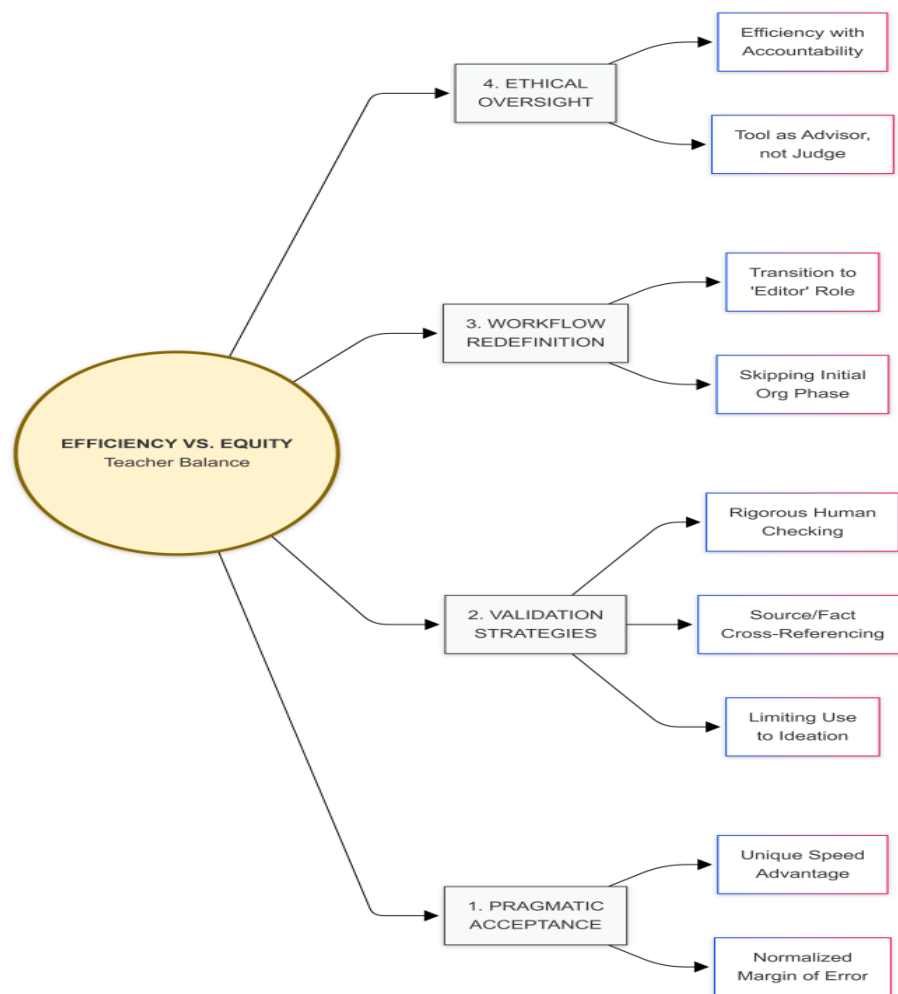
The answer to whether a discriminatory margin of error is acceptable for time savings is not a simple yes or no, but rather a negotiation between convenience and human oversight. When directly addressing this dilemma, teachers' responses split into two rather competing stances: Pragmatic acceptance with strict conditions: There is a willingness to accept this trade-off, driven by the unique speed and ease AI provides. With Time-value tradeoff and strict validation tying for the highest frequency, the consensus is that teachers are willing to risk using these tools for the sake of efficiency, but only if they implement a rigorous human verification process afterward.

The red line of accountability: Teachers reject delegating the final verdict to the machine. Through the lenses of human-in-the-loop and non-delegation, the data demonstrates that while an initial algorithmic error margin is tolerated to skip the time-consuming search and organization phase, it becomes unacceptable if the teacher abdicates their role as the ultimate ethical anchor and final editor. In short, table 35 shows that teachers will accept the error margin as a drafting shortcut, but they strictly reject it as a final committing decision.

Table 35: Discussion on algorithmic bias in automated grading. Prompt: Is a discriminatory margin of error acceptable in exchange for significant time savings for the teacher?

Main Theme	Subtheme	Extract	Frequency
1. Pragmatic Risk Acceptance	Time-Value Tradeoff	the speed and ease are unique... the possibility of errors does not discourage me.	4
	Error normalization	reasonable to accept that some margin of error exists... doesn't necessarily mean we should avoid it.	3
2. Mitigation Strategies	Strict validation	I would always follow up AI-generated outputs with a more rigorous, almost austere validation process.	4
	Cross-Referencing	look for sources and cross-reference information from elsewhere that you aren't able to confirm yourself.	2
	Initial ideas	stopped trusting it for material production and use it only for initial ideas... it's logical for mistakes to happen.	1
3. Workflow Evolution	Editing help	Now I only do corrections... it will save me 90% of the work.	2
	Search help	allows you to skip the initial search and organization phase, which is often the most time-consuming part.	1
4. Accountability & Ethics	Human-in-the-loop	The ethical balance lies in combining efficiency with accountability... support tool rather than a decision-maker.	3
	Non-Delegation	if you want to be serious, you don't give the material to third parties before checking it.	2

Figure: first scenario



SECOND SCENARIO - teachers

According to the table (36), the ethical limit is breached when data collection crosses these lines:

Transparency and consent: From a governance perspective, the threshold is crossed the moment data tracking becomes non-transparent and non-consensual. For some, total anonymity (ensuring never any names involved) is the only baseline that keeps the process acceptable.

The loss of authenticity: Teachers argue that the ethical limit is reached when tracking alters student behavior. When students realize their every eye-movement is logged, they stop being authentic and begin performing for the machine —a psychological shift that critics warn is the first step toward a risky social credit system.

The compromise of human growth: The ethical boundary is also defined by the negative impact of hyper-personalization itself. Teachers argue that sheltering students from struggle cocoons them and spoils their resilience, violating a child's fundamental right to be unpredictable and impulsive, letting AI override the natural (and not always linear) evolution of their personality.

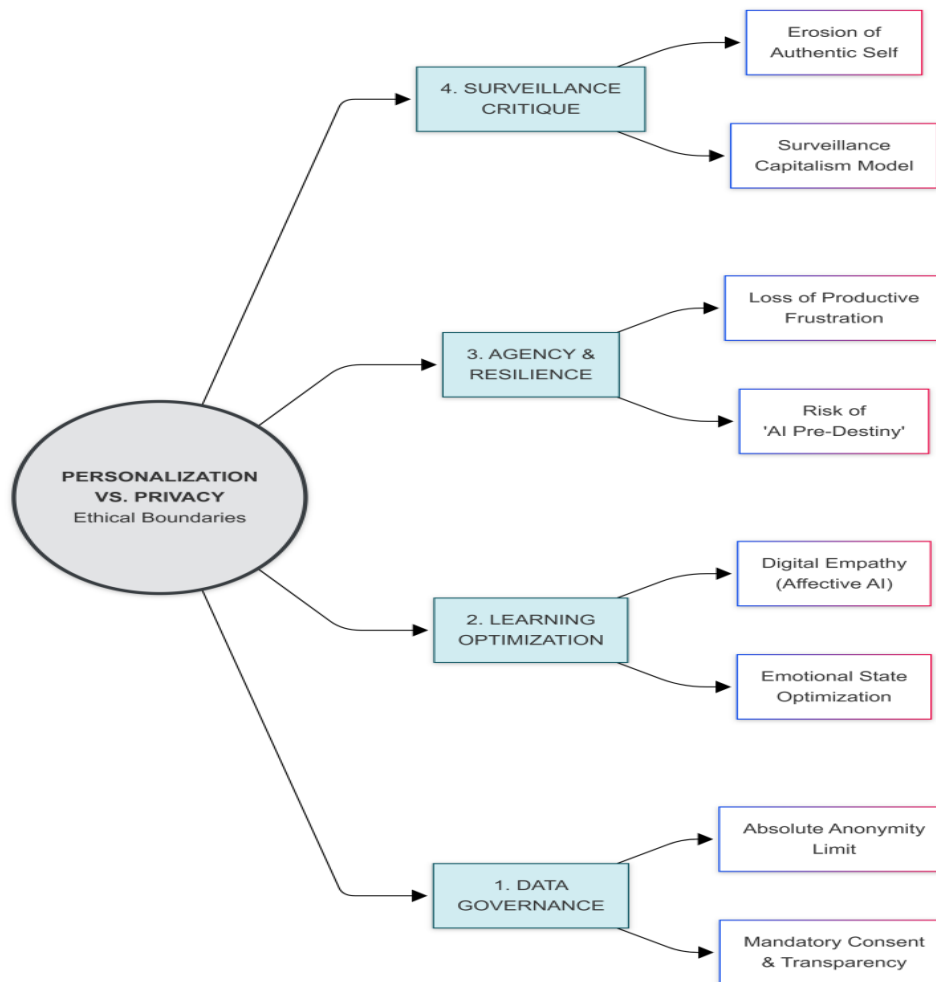
The Counter-argument: Conversely, a fraction of the data suggests the limit expands further if the outcome is purely supportive. From this viewpoint, tracking isn't surveillance—it is digital tuning that optimizes a student's emotional state for better learning.

In short, the table demonstrates that while some view emotional tracking as a tool for digital empathy, the ethical limit is crossed when data harvesting compromises student consent, forces children to perform mechanically, and strips away the necessary human friction required for real personal growth.

Table 36: Scenario B (Personalization vs. Privacy): Discussion on datafication. Prompt: What is the ethical limit in yielding students' behavioral data and emotions in exchange for hyper-personalized study paths?

Main Theme	Subtheme	Extract	Frequency
1. Data Governance & Anonymity	Anonymity as the Threshold	if the data is anonymous, the whole process should be fine... never any names involved.	1
	Consent & Transparency	The ethical limit is reached the moment the data collection becomes non-transparent and non-consensual.	1
2. Utilitarian Optimization	Digital Empathy	If an AI can detect that a kid's heart rate is spiking... and it immediately pivots... that's not surveillance—that's digital empathy.	1
	Emotional State-Based Learning	if we can optimize the emotional state, we optimize the human.	1
3. Developmental & Agency Risks	Erosion of Resilience	By hyper-personalizing everything... we are cocooning them... Real learning happens when you are frustrated and you push through it.	1
	The Right to be Unpredictable	I believe in the Right to be Unpredictable, and that AI pre-destiny is a threat to the natural evolution of a child's personality.	1
4. Surveillance & Socio-Political Risks	Performance for the Machine	When a child knows their every sigh and eye-movement is being logged... they stop being authentic. They start performing for the machine.	1
	Psychological Colonization	Mapping a child's emotions to sell them a study path is the first step toward a social credit system... it is predatory.	1

Figure: second scenario



THIRD SCENARIO - teachers

Increasing equity: Proponents argue that structuring with AI teaches students to be efficient in structuring data. This view aligns with emerging professional standard workflows in fields like law and journalism. Furthermore, it acts as a critical accessibility tool for students with learning differences, like dyslexia, who possess excellent ideas but struggle with the logistics of a blank page. It becomes a high-level skill when students engage in interactive revision—critiquing and rearranging the AI's template rather than accepting it blindly.

The case for plagiarism: Opponents argue that a student who finds the outline ready from an AI tool commits some kind of cognitive plagiarism. Because outlining is where the hardest intellectual work happens, outsourcing the hierarchy of information means the machine has effectively done the relevant, organizing thinking. This can lead to cognitive risks, including the homogenization of the human mind, which forces a default, mainstream, linear logic that erases eccentric, creative, or diverse ways of organizing thoughts.

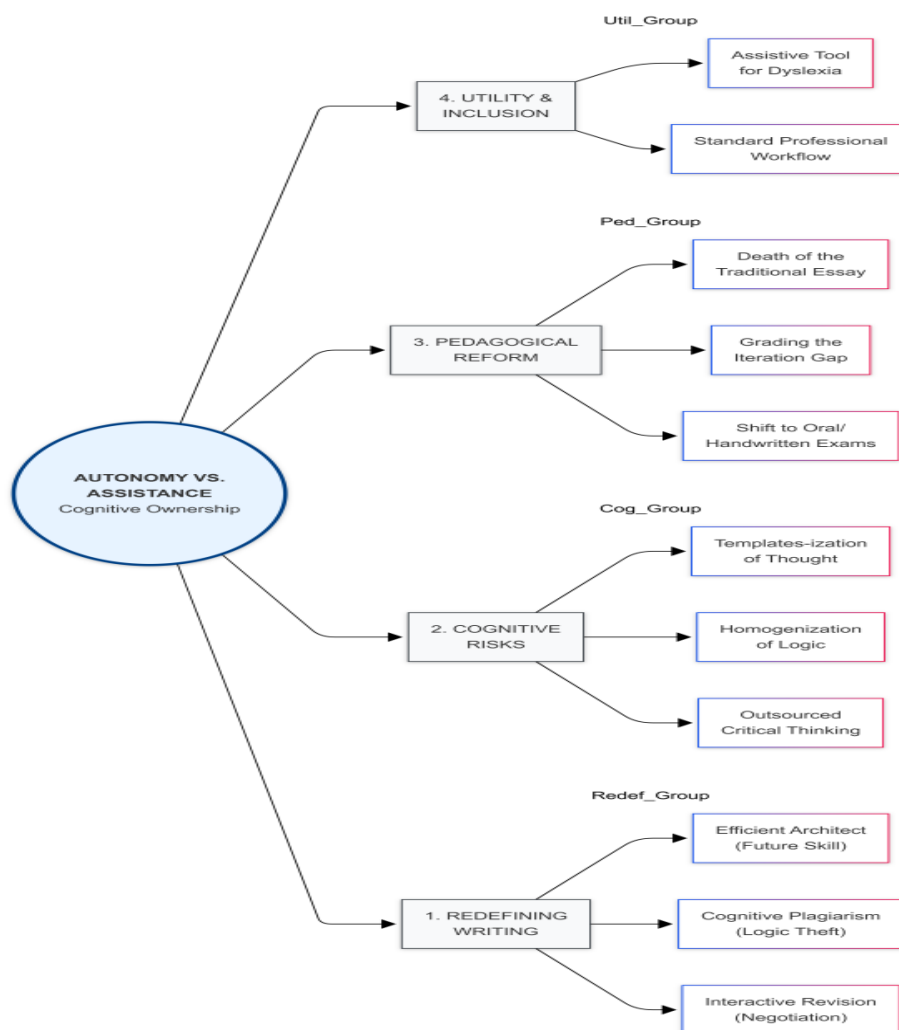
Because of this tension, table 37 suggests that in order to bridge the gap between future skill and plagiarism, there is a necessary shift where students are evaluated not just on the final text, but on how they prompted, modified, and justified the AI data.

Table 37: Scenario C (Autonomy vs. Assistance): Discussion on human agency. Prompt: If a student uses AI to structure an essay but writes the content themselves, is it a future skill or plagiarism?

Main Theme	Subtheme	Extract	Frequency
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1. Redefinition of Writing	Efficient data structuring	If a student can prompt an AI to generate a complex, logical structure... they aren't cheating; they're being an efficient architect.	2
	Cognitive plagiarism	Outlining is where the hardest intellectual work happens... You're essentially stealing from a logic model.	2
	Interactive revision	If a student uses AI to generate an outline, then critiques it, rearranges it... that is a high-level skill.	1
2. Cognitive Risks	Leading to a default approach	We are witnessing the templates-ization of the human mind... creative thinking will reduce and students will use more and more an AI default approach	1
	Homogenization	AI-driven structures lead to a Default Logic that erases eccentric, creative, or non-Western ways of organizing thoughts.	1
	Outsourcing logic	If the AI determines the priority and organization of information, it has effectively thought for the student, it has replaced him/her in an essential part of the learning process.	2
3. Pedagogical Shifts	Assessment obsolescence	the moment we allow AI to make the outline, the home essay as an assessment tool is dead.	1
	Process-based grading	I want to see the original prompt, the AI's structure, and the student's justification for why they changed it. Obviously checking just the output is not enough anymore	1
4. Inclusivity & Utility	Accessibility support	let's not forget kids with dyslexia who have brilliant ideas but struggle with the logistics of a blank page.	1
	Professional Standard	prepare the students for human-in-the-loop workflows that are becoming the standard in law, tech, and journalism.	2

Figure 20: third scenario



According to the teachers' input, such a model requires five fundamental pillars:

Systemic infrastructure: A sustainable model requires continuous human-in-the-loop oversight to monitor deployment, backed by domain-specific design built for classroom practices and continuous professional development to keep teachers digitally literate.

Transparency: To be useful, the model must feature AI that provides cognitive receipts—meaning it explicitly shows the data and logic behind its student evaluations. This clarity positions the AI as a co-pilot ensuring teachers understand its logic and feel empowered rather than replaced.

Collaborative intelligence: Instead of confining insights to a single classroom, AI can connect a school's collective intelligence, capturing and preserving the tacit, everyday teaching tricks that usually disappear when veteran teachers retire.

Adaptive pedagogy: It must feature agile scaffolding to create a liquid curriculum. Instead of a rigid, static lesson plan, a sustainable model dynamically adjusts the learning friction and difficulty in real-time for every individual desk, keeping students perfectly engaged in a state of learning flow.

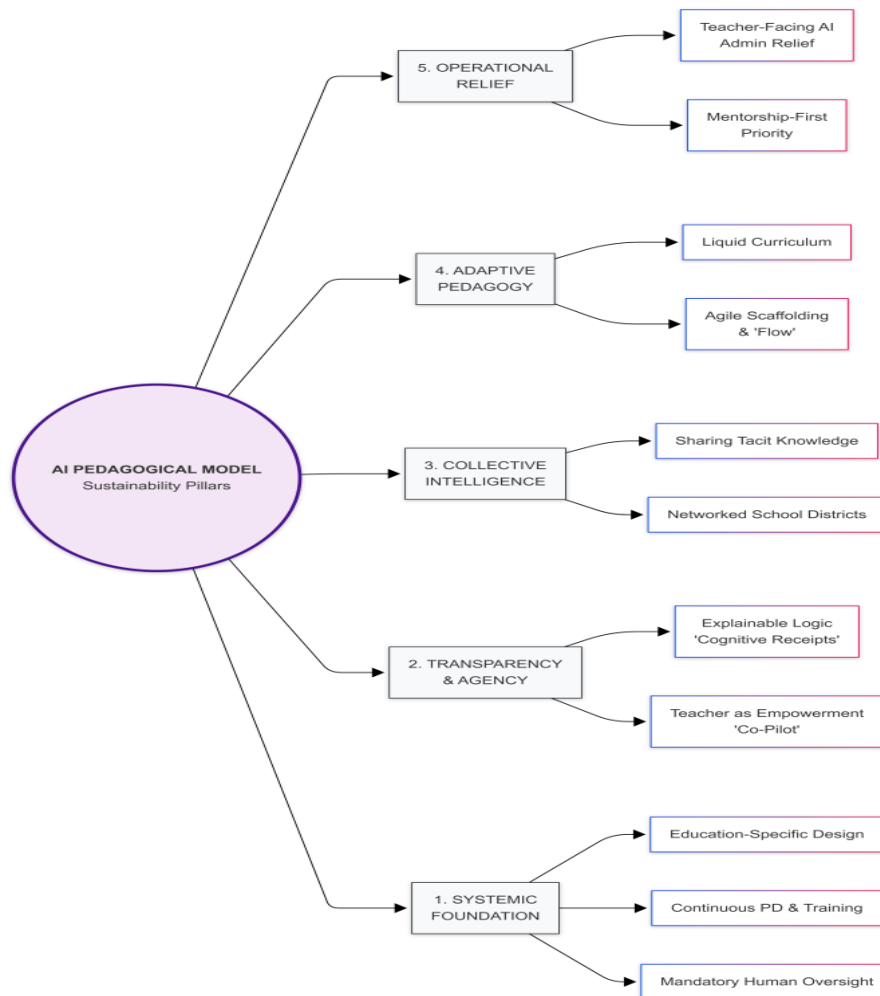
Operational sustainability: Teachers emphasize that the ultimate goal of educational AI must be to handle low-level cognitive and administrative clutter—like attendance patterns—solely to free up the teacher's time for high-value, emotional mentoring and relationship-building (table 38).

Table 38: What do you think should be the fundamental characteristics of an AI-based pedagogical model to be truly useful and sustainable for teachers?

Main Theme	Subtheme	Extract	Frequency
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1. Systemic Infrastructure	domain-specific design	built from the ground up specifically for education—tools that actually understand the classroom.	1
	continuous professional development	We need specialized training for both the teachers and the students... regular follow-ups to keep everyone on track.	1
	human-in-the-loop oversight	Humans have to stay in the loop to look at how the project is being used... keeping that human angle at every step. Ai can only be supportivw	2
2. Transparency & Agency	explainable ai	AI doesn't contribute in evaluating a student... so an AI model for education has to take into consideration the evaluation process	1
	teacher as co-pilot	when teachers understand the logic... they don't feel replaced—they feel empowered... Ai can be a diagnostic tool that sharpens intuition.	1
3. Collaborative Intelligence	networked knowledge sharing	facilitates the sharing of tacit school knowledge —those little teaching tricks that usually die when a teacher retires.	1
	breaking instructional silos	connects the experience of the entire school... moving from the idea of “My classroom” to the idea of “our classroom”.	1
4. Adaptive Pedagogy	liquid curriculum	... AI should constantly adjust the difficulty in real-time. in a sense it can contribute in the creation of a liquid curriculum that constantly self correct and self adjusts to the situational demands	1
	Tailored involvement	dynamically adjusting the difficulty for every single desk... ensure every student stays in a state of flow, with maximum involvement	1
5. Operational Sustainability	Administrative help	AI that handles the low-level cognitive load—like tracking attendance patterns... administrative work etc, helps immensely the teachers, freeing him from really dull work.	1
	mentorship preservation	clearing the mental clutter so that the only thing left for the human teacher to do is the high-value, emotional work of mentoring.	2

Figure 21: AI pedagogical model



STUDENTS

The distribution reflects a relatively coherent but uneven thematic structure centred on epistemic security, pedagogical adaptation, and learner autonomy. The most recurrent values (AF = 5; 11.6%) concentrate on institutional framing needs and dependency-related concerns, indicating that the dominant interpretive axis is not technical utility but governance of AI use within assessment and authorship contexts. Barriers and fears cluster around academic integrity risks such as cheating attribution, exposure anxiety, and content reliability, suggesting a strong orientation toward epistemic validation and control of knowledge production rather than purely technological skepticism. AI benefits are present but less structurally dominant, distributed across affective and cognitive facilitation functions such as non-judgmental tutoring, encouragement, scaffolding, and information efficiency, which positions AI primarily as a compensatory pedagogical support mechanism rather than a transformative instructional agent. AI drawbacks, although lower in frequency, point toward cognitive weakening and dependency patterns, with particular emphasis on reduced intellectual independence and overreliance dynamics, reinforcing the concern that AI may shift learning from production to validation-oriented behavior. The pedagogical frame category acts as a meta-level discourse, concentrating higher frequencies on the need for a unified regulatory and instructional structure, protection of academic integrity, and controlled integration of AI. This suggests that respondents conceptualize AI not as an isolated tool but as an element requiring systemic governance within higher education practice. Overall, the pattern is dominated by concerns over control, authorship, and dependency, with benefits acknowledged primarily in instrumental and supportive terms rather than epistemically transformative ones (table 39).

Table 39. Thematic analysis of students.

thematic areas	Codes	AF	AF%
barriers / fears	cheating accusations	4	9.3%
	fear of exposure	3	7.0%
	intellectual dependency	2	4.7%
	Unreliable content	4	9.3%
Ai benefits	Non-Judgmental Tutoring	2	4.7%
	Academic Encouragement	2	4.7%
	Cognitive Scaffolding (overcoming blank page)	2	4.7%
	Information Efficiency	3	7.0%
			11.6%
ai drawbacks	cognitive atrophy	5	7.0%
	Dependency	3	2.3%
	loss of personal voice	1	2.3%
	validation addiction	1	11.6%
Pedagogical frame	Need for a unified frame	5	11.6%
	Need to protect original work and meritocracy	5	2.3%
	Need to use AI controlling it and not being controlled by it	1	9.3%
Total		43	7.0%

More analytically and based on the interview data, students' approach AI offers four distinct patterns: Primary Activities: Students heavily favor AI as a functional shortcut for daily tasks. The highest frequency in the dataset shows that students use AI most for problem-solving and homework, relying on it for everything from Math exercises to History sources. This is closely supported by research and material gathering, alongside lighter usage as a writing composition aid to combat blank page syndrome and for final proofreading.

The fear of plagiarism: Even when students write the content themselves, the ghost of plagiarism haunts them. They worry about cheating accusations, fearing a teacher will say "this isn't yours" and accuse them of stealing. This is directly tied to a fear of exposure; students worry that if a teacher

asks follow-up questions about an AI-assisted assignment, they will be exposed because they don't actually comprehend the AI output.

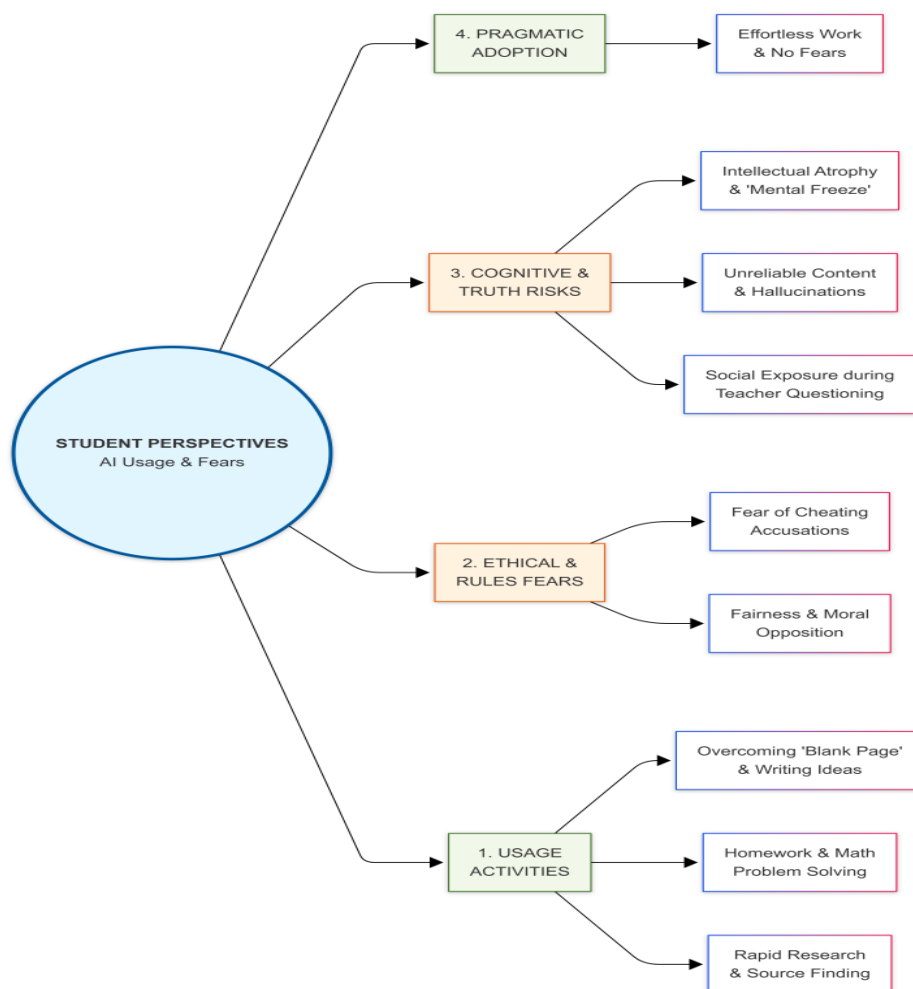
Cognitive and trust dilemmas: Students are remarkably self-aware regarding the mental risks of these tools. The data reveals an acute fear of intellectual dependency, where students worry their minds will freeze and they will forget what they already know due to the habit of just pressing a button. Furthermore, they struggle with information reliability, noting that the AI frequently throws out strange, unverified information. For some, parental pressure regarding fairness and moral avoidance pushes them to bypass the tool entirely just to maintain peace of mind.

The pragmatic counter-voice: In contrast to these anxieties, there is a slice of technological optimism. This segment of students reports feeling absolutely no fear or friction at all, operating on a purely pragmatic philosophy: why should I struggle when technology exists? In short, the table paints a picture of a student body that uses AI primarily as a swift homework engine, but remains anxious that this efficiency will result in cognitive decay, false data, or plagiarism accusations—unless they subscribe to a utilitarian mindset (table 40).

Table 40: For which school or personal study activities do you use AI the most? What difficulties or fears do you encounter (e.g., fear of getting false information, fear of being accused of cheating)?

Main Theme	Subtheme	Extract (Exact)	Frequency
1. ai usage activities	writing & composition aid	I ask AI to give me some ideas on how to start, because sometimes I get stuck on a blank page.	1
	problem solving & homework	I use it for everything! From solving Math exercises to finding History sources.	3
	research & material gathering	It helps me gather material quickly... from solving exercises to finding sources.	2
	correction & proofreading	before I hand something in, I send it to have a correction in my expressions.	1
2. ethical & disciplinary fears	cheating accusations	I m afraid they ll reject me, that the teacher will say this isn't yours and accuse me of stealing.	1
	fairness & moral avoidance	My parents tell me it s illegal or at least unfair... I prefer to avoid it to have my peace of mind.	1
3. cognitive & epistemic risks	intellectual dependency	I m afraid I ll forget even what I know... afraid my mind will freeze because I ve used to pressing a button.	1
	information reliability	The reliability... it throws out information that seems strange and I don't know if it s actually true.	1
	fear of exposure	if the teacher starts asking questions... I will be irredeemably exposed because I won t know the answer.	1
4. pragmatism & total trust	technological optimism	I m not afraid of anything at all... why should I struggle for nothing when technology exists?	1

Figure 22: students' perspectives



AI is perceived as a highly versatile support mechanism that extends far beyond a simple homework machine. According to the table, students find AI to be a valuable tool across four core areas:

Information efficiency: Students value AI as a hyper-targeted search engine that instantly satisfies their curiosity and saves them from searching for hours on Google. This is paired with a sense of democratic access, with students viewing AI as a massive, always-open library accessible even to those living in remote villages.

Psychological safety: One of the most striking revelations in the data is how AI protects students' self-esteem. It provides non-judgmental tutoring, acting as a safe space where students can ask questions ten times over without the shame or hang-ups they might feel around humans. It also offers direct anxiety reduction by giving students a way to ensure their homework is perfectly correct, relieving the stress of being actually corrected by the teacher (and face criticism).

Socio-emotional support: AI actively influences the students' emotional state during study sessions. It offers validation and confidence, making them feel as secure as if a teacher had pre-checked their work before school. Remarkably, it even provides academic encouragement, serving as a motivation when a student feels down about their studies—described warmly by one student as having a friend who knows everything.

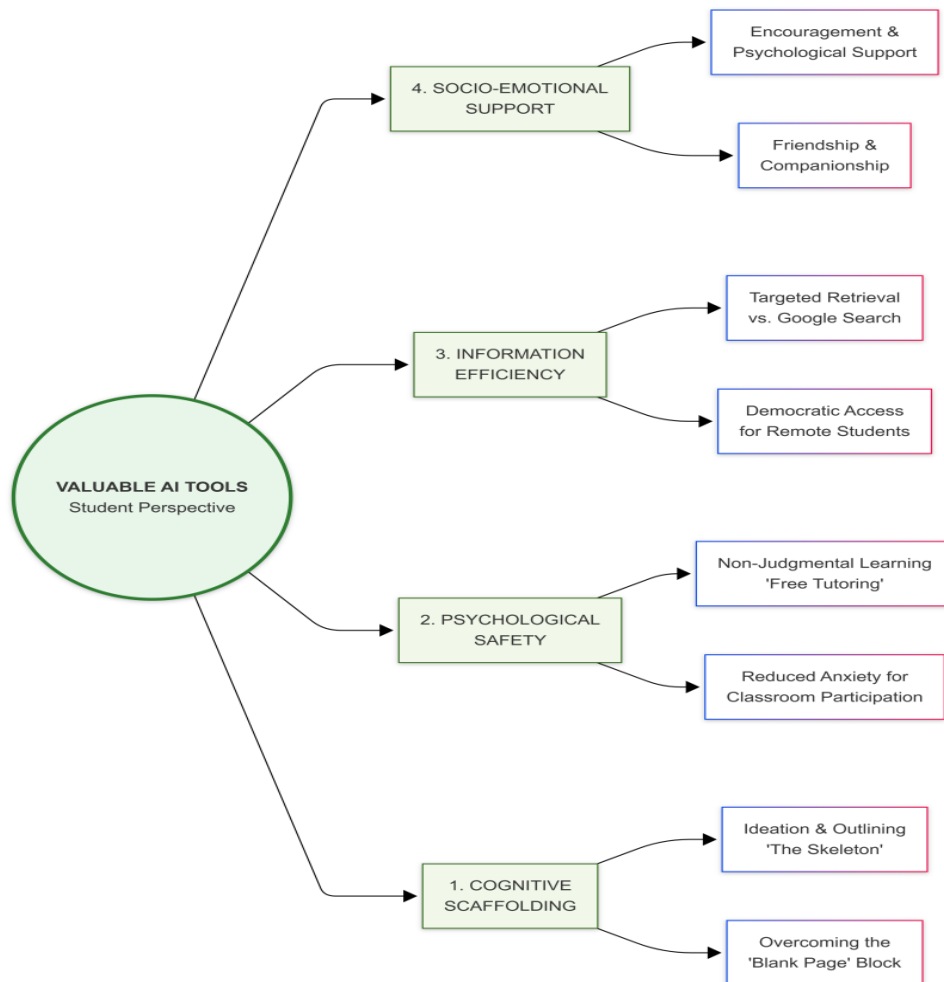
Cognitive scaffolding: AI helps with overcoming the blank page problem by unsticking students who don't know how to transition between paragraphs, and excels at ideation and outlining by throwing out arguments and ideas that the students admit they would have never thought of on their own. In short, the table shows that while AI's primary functional benefit is concentrated, efficient knowledge retrieval, its true value to students lies in how it acts as a private, stress-free buffer—boosting their

creative confidence, protecting them from academic embarrassment, and acting as an emotional anchor during difficult study sessions (Table 41).

Table 41: In which areas do you think AI is a valuable tool that helps you learn better, overcome blocks, or be more creative?

Main Theme	Subtheme	Extract	Frequency
1. Cognitive Scaffolding	Overcoming Blank Page	It helps me unstick when I m looking at the white page and I don't know how to connect the paragraphs.	1
	Ideation & Outlining	I tell it the topic and it throws out 5-6 arguments and ideas that I might have never thought of.	1
2. Psychological Safety	Non-Judgmental Tutoring	You might be ashamed to ask something for the tenth time... At AI, I don't have such hang-ups. It doesn't judge you.	1
	Anxiety Reduction	I know that my exercises are perfectly correct and I don't have the stress of being called to the board and making a fool of myself.	1
3. Information Efficiency	Direct Knowledge Retrieval	It's a tool that solves my curiosity without having to search for hours on Google... more targeted, more concentrated.	2
	Democratic Access	Like a huge library that is always open, wherever you are, even in the most remote village.	1
4. Socio-Emotional Support	Academic Encouragement	Give you encouragement if you've fallen psychologically with your studying... like having a friend who knows everything.	1
	Validation & Confidence	I feel a certainty... as if some teacher saw it before I go to school.	1

Figure 23: Valuable AI tools



The data reflects an awareness of how effortless technology can compromise human development, dividing their experiences into four distinct thematic categories:

Cognitive Atrophy: The highest frequency in this dataset centers on the loss of intellectual struggle, where students admit that the availability of a ready-made answer causes them to stop trying. This is compounded by concerns over superficial knowledge and rusty brain syndrome, illustrating a collective fear that their generation will lose learning and critical thinking skills.

Dependency & identity crisis: Students express a fear of losing their autonomy. The data highlights a subtheme of mental laziness without tech, where students question if they would have anything original to say if their phones were taken away. This is closely linked to the loss of a personal voice, with students fearing they simply copy-paste the ideas of others.

Behavioral & relational risks: students describe a validation addiction, where the AI's constant positive feedback (bravo) becomes an addictive substitute for human reassurance. This enables the creation of a safe social bubble, causing students to retreat into a calm, frictionless virtual world to avoid real-world disagreements. Additionally, time displacement turns AI usage into a time-consuming game of chasing pleasing answers.

The resilience argument: In contrast to these anxieties, a small segment offers a more resilient outlook. One viewpoint claims that AI actually boosts critical thinking by rapidly providing global arguments. Another leans toward the normalization of addiction dismissing these risks by noting that AI is simply the next iteration of social media tools like TikTok or Instagram.

In short, the table demonstrates that while a minority views AI as an innocent tool or an intellectual accelerator, the overwhelming student sentiment signals a need for AI boundaries to prevent cognitive and emotional isolation (table 42).

Table 42: Ethical impact and well-being - Slow Tech paradigm

Main Theme	Subtheme	Extract (Exact)	Frequency
1. cognitive atrophy	loss of intellectual struggle	When you know there is a button that will give you the ready and easy answer, you stop struggling.	3
	superficial knowledge	I m afraid we ll become a generation that knows everything superficially but nothing in depth.	2
	rusty brain syndrome	I feel my mind rusting ... If I continue like this, my critical thinking will go for a walk.	2
2. dependency & identity	loss of personal voice	I ll become a person who just copy-pastes the ideas of others without having their own opinion.	1
	mental paralysis without tech	If tomorrow someone asks me to speak about a topic without my phone, will I have anything of my own to say?	2
3. behavioral & relational risks	validation addiction	It s addictive to have someone who always answers bravo or very good question ... I end up looking for it like a best friend.	1
	the safe social bubble	Instead of going out to talk to real people who might disagree with me, I close myself in a bubble where everything is easy and calm.	1
	time displacement	I see friends of mine spending whole hours trying to get AI to give them the perfect answer... like a game.	1
4. the resilience argument	augmented analysis	I believe my critical thinking has increased... [AI] provides global arguments that you alone would take days to find.	1
	normalization of addiction	It s nothing more than what happened to us with TikTok or Instagram... It s just another tool.	1

Figure 24: cognitive and mental risks

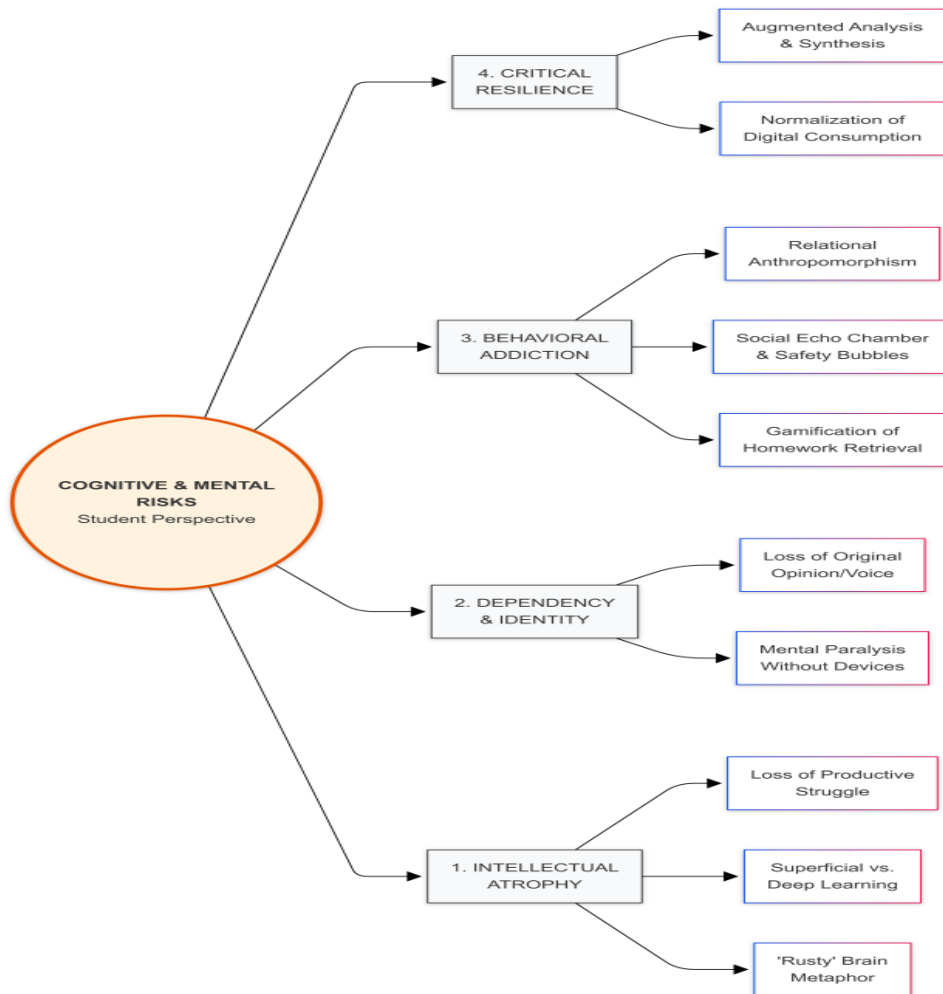


table 43 captures a student consensus regarding the need for clear boundaries, mapping their experiences of structural confusion into four key themes: institutional chaos and vacuum, crisis of fairness and meritocracy, proposed frameworks, and pedagogical transition.

A demand for stability: students favor a unified school policy asking for a common, school-wide line so they can stop guessing where the boundaries lie. Students also call for technical enforcement through AI text detectors and live verification suggesting that teachers must mandate in-class, live oral checks rather than trusting a submitted piece of paper. **Exhaustion from institutional vacuum:** Students are feeling the lack of clear rules. They describe their current reality as fragmented expectations, noting that every individual teacher acts on their own religion regarding AI, forcing students to behave like chameleons just to survive.

The erosion of trust: students point out that while everyone knows AI is being used, the lack of official intervention has destroyed academic meritocracy. They view the current environment as an evaluation failure, noting that when teachers blindly hand out top marks without an oral check, they are simply fooling themselves.

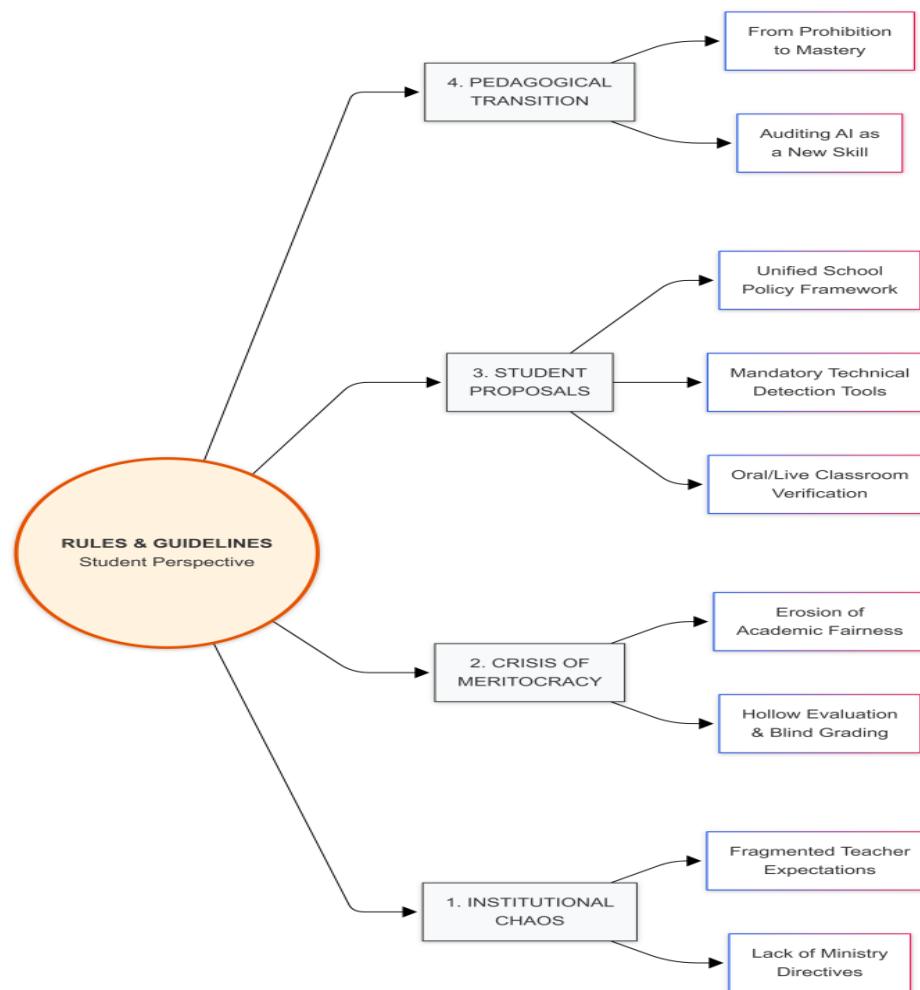
Positive adaptation: Despite the chaos, students do not want a blunt instrument. A final subtheme focuses on a pedagogical transition from ban to mastery, indicating that the precise guidelines students want should not simply scream 'don't touch it,' but rather teach them how to control and verify the tool so they can truly learn to think twice.

In short, the table demonstrates that students feel a lack of clear rules at school. They are actively demanding a unified, precise guideline framework that eliminates teacher-by-teacher bias, restores classroom meritocracy through live checks, and shifts the instructional focus from outright prohibition to responsible mastery.

Table 43: Do you feel a lack of clear rules at school about what is allowed and what is not regarding the use of AI? Would you like more precise guidelines from teachers?

Main Theme	Subtheme	Extract	Frequency
1. institutional chaos & vacuum	fragmented expectations	Every teacher has their own religion regarding AI and we have to act like chameleons... it's exhausting.	3
	regulatory absence	No regulations, no guidelines from the Ministry or the management. It's like trying to drive on a road without signs.	2
2. crisis of fairness & meritocracy	the elephant in the room	Everyone sees it, everyone knows it's there... but no one dares to touch it seriously. Meritocracy has been lost.	3
	evaluation failure	When the teacher gives a 20 to such a work without examining him orally... he is essentially fooling himself.	2
3. proposed frameworks	unified school policy	I would prefer a common framework, a line for the whole school... so we know where we stand and where the boundaries are.	4
	technical enforcement	Schools should sooner or later put official AI text detectors... silence of the teachers is like giving permission to deception.	2
	live verification	Need guidelines that oblige teachers to check knowledge in class, live, and not rely on a piece of paper.	2
4. pedagogical transition	from ban to mastery	The framework I want: not don't touch it, but learn to control it. That's how you learn to think twice.	1

Figure 25: rules and guidelines



Dilemma Scenarios Analysis (Efficiency vs. Equity, Personalization vs. Privacy, Autonomy vs. Assistance)

First scenario

the table reveals four different mindsets:

Surgical and strategic editing: Rather than a blunt submit or cut, these students choose to rewrite sections, inserting their own voices into various places so the essay still represents them. This is paired with editing where students proofread the text to identify and throw away the parts that stink of AI deception.

Ethical integrity: For the ethically minded students, the only acceptable option when discovering a fake citation is to ask for a time extension. This group states they would rather accept a lower grade due to a late submission than build an assignment on a non-existent source. They treat the dilemma as a self-improvement focus, arguing that turning in fake data is simply deceiving yourself and forfeiting the actual right to learn.

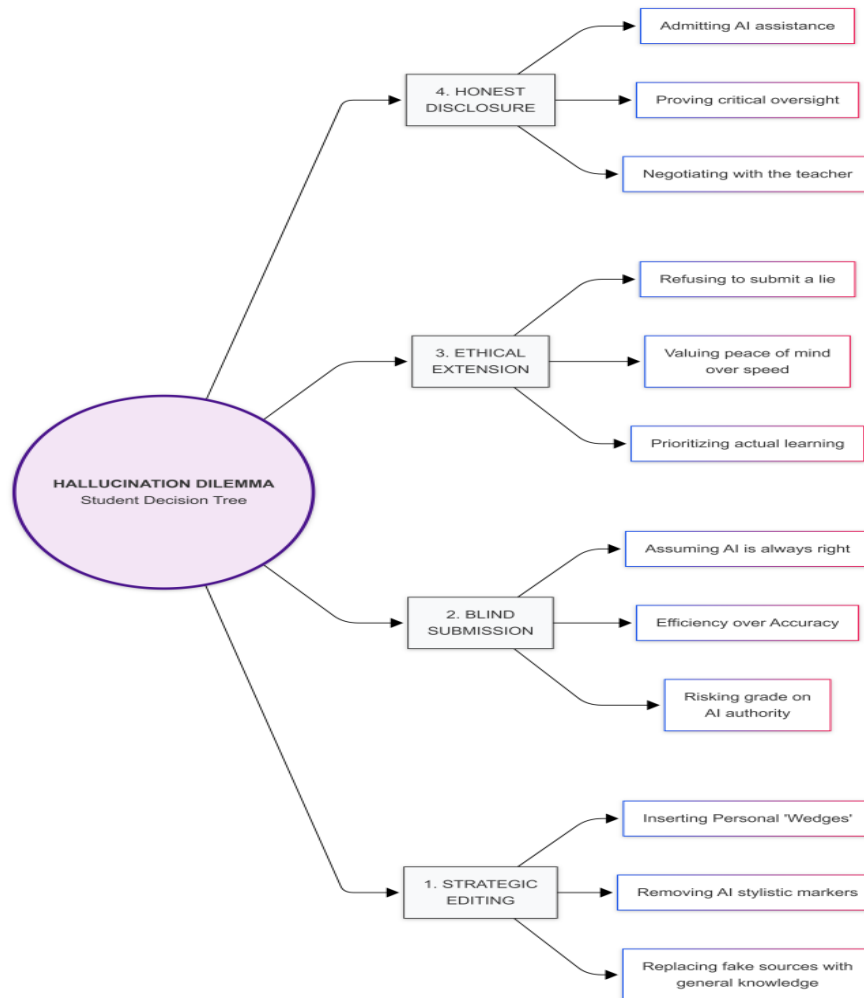
Radical Transparency: Another faction chooses to submit the work but pairs it with an honest acceptance of reality. They handle grade pressure by being transparent with the teacher, openly by admitting AI use and by pointing out the hallucination, building in this way a critical user identity.

Pragmatic acceptance : In contrast to the ethical and transparent paths, a pragmatic slice of students prioritizes efficiency over ethics . Driven by the pressure of grades, they choose to submit the essay exactly as it is without changing anything. This is fueled by blind trust in AI; when under pressure, these students experience a gap in self-confidence, assuming that if the citation looks strange, it is simply because they themselves don't know how to search correctly (table 44).

Table 44: Scenario A (Academic Integrity & AI Hallucinations -Which decision would you make among the proposed options (submit, cut, generalize, ask for an extension) and why? How do you handle the pressure of grades when you realize that the AI might have hallucinated data?

Main Theme	Subtheme	Extract	Frequency
1. strategic adaptation	personalized wedges	I would put my own wedges in various places... to make it more personalized, to represent me even a little.	2
	surgical editing	I would read it very carefully and immediately throw away the parts that stink of AI... surgical intervention on the text.	1
2. pragmatic acceptance	blind trust in ai	I would give it as it is, without changing a single comma... the most probable thing is that I don't know how to search correctly.	1
	efficiency over ethics	when something serves you and is at your disposal, you don't think about it much because efficiency comes first.	1
3. ethical integrity	academic extension	the only correct solution would be to ask for an extension... I prefer to take a lower grade due to delay than to build a work on a source that doesn't exist.	1
	self-improvement focus	don't you want to learn something as well? ... you are essentially deceiving yourself.	1
4. radical transparency	honest disclosure	I would give the assignment to the teacher, but I would tell him the truth... Sir, I used AI to help me with the organization .	1
	critical user identity	I show that I have critical thinking, that I understood the machine's mistake and that I am not just a passive user.	1

Figure 26: First scenario - students



The conflict between protecting personal data and giving in to social pressure reveals a psychological divide among students. When forced to choose between privacy and peer inclusion, the majority admit that social belonging heavily outweighs abstract data security risks. When directly answering what they would do and how much FOMO weighs against data protection, the table exposes four distinct student reactions:

The Dominance of FOMO: For most students, social isolation is a far more terrifying prospect than data exploitation. FOMO dominance stands as the highest frequency in the dataset, with students admitting that the fear of being labeled the only uncool peer completely eclipses data anxieties. This is heavily reinforced by a strong drive for immediate belonging since students admit the psychological need to fit into a peer group as an immediate reality.

Normalization and resignation: A large cluster of students handle the dilemma by minimizing the value of privacy through various approaches, such as: Surveillance resignation where students shrug off the danger, arguing that since platforms like Instagram and TikTok already know everything, one more app won't make a difference. Others adopt a transaction mindset, viewing their personal data as a basic currency to pay for a desired social product, or seek comfort in Safety in Numbers, assuming hackers won't target them personally out of millions of users.

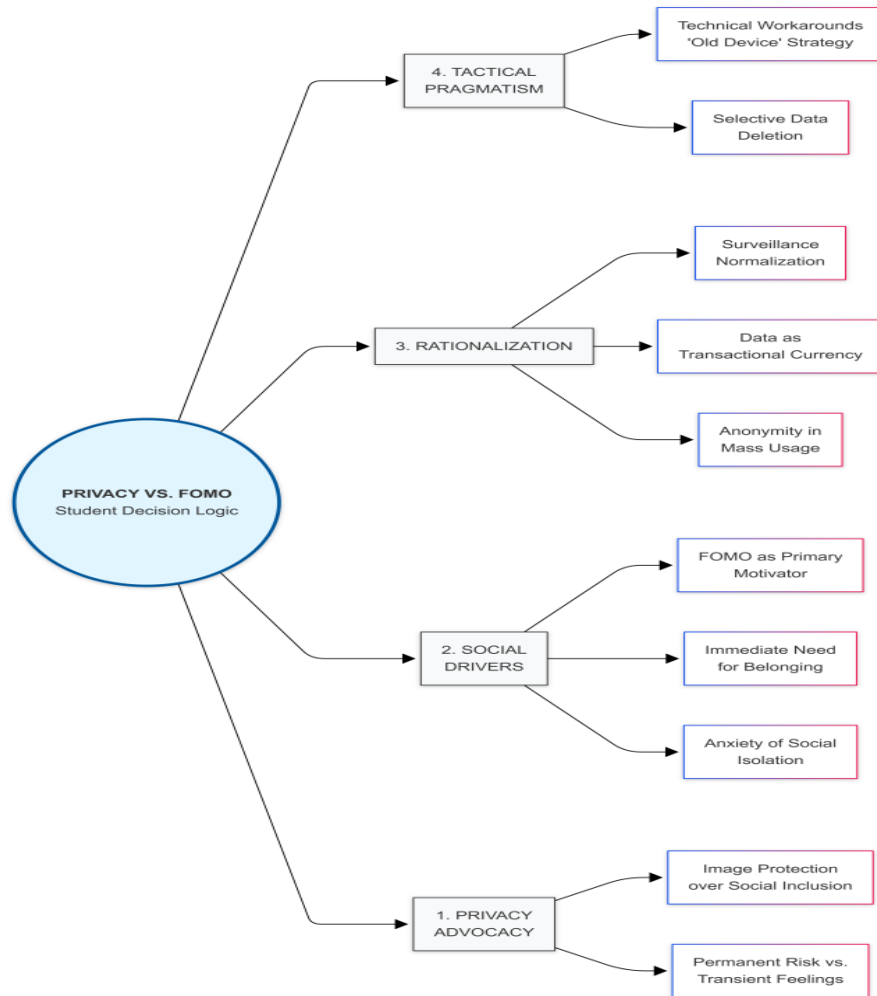
Principled refusal: In sharp contrast, a smaller faction stands firm on privacy advocacy. Students choosing a refusal state that protecting their personal image is their priority, though they acknowledge that the price of this choice is feeling isolated from their friends.

Tactical pragmatism; Finally, some students refuse to accept the choice between total exclusion or total exposure. They try to find a middle path by downloading the viral app onto a wiped, old phone or manually deleting their most private personal photos before granting the application full device access (Table 45).

Table 45: Scenario B (Data Privacy vs. Social Pressure -What would you do and why? In your daily choices, how much does the fear of missing out (FOMO) weigh against the importance of protecting your personal data and photos?

Main Theme	Subtheme	Extract	Frequency
1. Privacy Advocacy	Principled Refusal	For me, the protection of my image is more important, but the price is that I feel isolated.	2
	Permanent Risk Awareness	FOMO is a feeling of the moment, while your data, if stolen, is out there forever.	1
2. Social & Psychological Drivers	FOMO Dominance	The FOMO for me is much stronger than the fear for the data... I don't want to be the only uncool one.	3
	Immediate Belonging	The need to belong somewhere is more immediate than a theoretical risk to your private data.	2
3. Normalization & Rationalization	Surveillance Resignation	Instagram and TikTok already know everything about us. What difference will one more app make?	1
	Data as Currency	I would see it as a transaction. I want the product ... I pay with my data.	1
	Safety in Numbers	If millions of people use it, I say to myself: they won't target me personally.	1
4. Tactical Pragmatism	Technical Workarounds	I would download it on an old phone... or delete the very personal ones before giving access.	1

Figure 27: Second scenario - students



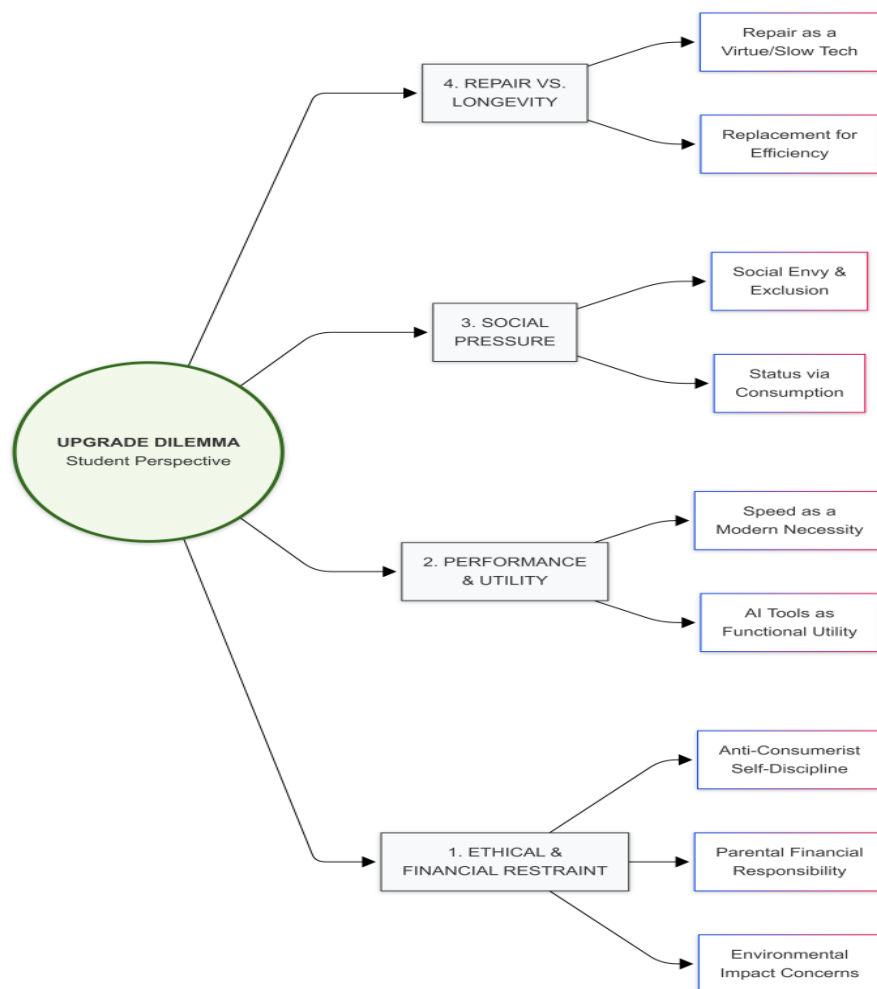
Some resist to this blind consumerism for different reasons, mostly financial pressure, but also green awareness and need to discipline their irrational needs and to impose correct will on their desires. Some admit that they just can not allow themselves to stay behind technological evolution and that they must follow up. Others admit that not following will lead to their social isolation and the diminished self image. Few state the correct approach is to keep the phone as long as it functions and to ignore the new models (Table 46).

Table 46: Scenario C (Slow Tech & Planned Obsolescence) - Which option would you choose and why? How much do you feel the need to have the latest available technology at the expense of repair or reuse?

Main Theme	Subtheme	Extract (Exact)	Frequency
1. resistance to consumerism	ethical/financial restraint	Will parents work just so we can get devices we don't need? Only for the fun of it? It's not worth it at all.	2
	environmental awareness	Protection of the environment and my own financial situation are much more important than having an AI avatar.	1
	self-discipline	I would keep it for at least another year to prove to myself that marketing does not control me.	2

2. performance and functional fomo	speed as a necessity	When you see the person next to you doing things with AI in seconds... you get frustrated. Speed is everything.	2
	utility of ai tools	If the new model has AI that solves my problems... my old phone is already useless in my eyes.	2
3. socio-psychological pressure	social envy & stigma	I would feel bad every time it froze a little or others showed something cool that I can't do.	2
	identity through consumption	In the end, we live in a society where you are what you consume.	1
4. maintenance vs. replacement	repair as waste of time	For me, repair is a waste of time. I prefer to give the old one for recycling and get the new one.	1
	longevity over speed	We must learn to value duration and not speed... I keep my phone until it completely gives out.	2

Figure 28: third scenario - students



Students perceive AI as driving a fundamental shift in education, emphasizing that teaching, assessment, and assignments must adapt rather than resist its presence. At the same time, they recognize the need for structural measures, such as supervised in-class work and stricter quality control, to preserve academic integrity. Beyond practical concerns, students value AI for providing a supportive, non-judgmental environment that encourages questioning and learning from mistakes, highlighting interpersonal qualities they feel are sometimes lacking in traditional classrooms (Table 47).

Table 47: What is the most important thing you would like your teachers or the school to understand about how your generation experiences and uses Artificial Intelligence?

Main Theme	Subtheme	Extract	Frequency
1. pedagogical evolution	assessment reform	the way lessons are done must change, the way assignments are done must change, the exams must change.	2
	correct usage integration	let them find a way for us to use it correctly at least... embrace it as a core fact.	1
2. structural oversight	physical boundaries	perhaps we should do assignments in class and without access to the internet or devices.	2
	strict quality control	more effort to exclude all assignments done with AI and return them... until we... do them ourselves.	1
3. affective environment	non-judgmental support	The AI shows us understanding... this is what teachers should learn, that we need understanding and politeness.	1
	safety in error	You aren't ashamed to talk, to ask and to make mistakes... not shouting, comparisons and punishments.	1
4. technological realism	pragmatic inevitability	AI is here and will stay... no matter what measures they take we will use it because it makes life easier.	2
	irresistible temptation	the temptation of AI is very big... in any case, convenience will win.	1

Figure 29: pedagogical approach



4.3 Triangulation (Integration of qualitative and quantitative key findings)

In general, the quantitative and qualitative findings demonstrate clear triangulation by converging on the same overarching patterns. Both datasets indicate that AI has become an established part of educational practice, making adaptation a necessity. While the quantitative findings show moderate confidence in AI competence and generally positive perceptions of its usefulness, the qualitative data reveal the limitations of this confidence by exposing superficial use, dependence on AI-made answers, and concerns about declining critical thinking. Similarly, the widespread recognition of AI's educational value is reinforced by qualitative calls for reforms in teaching, assessment, and classroom practices. The triangulation underlines the need for ethical guidance and institutional safeguards, with participants advocating clear rules and supervised use to preserve academic integrity. Finally, the qualitative evidence extends the quantitative findings by showing that students value AI not only as a learning tool but also as a non-judgmental source of support, highlighting an interpersonal dimension that complements the broader patterns identified in the survey data.

More specifically, among teachers, the quantitative and qualitative findings converge in portraying a generally positive but measured orientation toward AI. Survey data indicate moderate-to-high self-reported competence, perceived usefulness, and digital literacy, together with relatively low anxiety, particularly among teachers who actively integrate AI into teaching. Quantitative findings also show that AI is valued primarily for increasing efficiency, reducing workload, and supporting lesson preparation, while teachers remain reluctant to delegate pedagogically sensitive tasks such as assessment or instructional judgement. The qualitative evidence reinforces these patterns by

explaining that teachers perceive AI as a support tool rather than a substitute for professional expertise. While they acknowledge substantial gains in productivity, they consistently emphasize the need for human oversight, transparent AI processes, ethical safeguards, and continuous professional development. Focus group discussions also reveal concerns that excessive dependence on AI may weaken students' critical thinking and originality, thereby explaining why teachers simultaneously endorse AI adoption and advocate clear institutional rules governing its educational use.

Among students, quantitative and qualitative findings likewise demonstrate substantial convergence. Survey results show that AI is already embedded in students' learning practices, with most using it at least occasionally and generally perceiving it as beneficial for learning when used appropriately. Students report moderate confidence in their AI-related competencies, positive behavioural intentions toward future AI use, and relatively strong ethical awareness despite recognizing potential risks. The qualitative findings, however, add important nuance by showing that this confidence often masks superficial engagement with AI. Students describe relying on AI for ready-made answers, experiencing reduced independent thinking, and feeling uncertain about the extent to which AI use is academically acceptable. At the same time, they identify AI as a supportive, non-judgmental learning companion that facilitates understanding and lowers anxiety when seeking help. Across both datasets, students express a clear need for consistent school-wide expectations and explicit ethical guidance, indicating that positive attitudes toward AI coexist with uncertainty about responsible educational use.

5. Case Studies

5.1 Selection and Description of 2-3 National Good Practices on AI Use

Greece is advancing its AI educational integration approach through different national initiatives. First, the Ministry of Education is developing EduAI, an AI-based system designed to upgrade the national Digital Tutor platform from a repository of educational materials into a comprehensive, interactive learning environment. This system utilizes AI-driven mechanisms to generate personalized exercises, adaptive learning pathways, and tailored feedback based on each student's knowledge level and progress, functioning as an AI tutor.

Also, Greece is implementing the AI in Schools pilot program across twenty selected secondary schools. This initiative introduces AI to empower upper secondary school teachers and students with the skills for the responsible, creative, and pedagogically meaningful use of Generative AI. Last, Ministry of Education invests on teachers' professional development and digital literacy through systematic training courses.

5.2 Analysis of Pedagogical Results and Student Engagement in the Presented Cases

The integration of these AI initiatives is designed to transform passive AI content consumption into active, data-informed learning experiences that significantly boost student engagement. Within the EduAI framework, the ministry of education aims to adapt to students' needs, and provide targeted educational content. This adaptive and responsive learning experience ensures that students can better assess their own understanding, while providing teachers and parents with meaningful analytics regarding academic progress. Simultaneously, the AI program in pilot schools adopts a human-centered approach, training educators to safely integrate generative AI tools like custom GPTs into their classrooms. By allowing students to interact with AI in a structured, supervised environment, the initiative fosters critical thinking, creativity, collaboration, and problem-solving skills, while firmly grounding their engagement in ethical awareness, digital safety, and responsible digital citizenship.

6. Conclusions and Recommendations

6.1 Main Training Gaps and Identified Needs

The data of our study showed significant training gaps exist for both teachers and students, characterized by superficial engagement and a lack of systemic support. While teachers self-report feeling averagely prepared for AI use, those restricted to basic administrative tasks experience high technological stress and describe an overwhelming professional burden to integrate AI without proper systemic training. Conversely, students suffer from an illusion of knowledge, where they report knowing how to navigate AI applications but admit to frequently copy-pasting content without comprehending the underlying logic. This lack of active human involvement causes critical thinking to reduce, which is compounded by their overall low active engagement and refusal to devote time to studying educational materials or discussing AI with peers. Furthermore, students explicitly report feeling less prepared to acquire knowledge and skills about AI, resulting in a contradictory experience of confusion and an active demand for unified policies to resolve fragmented teacher expectations. Other studies regarding greek context showed similar findings:

Lack of training

Velli and Zafiroopoulos (2024) state that in the Greek educational system, despite government investments in technological resources, there is a gap in teachers' familiarity and comfort with technological tools. Challenges persist, particularly concerning teacher training. Furthermore, the study's sample revealed that only about one-third of the participating teachers had attended any professional development program regarding AI educational use. Teachers may recognize the benefits of technology, but without comprehensive training and support, the effective integration of technology into teaching practices is hindered. In the same context, Theodoropoulou and Chiotelis (2026) identifies a significant training gap among Greek secondary education teachers, revealing that 72.7% of the respondents have not received any training in Artificial Intelligence. This inadequate preparation is considered one of the main challenges, as current training offerings are described as sporadic and unsystematic. Consequently, a large percentage of educators acknowledge that they lack sufficient information, knowledge, and skills regarding AI. The continuous and rapid release of new AI tools further widens the gap in fundamental AI literacy, making it difficult for teachers to stay updated. Despite these gaps, there is a strongly identified need and willingness for improvement; among the teachers who have not been trained, 90.9% explicitly expressed a desire to receive training. To address this, the literature suggests investing in professional development programs that provide practical education on using AI for pedagogical purposes.

Misalignment of policies and teachers' readiness to use AI

Stoumpos, Stoumpou and Tsiantos (2026) also highlight a systemic gap in the Greek educational context, noting the absence of quantitative studies examining teacher readiness, which indicates a broader need for systematic data to inform future training policies. Ultimately, while teachers express a willingness to adopt AI, this is strictly conditional upon receiving the appropriate training and support. Furthermore, according to Moschaki et al, 2026, in the Greek educational context, there is a gap between teachers' optimistic intentions towards AI and their actual meaningful application of it, indicating a strong need for systematic training, improved infrastructure, and administrative support.

Lack of guidance for correct pedagogical AI use

Thus, a training gap exists in digital literacy, digital citizenship, and AI-related critical thinking, evidenced by the fact that only a small minority of teachers use AI for explicit pedagogical purposes, such as instructing students on its critical use and limitations (Stoumpos et al, 2026). Within the same frame of proper pedagogical AI use, it is worth mentioning that although Greek teachers, including those teaching Modern Greek Literature, recognize the potential pedagogical benefits of AI, they feel they lack the sufficient knowledge required to utilize these tools, which significantly hinders their intention to adopt them (Alexopoulos et al., 2025 as cited in Mastrothanasis, 2025). Consequently, an overwhelming majority of Greek arts teachers (literature and theater courses) report that they have

not yet integrated AI into their lessons (Alexopoulos & Kladaki, 2025 as cited in Mastrothanasis, Alexopoulos, Andreadakis, Kladaki & Kostas 2025).

Lack of familiarization with education AI tools

Last, based on the research of Stoumpos, Stoumpou and Tsiantos (2026) the primary training gap in Greece is the lack of specific, targeted training and support required for teachers to effectively implement AI and digital tools. Therefore, teachers are currently facing challenges related to both their technical skills and the pedagogical adaptations necessary to utilize these technologies. It should not be omitted that there is a clear identified need for teachers to learn how to evaluate the educational effectiveness and the ethical dimensions of digital tools (Stoumpos et al, 2026).

6.2 Operational Suggestions and Requirements for the Development of AI-based Pedagogical Models

To successfully develop AI-based pedagogical models, institutions must move beyond mere technological implementation and establish a structured, ethically grounded pedagogical architecture that respects the human core of the classroom. Operationally, this requires the implementation of a unified school-wide policy that establishes clear boundaries of digital behavior, directly addressing the structural confusion and fragmented teacher expectations that students want eliminated. These models must incorporate the rigorous Human-in-the-Loop validation frameworks demanded by teachers to ensure pedagogical integrity, strictly avoiding automated grading systems or unverified materials that could compromise the student's right to learn. Pedagogically, these architectures must be designed to shift students away from viewing AI as a superficial copying shortcut and toward utilizing it as a constructive learning tool, which is shown to foster higher cognitive competence and ethical awareness. Finally, practical operational safeguards must be integrated to protect data privacy, as regular student users demonstrate a high willingness to compromise their privacy for social inclusion despite possessing a high awareness of technical risks. More specifically and using research that was conducted for Greek educational frame, the following suggestions have been mentioned, as such:

Focused training on pedagogically proper AI use

There is the need for policy support and educational planning to create a modern training framework that responds to evolving technological capabilities and teachers' real needs (Mastrothanasis et al, 2025).

Panagopoylos et al (2026) mention that the main educational gap in Greece centers around an adoption-trust paradox where the highly widespread use of Artificial Intelligence (AI) does not equate to unconditional trust regarding the reliability of the AI content. To address this gap, the study identifies the need for universities to treat AI literacy as a core academic competence embedded across all curricula, rather than limiting it to optional technical modules. Furthermore, teachers require structured preparation regarding bias awareness, privacy, citation, and how to pedagogically and responsibly integrate AI into lesson planning, feedback, and assessment. To address this, Greek teachers have explicitly highlighted the need for targeted training as a facilitating factor. They specifically suggest flexible, distance, and self-directed learning programs that also incorporate practical, workshop-based elements. Furthermore, their desired training focus includes multimedia content production, lesson planning, activity development, assessment, and the creation of texts.

Pedagogically sound integration strategies

According Moschaki et al (2026) to successfully develop AI-based pedagogical models, operational strategies must prioritize the implementation of creative and pedagogically sound integration strategies rather than simply focusing on the presence of digital tools. A primary requirement is that education departments, such as the Ministry of Education, develop and popularize specific ethical guidelines and recommended AI applications that are tailored to the distinct needs of different educational tiers and specific subject areas. Suggested operational interventions include establishing short-term training programs that combine basic AI literacy with the hands-on design of AI-enhanced

lessons, alongside fostering school-based communities of practice where teachers can collaboratively experiment and reflect. Furthermore, the execution of pilot projects testing new AI-assisted teaching approaches across various grades and subjects is recommended to generate valuable data for evaluating learning outcomes and optimizing future educational policies.

According Stoumpos, Stoumpou and Tsiantos (2026) for the development of AI-based educational strategies, policies should be built on a documented basis that simultaneously addresses both the teachers' attitudes and their technical familiarity. A fundamental operational requirement is the implementation of targeted training programs, which are identified as the catalyst for effectively integrating AI into teaching practices. Additionally, any future pedagogical models must adopt a critical approach that actively addresses pedagogical and ethical issues, specifically transparency and personal data protection. Finally, there is an operational requirement for future experimental studies to measure the actual contribution of AI tools to learning outcomes, which is necessary to bridge the gap between technological expectations and actual results.

AI as auxiliary tool – Human in the loop

Theodoropoulou and Chiotelis (2026) state that the primary requirement for any AI pedagogical integration is that AI must function strictly as an auxiliary tool rather than a replacement for traditional teaching. Educators emphasize that the human factor, classroom dynamics, and student-teacher interactions are irreplaceable pedagogical elements. Operationally, the development of such models requires addressing ethical issues, specifically ensuring fairness, transparency, and accessibility in AI-based systems. Furthermore, pedagogical models must be designed to mitigate specific risks highlighted by teachers, such as internet addiction, the loss of investigative and original thinking among students, and the uncritical reproduction of information without personal effort. Finally, successful implementation requires systematic professional development programs to build teachers' confidence and practical skills.

According Panagopoulos et al (2026) education systems must establish clear governance frameworks that link innovation with accountability. At the classroom level, it is suggested that every course include a brief AI-use statement outlining permitted uses, disclosure requirements, and expectations for verifying AI-generated content.

Orientation to pedagogical objectives

Velli and Zafeiropoulos (2024) mention that in order to successfully develop and integrate AI-based models in Greece, the utilization of AI systems must be oriented towards pedagogical objectives rather than being limited merely to technological possibilities. By incorporating teachers' expertise and actively responding to their concerns, educational AI frameworks can be designed to meet specific pedagogical goals. Additionally, it is required to provide adequate resources and professional development programs that promote constructivist, student-oriented pedagogical approaches, which align well with the potential of AI tools.

Ethical guidelines

Finally, it is essential to establish robust ethical guidelines, regulate AI systems, and address ethical concerns related to data privacy, algorithmic opacity, and bias in order to foster a culture of innovation and trust. Additionally, there is a need to address technological insecurity and resource constraints, as some teachers have never engaged with AI tools at all. Consequently, there is an urgent need to design targeted professional education that shifts the current focus from using AI merely for administrative efficiency toward advanced, student-centered pedagogical uses and responsible implementation (Moschaki et al, 2026).

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ANNEX I

Teachers

Teachers maintain a neutral stance for many of the items they were asked (neither disagree, nor agree). They reported agreement for COMP1 (M=3.75, SD=.982), for COMP6 (M=3.66, SD=1.20), for COMP11 (M=3.54, SD=1.11), for COMP15 (M=4.06, SD=.89), for COMP16 (M=3.56, SD=1.33), for COMP167 (M=4.08, SD=.90), for COMP18 (M=3.77, SD=1.30), for COMP20 (M=4.03, SD=1.00), for COMP21 (M=4.13, SD=.94) and for COMP22 (M=3.76, SD=.99). They also reported agreement for UTIL32 (M=3.72, SD=.97), for UTIL36 (M=3.54, SD=1.06), for INF1 (M=3.68, SD=1.13), for INF2 (M=3.68, SD=.99) and for DIGSAF43 (M=3.77, SD=.84).

On the contrary, teachers expressed disagreement with ANX23 (M=1.97, SD=.98), with ANX24 (M=2.46, SD=1.18), with ANX25 (M=2.00, SD=1.14), with ANX26 (M=1.70, SD=1.07), with ANX27 (M=2.77, SD=1.20), with ANX28 (M=1.65, SD=.97), with ANX29 (M=2.39, SD=1.31) and with UTIL34 (M=2.48, SD=1.18). In general, Teachers reported average AI competence. They agree that AI offers faster access to data, AI can support solving daily life problems, AI save time in general and time specifically in work matters. Teachers agree they are very willing to develop educational material using AI. Teachers disagree that AI have a negative impact on teaching, on learning, on performance etc. They have an average generalized worry regarding the use of AI in education. But in all specific anxiety items they reported very low anxiety scores. Teachers declared average or high utility of AI, mostly praising AI being useful for daily life and increasing productivity. Teachers find themselves very able in using advanced strategies during internet searches, and in locating fake news and in avoiding technostress. Regarding the rest digital literacy issues (safety etc) they reported average ability.

Table 48: Means and standard deviations (teachers)

ITEMS	N	Minimu m	Maximu m	Mean	SD
COMP1	71	1	5	3,75	,982
COMP2	71	1	5	3,11	1,090
COMP3	71	1	5	3,41	1,077
COMP4	71	1	5	3,27	1,095
COMP5	71	1	5	3,32	1,106
COMP6	71	1	5	3,66	1,206
COMP7	71	1	5	3,11	1,076
COMP8	71	1	5	3,44	1,156
COMP9	71	1	5	3,45	1,131
COMP10	71	1	5	3,45	1,193
COMP11	71	1	5	3,54	1,119
COMP12	71	1	5	3,31	1,272
COMP13	71	1	5	3,42	1,179
COMP14	71	1	5	3,38	1,235
COMP15	71	2	5	4,06	,893
COMP16	71	1	5	3,56	1,339
COMP17	71	1	5	4,08	,906
COMP18	71	1	5	3,77	1,301
COMP19	71	1	5	3,25	1,065
COMP20	71	1	5	4,03	1,000
COMP21	71	1	5	4,13	,940
COMP22	71	1	5	3,76	,992
ANX23	71	1	4	1,97	,985
ANX24	71	1	5	2,46	1,181
ANX25	71	1	5	2,00	1,146
ANX26	71	1	5	1,70	1,006
ANX27	71	1	5	2,77	1,209

ANX28	71	1	5	1,65	,972
ANX29	71	1	5	2,39	1,315
ANX30(rev)	71	1	5	1,97	1,042
UTIL31	71	1	5	2,96	1,006
UTIL32	71	1	5	3,72	,974
UTIL33	71	1	5	2,85	1,091
UTIL34	71	1	5	2,48	1,182
UTIL35	71	1	5	3,37	1,124
UTIL36	71	1	5	3,54	1,067
INF1	71	1	5	3,68	1,131
INF2	71	1	5	3,68	,997
DIGCOM	71	1	5	3,38	1,087
DIGCRE	71	1	5	3,08	1,168
DIGSAF42	71	1	5	3,35	,912
DIGSAF43	71	1	5	3,77	,848
DIGSAF44	71	1	5	3,38	,851
DIGPRO	71	1	5	3,34	,909
1ST SCENARIO	71	0	3	2,10	,700
2ND SCENARIO	71	0	3	2,27	,774
3D SCENARIO	71	0	3	1,92	,967
N (listwise)	71				

Frequencies

The N distribution for the first item (COMP1) shows that teachers tended to cluster around the agreement category, with 42.3% (N = 30) selecting agree. When combining the two positive response categories (agree and totally agree), 64.8% of the sample expressed agreement. In contrast, 25.4% of respondents remained neutral, while a smaller proportion expressed disagreement, with 7.0% selecting disagree and 2.8% totally disagree.

Table 49: Frequencies of all items (teachers)

Items	Likert scale	N	%
COMP1	totally disagree	2	2,8%
	Disagree	5	7,0%
	Neutral	18	25,4%
	Agree	30	42,3%
	totally agree	16	22,5%
COMP2	totally disagree	8	11,3%
	Disagree	8	11,3%
	Neutral	29	40,8%
	Agree	20	28,2%
	totally agree	6	8,5%
COMP3	totally disagree	5	7,0%
	Disagree	7	9,9%
	Neutral	23	32,4%
	Agree	26	36,6%
	totally agree	10	14,1%
COMP4	totally disagree	6	8,5%
	Disagree	8	11,3%
	Neutral	27	38,0%
	Agree	21	29,6%
	totally agree	9	12,7%

COMP5	totally disagree	5	7,0%
	Disagree	10	14,1%
	Neutral	23	32,4%
	Agree	23	32,4%
	totally agree	10	14,1%
COMP6	totally disagree	6	8,5%
	Disagree	5	7,0%
	Neutral	16	22,5%
	Agree	24	33,8%
	totally agree	20	28,2%
COMP7	totally disagree	6	8,5%
	Disagree	14	19,7%
	Neutral	22	31,0%
	Agree	24	33,8%
	totally agree	5	7,0%
COMP8	totally disagree	6	8,5%
	Disagree	8	11,3%
	Neutral	18	25,4%
	Agree	27	38,0%
	totally agree	12	16,9%
COMP9	totally disagree	6	8,5%
	Disagree	5	7,0%
	Neutral	24	33,8%
	Agree	23	32,4%
	totally agree	13	18,3%
COMP10	totally disagree	6	8,5%
	Disagree	8	11,3%
	Neutral	20	28,2%
	Agree	22	31,0%
	totally agree	15	21,1%
COMP11	totally disagree	5	7,0%
	Disagree	6	8,5%
	Neutral	20	28,2%
	Agree	26	36,6%
	totally agree	14	19,7%
COMP12	totally disagree	9	12,7%
	Disagree	9	12,7%
	Neutral	17	23,9%
	Agree	23	32,4%
	totally agree	13	18,3%
COMP13	totally disagree	5	7,0%
	Disagree	10	14,1%
	Neutral	21	29,6%
	Agree	20	28,2%
	totally agree	15	21,1%
COMP14	totally disagree	7	9,9%
	Disagree	10	14,1%
	Neutral	17	23,9%
	Agree	23	32,4%
	totally agree	14	19,7%
COMP15	totally disagree	0	0,0%
	Disagree	6	8,5%
	Neutral	8	11,3%
	Agree	33	46,5%
	totally agree	24	33,8%

COMP16	totally disagree	9	12,7%
	Disagree	7	9,9%
	Neutral	10	14,1%
	Agree	25	35,2%
	totally agree	20	28,2%
COMP17	totally disagree	1	1,4%
	Disagree	3	4,2%
	Neutral	11	15,5%
	Agree	30	42,3%
	totally agree	26	36,6%
COMP18	totally disagree	7	9,9%
	Disagree	5	7,0%
	Neutral	12	16,9%
	Agree	20	28,2%
	totally agree	27	38,0%
COMP19	totally disagree	5	7,0%
	Disagree	11	15,5%
	Neutral	23	32,4%
	Agree	25	35,2%
	totally agree	7	9,9%
COMP20	totally disagree	2	2,8%
	disagree	4	5,6%
	neutral	10	14,1%
	Agree	29	40,8%
	totally agree	26	36,6%
COMP21	totally disagree	1	1,4%
	disagree	5	7,0%
	neutral	6	8,5%
	Agree	31	43,7%
	totally agree	28	39,4%
COMP22	totally disagree	2	2,8%
	disagree	5	7,0%
	neutral	18	25,4%
	Agree	29	40,8%
	totally agree	17	23,9%
ANX23	totally disagree	28	39,4%
	disagree	24	33,8%
	neutral	12	16,9%
	Agree	7	9,9%
	totally agree	0	0,0%
ANX24	totally disagree	17	23,9%
	disagree	23	32,4%
	neutral	16	22,5%
	Agree	11	15,5%
	totally agree	4	5,6%
ANX25	totally disagree	29	40,8%
	disagree	27	38,0%
	neutral	4	5,6%
	Agree	8	11,3%
	totally agree	3	4,2%
ANX26	totally disagree	40	56,3%
	disagree	20	28,2%
	neutral	4	5,6%
	Agree	6	8,5%
	totally agree	1	1,4%

ANX27	totally disagree	10	14,1%
	disagree	23	32,4%
	neutral	19	26,8%
	Agree	11	15,5%
	totally agree	8	11,3%
ANX28	totally disagree	43	60,6%
	disagree	16	22,5%
	neutral	7	9,9%
	Agree	4	5,6%
	totally agree	1	1,4%
ANX29	totally disagree	23	32,4%
	disagree	19	26,8%
	neutral	14	19,7%
	Agree	8	11,3%
	totally agree	7	9,9%
ANX30	totally disagree	8	11,3%
	disagree	9	12,7%
	neutral	31	43,7%
	Agree	19	26,8%
	totally agree	4	5,6%
UTIL31	totally disagree	7	9,9%
	disagree	13	18,3%
	neutral	30	42,3%
	Agree	18	25,4%
	totally agree	3	4,2%
UTIL32	totally disagree	1	1,4%
	disagree	7	9,9%
	neutral	19	26,8%
	Agree	28	39,4%
	totally agree	16	22,5%
UTIL33	totally disagree	10	14,1%
	disagree	16	22,5%
	neutral	22	31,0%
	Agree	21	29,6%
	totally agree	2	2,8%
UTIL34	totally disagree	19	26,8%
	disagree	17	23,9%
	neutral	20	28,2%
	agree	12	16,9%
	totally agree	3	4,2%
UTIL35	totally disagree	6	8,5%
	disagree	10	14,1%
	neutral	15	21,1%
	agree	32	45,1%
	totally agree	8	11,3%
UTIL36	totally disagree	4	5,6%
	disagree	9	12,7%
	neutral	13	18,3%
	agree	35	49,3%
	totally agree	10	14,1%
INF1	not at all able	3	4,2%
	not so able	8	11,3%
	neutral	18	25,4%
	rather able	22	31,0%
	very able	20	28,2%

INF2	not at all able	2	2,8%
	not so able	6	8,5%
	neutral	20	28,2%
	rather able	28	39,4%
	very able	15	21,1%
DIGCOM	no control	6	8,5%
	little control	6	8,5%
	neutral	23	32,4%
	some control	27	38,0%
	absolute control	9	12,7%
DIGCRE	totally	8	11,3%
	a bit	13	18,3%
	neutral	23	32,4%
	much	19	26,8%
	absolutely	8	11,3%
DIGSAF42	not at all able	3	4,2%
	not so able	8	11,3%
	neutral	25	35,2%
	rather able	31	43,7%
	very able	4	5,6%
DIGSAF43	not at all able	1	1,4%
	not so able	4	5,6%
	neutral	17	23,9%
	rather able	37	52,1%
	very able	12	16,9%
DIGSAF44	not at all informed	1	1,4%
	a bit informed	9	12,7%
	neutral	28	39,4%
	much informed	28	39,4%
	absolutely informed	5	7,0%
DIGPRO	not at all informed	3	4,2%
	a bit informed	7	9,9%
	neutral	29	40,8%
	much informed	27	38,0%
	absolutely informed	5	7,0%
1ST SCENARIO	total delegation	2	2,8%
	total refusal	8	11,3%
	use for drafts	42	59,2%
	brainstorming	19	26,8%
2ND SCENARIO	pure performance	2	2,8%
	I advise against it	8	11,3%
	limited use	30	42,3%
	active method	31	43,7%
	plagiarism	4	5,6%
3D SCENARIO	redo without AI	24	33,8%
	penalty	17	23,9%
	co-creation	26	36,6%

COMPARISONS

Gender

Next table presents gender-based means for the variables. An analysis of the project data was conducted to evaluate potential gender differences across key variables among 71 teachers (22 men, 49 women). While slight numerical variations were observed in the mean scores—for instance, men reported marginally higher technology-related anxiety (2.37 vs. 2.03) and digital literacy (3.63 vs. 3.38), while women reported slightly higher competence (3.66 vs. 3.33)—the results of an independent samples t-test indicated these differences were not statistically significant for any of the measured variables ($p > .05$).

Table 50: Means based on gender

Variables	Gender	N	Mean	SD
1ST	Man	22	2,05	,722
SCENARIO	Woman	49	2,12	,696
2ND	Man	22	2,32	,568
SCENARIO	Woman	49	2,24	,855
3D SCENARIO	Man	22	1,68	,894
	Woman	49	2,02	,989
ANXIETY	Man	22	2,37	1,135
	Woman	49	2,03	,638
UTIL	Man	22	3,18	,876
	Woman	49	3,13	,762
COMP	Man	22	3,33	1,146
	Woman	49	3,65	,669
DIGITAL	Man	22	3,63	,775
LITERACY	Woman	49	3,38	,641

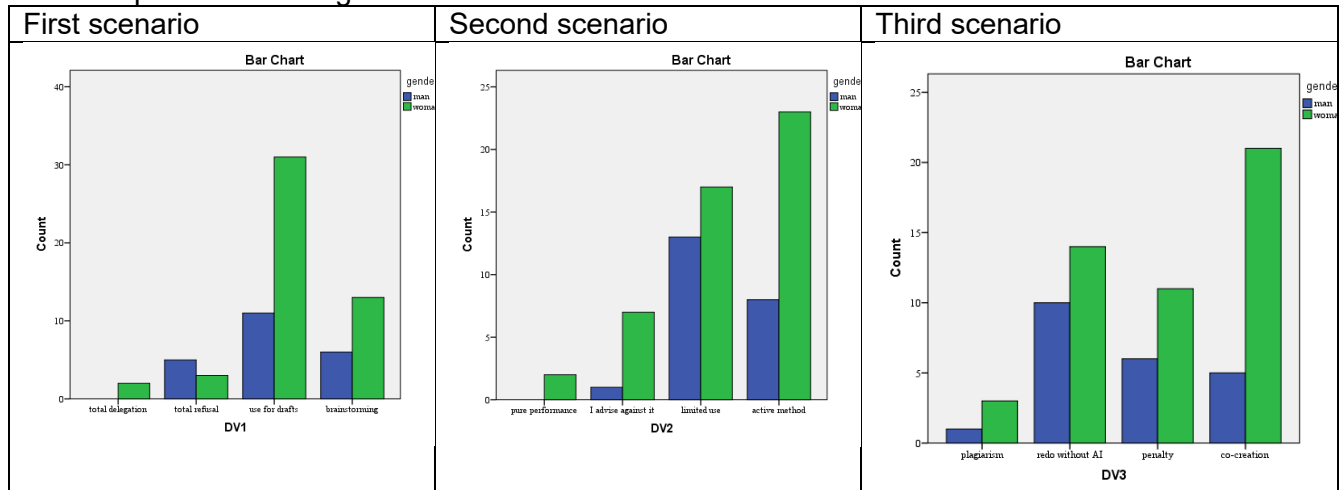
An analysis of the project data was conducted to evaluate potential gender differences across key variables, including digital literacy (DIGITAL LITERACY), competence (COMP), utility (UTIL), and anxiety. The results of an independent samples t-test indicated no statistically significant differences between the groups for any of the measured variables ($p > .05$). This suggests that teachers' perceptions and skill levels across these dimensions are consistent regardless of gender.

Table 51: Differences based on gender

Variables	Levene's Test					
	Equal variances	F	Sig.	T	Df	Sig. (2-tailed)
1ST SCENARIO	Assumed	,180	,673	-,426	69	,671
	not assumed			-,420	39,192	,677
2ND SCENARIO	Assumed	4,027	,049	,367	69	,715
	not assumed			,426	58,816	,672
3D SCENARIO	Assumed	,292	,591	-1,373	69	,174
	not assumed			-1,427	44,563	,160
ANXIETY	Assumed	18,603	,000	1,602	69	,114
	not assumed			1,307	27,141	,202

UTIL	Assumed	,556	,458	,277	69	,783
	not assumed			,262	35,878	,795
COMP	Assumed	11,670	,001	-1,505	69	,137
	not assumed			-1,242	27,642	,225
DIGITAL LITERACY	Assumed	,972	,328	1,424	69	,159
	not assumed			1,325	34,470	,194

A visual presentation of gender based means follows.



Graph: Scenaria and teachers gender

AGE

To explore potential age-related trends among the teachers, descriptive statistics were calculated for all key variables across four age categories: 25-34 (n=2), 35-44 (n=19), 45-54 (n=33), and over 55 (n=17). A review of the mean scores reveals some variations across age groups. For instance, the youngest cohort (25-34) reported the lowest mean anxiety (1.21) and the highest perceived competence (4.18), whereas the oldest cohort (>55) reported the highest anxiety (2.37) and the lowest competence (3.11). Interpretations of the youngest group are not statistically solid due to its very small sample size (n=2).

Table 52: Means based on age

Variables	Age		Mean	SD
1ST SCENARIO	25-34	2	2,00	,000
	35-44	19	2,11	,737
	45-54	33	2,12	,696
	>55	17	2,06	,748
	Total	71	2,10	,700
2ND SCENARIO	25-34	2	2,50	,707
	35-44	19	2,21	,855
	45-54	33	2,18	,769
	>55	17	2,47	,717
	Total	71	2,27	,774
3D SCENARIO	25-34	2	2,00	,000
	35-44	19	1,63	,955
	45-54	33	2,09	,947

	>55	17	1,88	1,054
	Total	71	1,92	,967
	25-34	2	1,21	,101
	35-44	19	2,18	,589
ANXIETY	45-54	33	2,03	,846
	>55	17	2,37	1,005
	Total	71	2,13	,831
	25-34	2	3,91	,353
	35-44	19	2,91	,676
UTIL	45-54	33	3,31	,699
	>55	17	3,00	1,018
	Total	71	3,15	,793
	25-34	2	4,18	,064
	35-44	19	3,71	,694
COMP	45-54	33	3,65	,727
	>55	17	3,11	1,123
	Total	71	3,55	,851
	25-34	2	3,50	,353
	35-44	19	3,52	,575
DIGITAL	45-54	33	3,59	,640
LITERACY	>55	17	3,10	,839
	Total	71	3,45	,690

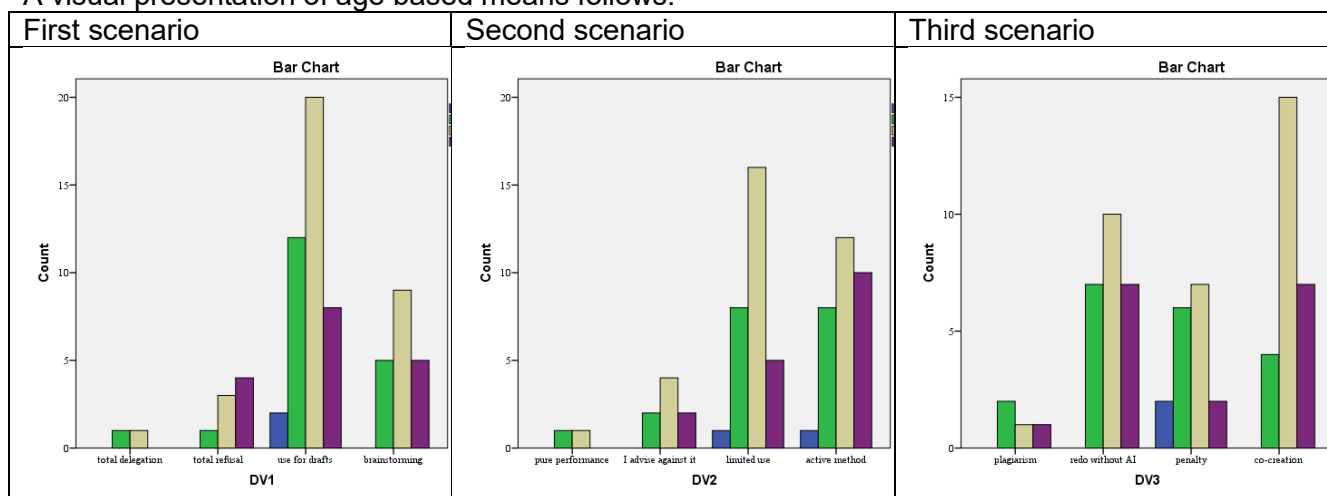
Age did not have a statistically significant effect on any of the measured variables (all $p > .05$). While perceived competence (COMP) showed the most variation among the age groups, it still did not reach the threshold for statistical significance ($F = 2.421$, $p = .074$). Therefore, consistent with the gender analysis, the data indicates that teachers' digital literacy, anxiety, and perceived utility remain relatively uniform regardless of their age.

Table 53: Differences based on age

		Sum Squares	of df	Mean Square	F	Sig.
1ST SCENARIO	Between Groups	,064	3	,021	,042	,989
	Within Groups	34,246	67	,511		
	Total	34,310	70			
2ND SCENARIO	Between Groups	1,113	3	,371	,609	,611
	Within Groups	40,802	67	,609		
	Total	41,915	70			
3D SCENARIO	Between Groups	2,580	3	,860	,916	,438
	Within Groups	62,913	67	,939		
	Total	65,493	70			
ANXIETY	Between Groups	3,058	3	1,019	1,507	,221
	Within Groups	45,327	67	,677		
	Total	48,385	70			
UTIL	Between Groups	3,462	3	1,154	1,904	,137

COMP	Within Groups	40,603	67	,606		
	Total	44,064	70			
	Between Groups	4,964	3	1,655	2,421	,074
	Within Groups	45,780	67	,683		
	Total	50,744	70			
DIGITAL LITERACY	Between Groups	2,887	3	,962	2,115	,107
	Within Groups	30,487	67	,455		
	Total	33,373	70			

A visual presentation of age based means follows.



Graph: Scenaria and teachers age

YEARS OF SERVICE

To evaluate whether teaching experience influences the measured variables, descriptive statistics were calculated across four categories for Years of Service : less than 5 years (n=9), 6-15 years (n=23), 16-25 years (n=25), and over 25 years (n=14). Both perceived competence (COMP) and digital literacy (DIGITAL LITERACY) decrease steadily as years of service increase, with the newest teachers scoring the highest and the most experienced teachers scoring the lowest. Conversely, technology-related anxiety shows a gradual increase alongside years of service.

Table 54: Means based on years of service

Variables	Years of service	N	Mean	SD
1ST SCENARIO	<5	9	2,11	,928
	6-15	23	2,22	,518
	16-25	25	2,08	,640
	>25	14	1,93	,917
	Total	71	2,10	,700
2ND SCENARIO	<5	9	2,22	1,093
	6-15	23	2,30	,635
	16-25	25	2,32	,690

3D SCENARIO	>25	14	2,14	,949
	Total	71	2,27	,774
	<5	9	1,67	,707
	6-15	23	1,91	,996
	16-25	25	2,04	,978
ANXIETY	>25	14	1,86	1,099
	Total	71	1,92	,967
	<5	9	2,00	,742
	6-15	23	2,06	,703
	16-25	25	2,20	,885
UTIL	>25	14	2,22	1,028
	Total	71	2,13	,831
	<5	9	2,94	,759
	6-15	23	3,31	,762
	16-25	25	3,15	,673
COMP	>25	14	3,01	1,057
	Total	71	3,15	,793
	<5	9	3,86	,620
	6-15	23	3,77	,734
	16-25	25	3,48	,794
DIGITAL LITERACY	>25	14	3,12	1,106
	Total	71	3,55	,851
	<5	9	3,80	,655
	6-15	23	3,52	,599
	16-25	25	3,47	,577
	>25	14	3,08	,916
	Total	71	3,45	,690

Years of service did not have a statistically significant effect on any of the measured variables (all $p > .05$). Therefore, statistically speaking, teaching experience does not significantly differentiate the participants' outcomes.

Table 55: Differences based on years of service

		Sum of Squares	df	Mean Square	F	Sig.
1ST SCENARIO	Between Groups	,739	3	,246	,492	,689
	Within Groups	33,571	67	,501		
	Total	34,310	70			
2ND SCENARIO	Between Groups	,336	3	,112	,181	,909
	Within Groups	41,579	67	,621		
	Total	41,915	70			
3D SCENARIO	Between Groups	,993	3	,331	,344	,794
	Within Groups	64,500	67	,963		
	Total	65,493	70			
ANXIETY	Between Groups	,523	3	,174	,244	,865
	Within Groups	47,862	67	,714		
	Total	48,385	70			

UTIL	Between Groups	1,248	3	,416	,651	,585
	Within Groups	42,816	67	,639		
	Total	44,064	70			
COMP	Between Groups	4,712	3	1,571	2,286	,087
	Within Groups	46,032	67	,687		
	Total	50,744	70			
DIGITAL LITERACY	Between Groups	3,108	3	1,036	2,293	,086
	Within Groups	30,266	67	,452		
	Total	33,373	70			

A visual presentation of years of service based means follows.

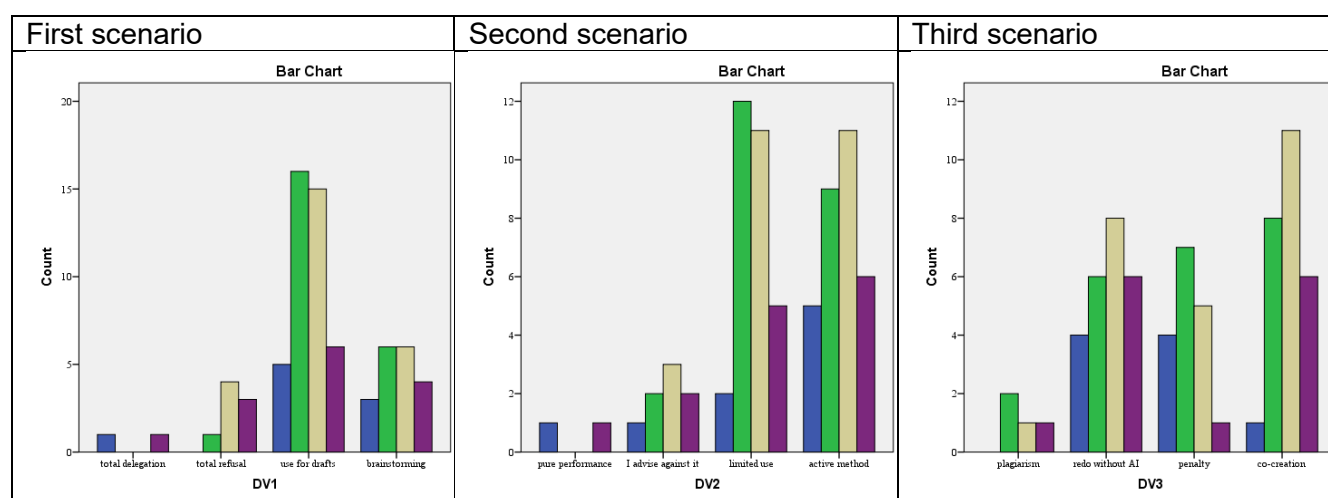


Table: Scenaria and teachers years of service

TYPE OF SCHOOL

To examine the potential impact of the educational setting on the measured variables, participants were categorized by the type of school where they teach: Middle school (n=33), High school (n=33), and Vocational/Other (n=5). Descriptive statistics reveal striking numerical differences for the Vocational/Other group compared to the traditional secondary education groups. The Vocational/Other category is very small and statistically unreliable due to size. The mean scores for Middle and High school teachers remained relatively similar to one another across all dimensions.

Table 56: Means based on school type

Variables	School type	N	Mean	SD
1ST SCENARIO	Middle school	33	2,24	,663
	High school	33	1,91	,723
	Vocational/Other	5	2,40	,548
	Total	71	2,10	,700
2ND SCENARIO	Middle school	33	2,27	,674
	High school	33	2,21	,857

3D SCENARIO	ANXIETY	Vocation al/Other	5		2,60	,894
		Total	71		2,27	,774
		Middle school		33	1,94	,998
		High school	33		1,88	,927
	UTIL	Vocation al/Other	5		2,00	1,225
		Total	71		1,92	,967
		Middle school		33	2,28	0,85
		High school	33		2,06	0,81
	COMP	Vocation al/Other	5		1,71	0,82
		Total	71		2,14	0,83
		Middle school		33	3,13	0,77
		High school	33		3,06	0,81
DIGITAL LITERACY	ANXIETY	Vocation al/Other	5		3,90	0,56
		Total	71		3,15	0,79
		Middle school		33	3,50	0,84
		High school	33		3,49	0,87
	UTIL	Vocation al/Other	5		4,39	0,28
		Total	71		3,56	0,85
		Middle school		33	3,43	0,63
		High school	33		3,36	0,67
	COMP	Vocation al/Other	5		4,30	0,76
		Total	71		3,46	0,69

While most variables did not yield significant results ($p > .05$), the analysis revealed a statistically significant main effect for Digital Literacy (DIGITAL LITERACY) based on school type, $F(2,68) = 4.489$, $p = .015$. This indicates that the educational setting plays a significant role in determining a teacher's digital literacy score.

Table 57: Differences based on school type

		Sum of Squares	df	Mean Square	F	Sig.
1ST SCENARIO	Between Groups	2,322	2	1,161	2,468	,092
	Within Groups	31,988	68	,470		
	Total	34,310	70			
2ND SCENARIO	Between Groups	,655	2	,327	,540	,585
	Within Groups	41,261	68	,607		
	Total	41,915	70			
3D SCENARIO	Between Groups	,099	2	,050	,051	,950
	Within Groups	65,394	68	,962		
	Total	65,493	70			

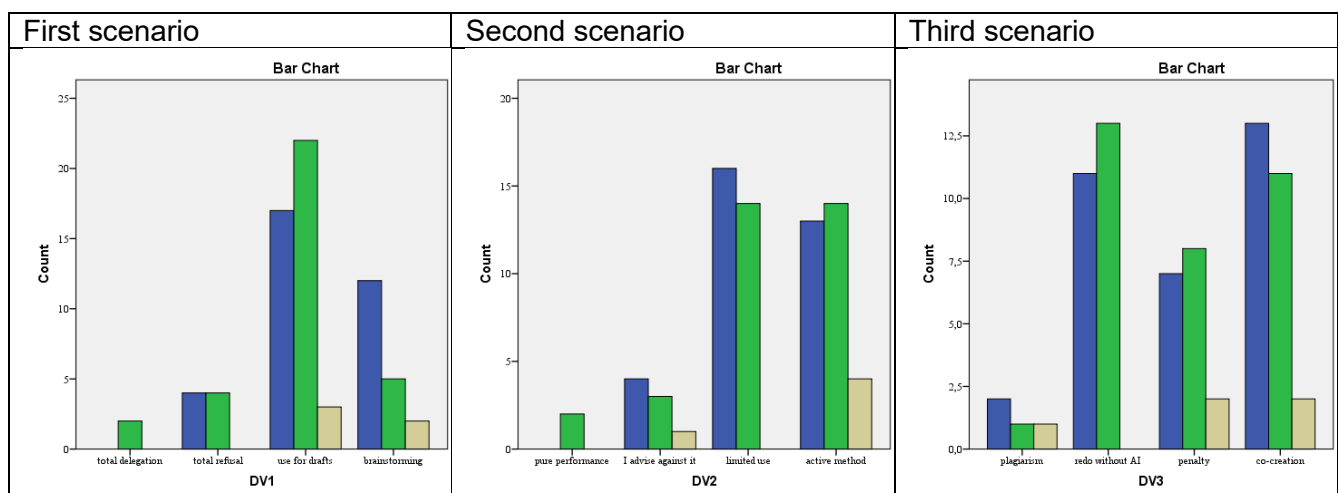
ANXIETY	Between Groups	1,796	2	,898	1,311	,276
	Within Groups	46,589	68	,685		
	Total	48,385	70			
UTIL	Between Groups	3,095	2	1,547	2,568	,084
	Within Groups	40,969	68	,602		
	Total	44,064	70			
COMP	Between Groups	3,738	2	1,869	2,704	,074
	Within Groups	47,006	68	,691		
	Total	50,744	70			
DIGITAL LITERACY	Between Groups	3,892	2	1,946	4,489	,015
	Within Groups	29,481	68	,434		
	Total	33,373	70			

There was no statistically significant difference in digital literacy between Middle school and High school teachers ($p = .907$) according post hoc comparisons. Only teaching in a vocational or alternative setting is associated with higher digital literacy compared to traditional secondary settings, though interpretations should consider the small sample size of the vocational cohort ($n=5$).

Table 58: Post hoc comparison based on school type

(I) schoolType	(J) schoolType	Mean Difference (I-J)	Std. Error	Sig.
Middle school	High school	,06818	,16210	,907
	Vocational/Other	-,87197	,31598	,020
High school	Middle school	-,06818	,16210	,907
	Vocational/Other	-,94015	,31598	,011
Vocational/Other	Middle school	,87197	,31598	,020
	High school	,94015	,31598	,011

*. The mean difference is significant at the 0.05 level.



Graph: Scenaria and teachers school type

STUDIES

To investigate whether a teacher's academic background influences their responses, descriptive statistics were generated across four categories of study: humanistics (n=32), science (n=31), social studies (n=2), and a combined group encompassing physical education, special education, and other specialties (n=6).

Table 59: Means based on studies

		N	Mean	SD
1ST SCENARIO	humanistics	32	2,22	0,66
	science	31	2,00	0,73
	social studies	2	1,50	0,71
	Physical education, special education, other	6		
	Total	71	2,17	0,75
	humanistics	32	2,10	0,70
	science	31	2,31	0,74
2ND SCENARIO	social studies	2	2,16	0,78
	Physical education, special education, other	6	2,00	1,41
	Total	71	2,67	0,82
	humanistics	32	2,27	0,77
	science	31	1,88	0,98
	social studies	2	2,03	0,91
	Physical education, special education, other	6	1,00	1,41
3D SCENARIO	Total	71	1,83	1,17
	humanistics	32	1,92	0,97
	science	31	1,89	0,63
	social studies	2	2,38	0,85
	Physical education, special education, other	6	2,36	1,52
	Total	71	1,89	0,63
	humanistics	32	2,38	0,85
ANXIETY	science	31	2,36	1,52
	social studies	2		
	Physical education, special education, other	6		
	Total	71	2,14	1,28
	humanistics	32	2,14	0,83
	science	31	3,27	0,68
	social studies	2	2,99	0,78
UTIL	Physical education, special education, other	6	3,00	1,65
	Total	71	3,39	1,19
	humanistics	32	3,15	0,79
	science	31		

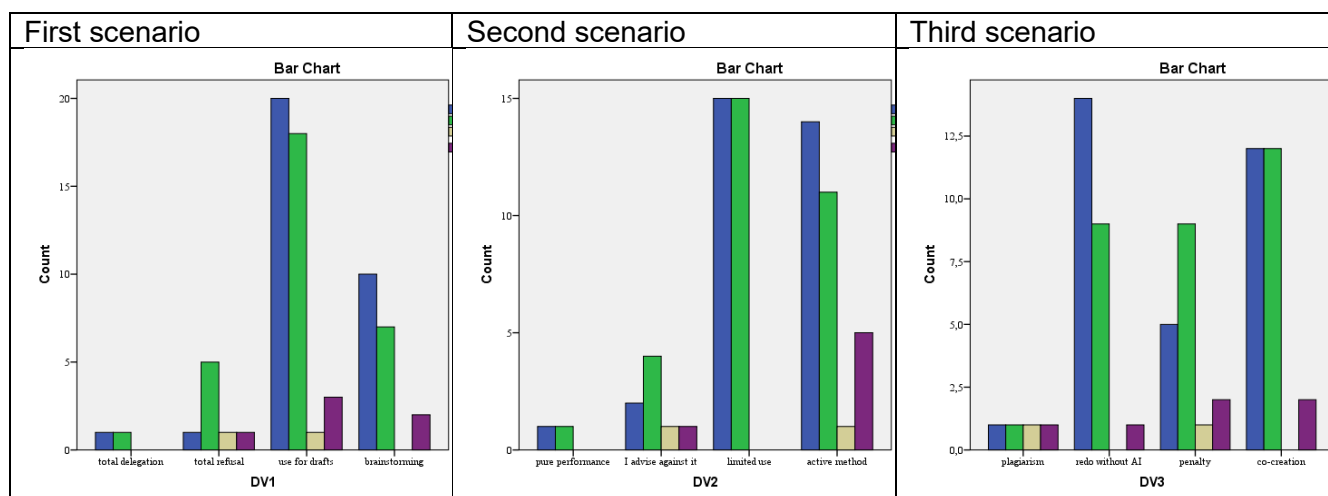
COMP	humanistics	32	3,58	0,60
	science	31	3,52	0,97
	social studies	2	3,02	1,57
	Physical education, special education, other	6		
	Total	71	3,78	1,24
			3,56	0,85
DIGITAL LITERACY	humanistics	32	3,30	0,58
	science	31	3,60	0,66
	social studies	2	2,63	1,59
	Physical education, special education, other	6		
	Total	71	3,81	0,88
			3,46	0,69

Academic background did not have a statistically significant main effect on any of the measured variables (all $p > .05$). It is noteworthy that the variance in digital literacy (DIGITAL LITERACY) scores strongly approached statistical significance ($F = 2.638$, $p = .057$), but ultimately did not cross the .05 alpha level. Consequently, the data suggests that teachers across these different academic disciplines maintain relatively consistent levels of digital literacy, perceived utility, competence, and anxiety.

Table 60: Differences based on studies

		Sum of Squares	df	Mean Square	F	Sig.
1ST SCENARIO	Between Groups	1,508	3	,503	1,027	,387
	Within Groups	32,802	67	,490		
	Total	34,310	70			
2ND SCENARIO	Between Groups	1,514	3	,505	,837	,478
	Within Groups	40,402	67	,603		
	Total	41,915	70			
3D SCENARIO	Between Groups	2,192	3	,731	,773	,513
	Within Groups	63,301	67	,945		
	Total	65,493	70			
ANXIETY	Between Groups	3,874	3	1,291	1,944	,131
	Within Groups	44,512	67	,664		
	Total	48,385	70			
UTIL	Between Groups	1,656	3	,552	,872	,460
	Within Groups	42,408	67	,633		
	Total	44,064	70			
COMP	Between Groups	,926	3	,309	,415	,743
	Within Groups	49,818	67	,744		
	Total	50,744	70			

DIGITAL LITERACY	Between Groups	3,526	3	1,175	2,638	,057
	Within Groups	29,847	67	,445		
	Total	33,373	70			



Graph: Scenaria and teachers studies

USE OF AI

To explore the impact of artificial intelligence integration, participants were categorized based on their primary Use of AI : administrative work (n=11), teaching (n=35), and active use (n=25). A preliminary review of the mean scores reveals distinct and compelling trends. Teachers who describe their AI use as active consistently reported the highest levels of perceived competence (4.16), digital literacy (3.78), and utility (3.52), while simultaneously reporting the lowest technology-related anxiety (1.87). Conversely, teachers who restrict their AI use primarily to admin work reported the highest anxiety (2.76) and the lowest scores across competence, utility, and digital literacy.

Table 61: Means based on AI use

		N	Mean	SD
1ST SCENARIO	admin work	11	1,45	,820
	teaching	35	2,26	,611
	active	25	2,16	,624
	Total	71	2,10	,700
2ND SCENARIO	admin work	11	2,09	,831
	teaching	35	2,31	,583
	Active	25	2,28	,980
	Total	71	2,27	,774
3D SCENARIO	admin work	11	1,64	,809
	teaching	35	1,80	,933
	Active	25	2,20	1,041
	Total	71	1,92	,967
ANXIETY	admin work	11	2,76	,91979
	teaching	35	2,12	,85066
	Active	25	1,87	,62040

UTIL	Total	71	2,1368	,83139
	admin work	11	2,4848	,94415
	teaching	35	3,0905	,72574
	Active	25	3,5267	,60223
COMP	Total	71	3,1502	,79340
	admin work	11	2,6364	,98207
	teaching	35	3,4130	,70783
	Active	25	4,1655	,44534
DIGITAL LITERACY	Total	71	3,5576	,85142
	admin work	11	3,1250	,74791
	teaching	35	3,3321	,61830
	Active	25	3,7800	,65876
	Total	71	3,4577	,69048

Unlike previous demographic variables, the Use of AI yielded highly statistically significant results across almost all measured dimensions. The analysis confirmed significant main effects for 1ST SCENARIO

, $F(2,68) = 6.543$, $p = .003$, Anxiety, $F(2,68) = 4.891$, $p = .010$, perceived Utility, $F(2,68) = 8.171$, $p = .001$, Competence, $F(2,68) = 20.877$, $p < .001$ and Digital Literacy, $F(2,68) = 5.118$, $p = .009$. This data strongly indicates that the manner of a teacher's engagement with AI is a major defining factor in their overall digital profile.

Table 62: Differences based on AI use

		Sum of Squares	Df	Mean Square	F	Sig.
1ST SCENARIO	Between Groups	5,537	2	2,768	6,543	,003
	Within Groups	28,773	68	,423		
	Total	34,310	70			
2ND SCENARIO	Between Groups	,424	2	,212	,347	,708
	Within Groups	41,492	68	,610		
	Total	41,915	70			
3D SCENARIO	Between Groups	3,348	2	1,674	1,831	,168
	Within Groups	62,145	68	,914		
	Total	65,493	70			
ANXIETY	Between Groups	6,085	2	3,042	4,891	,010
	Within Groups	42,301	68	,622		
	Total	48,385	70			

UTIL	Between Groups	8,538	2	4,269	8,171	,001
	Within Groups	35,527	68	,522		
	Total	44,064	70			
COMP	Between Groups	19,305	2	9,652	20,877	,000
	Within Groups	31,439	68	,462		
	Total	50,744	70			
DIGITAL LITERACY	Between Groups	4,366	2	2,183	5,118	,009
	Within Groups	29,007	68	,427		
	Total	33,373	70			

Multiple Comparisons based on AI use

The results reveal a clear hierarchy based on AI integration. Teachers with active AI use demonstrated significantly higher digital literacy than both the teaching and admin work groups. Furthermore, for perceived Competence (COMP), all three groups differed significantly from one another, indicating a clear, stepped progression as AI usage deepens. Finally, teachers using AI solely for admin work experienced significantly higher anxiety than active users ($p = .007$) and perceived significantly less utility in the technology than both other groups. Thus, preferred use of AI was the best demographic variable with the ones that reported active and innovative AI use having the lowest anxiety scores, the highest utility, competence and literacy scores compared to the ones that use AI for administrative work or as teaching support tool.

Table 63: Multiple comparisons and AI use

Dependent Variable	(I) AttAI	(J) AttAI	Mean Difference (I-J)	Std. Error	Sig.
1ST SCENARIO	admin work	teaching	-0,80	0,23	0,00
		active	-0,71	0,24	0,01
	Teaching	admin work	0,80	0,23	0,00
		active	0,10	0,17	0,84
	Active	admin work	0,71	0,24	0,01
		teaching	-0,10	0,17	0,84
	admin work	teaching	0,64	0,27	0,06
		active	0,89	0,29	0,01
	Teaching	admin work	-0,64	0,27	0,06
		active	0,25	0,21	0,45
	Active	admin work	-0,89	0,29	0,01
		teaching	-0,25	0,21	0,45
ANXIETY	admin work	teaching	0,64	0,27	0,06
		active	0,89	0,29	0,01
	Teaching	admin work	-0,64	0,27	0,06
		active	0,25	0,21	0,45
	Active	admin work	-0,89	0,29	0,01
		teaching	-0,25	0,21	0,45
UTIL	admin work	teaching	-0,61	0,25	0,05
		active	-1,04	0,26	0,00
	Teaching	admin work	0,61	0,25	0,05
		active	-0,44	0,19	0,06
	Active	admin work	-0,89	0,29	0,01
		teaching	-0,25	0,21	0,45

COMP	active	admin			
		work	1,04	0,26	0,00
		teachin			
	admin	g	0,44	0,19	0,06
		teachin			
		g	-0,78	0,24	0,00
	work	active	-1,53	0,25	0,00
		admin			
		work	0,78	0,24	0,00
	teachin	g	-0,75	0,18	0,00
DIGITAL LITERACY	active	admin			
		work	1,53	0,25	0,00
		teachin			
	admin	g	0,75	0,18	0,00
		teachin			
		g	-0,21	0,23	0,63
	work	active	-0,66	0,24	0,02
		admin			
		work	0,21	0,23	0,63
	teachin	g	-0,45	0,17	0,03
	active	admin			
		work	0,66	0,24	0,02
		teachin			
		g	0,45	0,17	0,03

First scenario	Second scenario	Third scenario
X2(6)=20.882, p=.002	X2(6)=12.395, p=.054	X2(6)=9.021, p=.172

Graph: Scenaria and AI use

Correlations

A correlation analysis was conducted to examine the relationships between the four main variables (anxiety, utility, competence, and digital literacy) and the three variables of the ethical decision making scenaria (FIRST SCENARIO, SECOND SCENARIO, and THIRD SCENARIO).

The four variables (anxiety, utility, competence, and digital literacy) demonstrated strong internal relationships. Technology-related anxiety was significantly and negatively correlated with both perceived utility ($r_s = -.54$, $p < .001$) and competence ($r_s = -.38$, $p = .001$). Conversely, perceived competence showed strong positive correlations with perceived utility ($r_s = .67$, $p < .001$) and digital literacy ($r_s = .53$, $p < .001$).

When examining the relationships between these four traits and the specific ethical based scenaria, distinct patterns emerged:

First scenario: No statistically significant correlations were found between first scenario and any of the measured core variables (all $p > .05$).

Second scenario demonstrated significant positive correlations with two core variables. Specifically, higher scores in the second scenario were moderately associated with higher perceived utility ($r_s = .33$, $p = .005$) and higher perceived competence ($r_s = .25$, $p = .039$).

Third scenario showed a significant negative correlation with anxiety ($r_s = -.26$, $p = .031$), indicating that higher third scenario scores are associated with lower technology-related anxiety. Additionally, third scenario had a significant positive correlation with perceived competence ($r_s = .24$, $p = .043$).

Table 64: Correlations

Variables	Utility	Comp	Digital literacy	1sce	2sce	3sce
Anxiety	-.538*	-.383*	-.049	-.181	-.153	-.256*
Utility		.670*	.352*	.126	.330*	.202
Competency			.528*	.045	.246*	.241*
Digital literacy				.094	.125	.030
FIRST SCENARIO (5)					.157	-.028
SECOND SCENARIO (6)						-.027

Regressions

First scenario

To determine how well the combination of technology-related anxiety (ANXIETY), perceived utility (UTIL), perceived competence (COMP), and digital literacy (DIGITAL LITERACY) predicts the outcome variable 1ST SCENARIO, a multiple linear regression analysis was conducted. The model summary presented in Table 27 reveals a multiple correlation coefficient (R) of .226 and an R Square value of .051. This indicates a very weak overall relationship, meaning that the four predictor variables combined account for only 5.1% of the variance observed in 1ST SCENARIO.

Table 65: First model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.226a	.051	-.006	.702

a. Predictors: (Constant), digital literacy, anxiety, utility, competence

Table 66: Significance of first model

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	1,754	4	,439	,889	,476b
Residual	32,556	66	,493		
Total	34,310	70			

a. Dependent Variable: 1ST SCENARIO

b. Predictors: (Constant), digital literacy, anxiety, utility, competence

The results indicate that the combined model does not significantly predict 1ST SCENARIO, yielding an F-statistic of .889 and a p-value of .476. Because this p-value is greater than the standard .05 significance threshold, the model is not considered a statistically valid fit for the data.

Table 67: Coefficients of first model

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.
	B	Beta		
1 (Constant)	1,540		2,377	,020
ANXIETY	-,052	-,061	-,426	,672
UTIL	,086	,097	,556	,580
COMP	,061	,074	,376	,708
DIGITAL LITERACY	,052	,051	,336	,738

a. Dependent Variable: 1ST SCENARIO

The p-values for anxiety ($p = .672$), utility ($p = .580$), competence ($p = .708$), and digital literacy ($p = .738$) all far exceed the .05 threshold. Consequently, the data suggests that a teacher's level of anxiety, perceived utility, competence, and digital literacy do not significantly influence or predict their outcomes on 1ST SCENARIO.

Second scenario

The model summary in Table 68 shows a multiple correlation coefficient (R) of .330 and an R Square value of .109. This means that the four predictor variables collectively account for roughly 10.9% of the variance in 2ND SCENARIO scores.

Table 68: Second model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,330a	,109	,055	,752

a. Predictors: (Constant), digital literacy, anxiety, utility, competence

The analysis yielded an F-statistic of 2.019 and a p-value of .102. Because this p-value is greater than the standard .05 alpha level, the overall model is not considered a statistically significant predictor of 2ND SCENARIO.

Table 69: Significance of second model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,570	4	1,142	2,019	,102b
	Residual	37,346	66	,566		
	Total	41,915	70			
a. Dependent Variable: 2ND SCENARIO						
b. Predictors: (Constant), digital literacy, anxiety, utility, competence						

While the overall model did not reach statistical significance, an examination of the individual predictors reveals a noteworthy finding: perceived utility (UTIL) emerged as a statistically significant individual predictor of 2ND SCENARIO ($p = .048$). The positive unstandardized coefficient ($B = .334$) suggests that higher perceived utility is associated with higher scores on 2ND SCENARIO. However, because the model is non-significant, this individual correlation is just an isolated instance with limited statistical use. The remaining variables—anxiety ($p = .631$), competence ($p = .858$), and digital literacy ($p = .923$)—did not significantly predict 2ND SCENARIO.

Table 70: Coefficients of second model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,027	,694		1,481	,143
	ANXIETY	,063	,130	,067	,482	,631
	UTIL	,334	,166	,342	2,013	,048
	COMP	,031	,174	,034	,179	,858
	DIGITAL LITERACY	-,016	,166	-,014	-,097	,923
a. Dependent Variable: 2ND SCENARIO						

Third scenario

The model summary in Table 33 indicates a multiple correlation coefficient (R) of .304 and an R Square of .092. This suggests that the combined independent variables account for only 9.2 % of the variance in 3D SCENARIO scores, indicating a weak overall relationship.

Table 71: Third model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,304a	,092	,037	,949
a. Predictors: (Constant), digital literacy, anxiety, utility, competence				

The analysis produced an F -statistic of 1.676 and a p -value of .166. Since this p -value is well above the standard .05 threshold, the overall model fails to significantly predict 3D SCENARIO.

Table 72: Significance of second model

Model	Sum of Squares	df	Mean Square	F	Sig.
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1	Regression	6,038	4	1,509	1,676	,166b
	Residual	59,455	66	,901		
	Total	65,493	70			
a. Dependent Variable: 3D SCENARIO						
b. Predictors: (Constant), digital literacy, anxiety, utility, competence						

Aligning with the non-significant overall ANOVA result, none of the independent variables emerged as significant predictors for 3D SCENARIO. The p-values for anxiety ($p = .176$), utility ($p = .920$), competence ($p = .291$), and digital literacy ($p = .651$) all far exceed the .05 significance level. Therefore, the data indicates that a teacher's level of anxiety, perceived utility, competence, and digital literacy do not effectively predict their outcomes on 3D SCENARIO.

Table 73: Coefficients of third model

Model	Unstandardized Coefficients		Standardized Coefficients		t	Sig.
	B	Std. Error	Beta			
1	(Constant)	1,958	,876		2,236	,029
	ANXIETY	-,224	,164	-,193	-1,366	,176
	UTIL	-,021	,209	-,017	-,101	,920
	COMP	,234	,220	,206	1,064	,291
	DIGITAL LITERACY	-,095	,210	-,068	-,454	,651
a. Dependent Variable: 3D SCENARIO						

The utilized Multiple Linear Regression to assess the relationships between the constructs (Anxiety, Utility, Competence, Digital Literacy) and scenario preferences yielded non-significant predictive models and weak coefficients and all three regressions failed. Therefore, an One-Way Analysis of Variance (ANOVA) will be complementary employed, which isolates and measures the between-group variance against the within-group variance aiming to comparative profiling.

Scenario based differences

AI assistant

The table that follows presents the means and standard deviations for each dimension based on the first scenario of an AI assistant that leads to reduced personal connection between teacher and material. Teachers presented different scores in all dimensions as p value indicates.

Table 74: Comparison of first model

Scenario	Level	Anxiety	Competences	Utility	Digital Literacy
1ST SCENARIO (AI Assist)	Techno-centric	1.35 (.30)	3.45 (1.09)	3.00 (1.64)	3.37 (.70)
	Conservative	3.21 (.77)	2.02 (.66)	1.93 (.35)	2.70 (.86)
	Prudent	1.98 (.66)	3.95 (.55)	3.44 (.66)	3.64 (.55)
	Digital Wisdom	2.09 (.89)	3.33 (.62)	3.01 (.59)	3.37 (.69)
	p-value (Sig.)	.000	.000	.000	.003

Teachers scored differently in the anxiety dimension, based to their preferences on the first scenario, with conservatives that totally refuse the AI assist ($M=3.21$, $SD=.77$) reporting much higher anxiety than all the other groups, such as technocentric that go for total delegation ($M=1.35$, $SD=.30$), prudent that use AI assistant for drafts ($M=1.98$, $SD=.66$) and digitally wise that use AI assistant for brainstorming ($M=2.09$, $SD=.89$), $F(3, 67)=6.949$, $p=.000$.

Regarding the utility dimension, post-hoc comparisons showed that conservatives that totally refuse the AI assistant ($M=1.93$, $SD=.35$) scored significantly lower in perceived utility compared to the prudent group that use AI for drafts ($M=3.44$, $SD=.66$) and the digitally wise group that use it for brainstorming ($M=3.01$, $SD=.59$). The technocentric group ($M=3.00$, $SD=1.64$) did not differ significantly from any of the other groups on utility.

Teachers also scored differently in the competences dimension, with conservatives that totally refuse the AI assist ($M=2.02$, $SD=.66$) reporting much lower competences than all the other groups, such as technocentric that go for total delegation ($M=3.45$, $SD=1.09$), prudent that use AI assistant for drafts ($M=3.95$, $SD=.55$) and digitally wise that use AI assistant for brainstorming ($M=3.33$, $SD=.62$), $F(3, 67)= 24.562$, $p=.000$.

Regarding the digital literacy dimension, there is significant difference among the groups, $F(3, 67)=5.034$, $p=.003$. Post-hoc comparisons showed that conservatives that totally refuse the AI assistant ($M=2.70$, $SD=.86$) scored significantly lower in digital literacy compared to the prudent group that use it for drafts ($M=3.64$, $SD=.55$). The technocentric and digitally wise groups did not differ significantly from any of the other groups on digital literacy.

Table 75: Significant differences of first model

Variables		Sum of Squares	df	Mean Square	F	Sig.
ANXIETY	Between Groups	11,483	3	3,828	6,949	,000
	Within Groups	36,903	67	,551		
	Total	48,385	70			
UTIL	Between Groups	15,880	3	5,293	12,583	,000
	Within Groups	28,184	67	,421		
	Total	44,064	70			
COMP	Between Groups	26,577	3	8,859	24,562	,000
	Within Groups	24,166	67	,361		
	Total	50,744	70			
DIGITAL LITERACY	Between Groups	6,139	3	2,046	5,034	,003
	Within Groups	27,235	67	,406		
	Total	33,373	70			

In the following table post hoc comparisons become available.

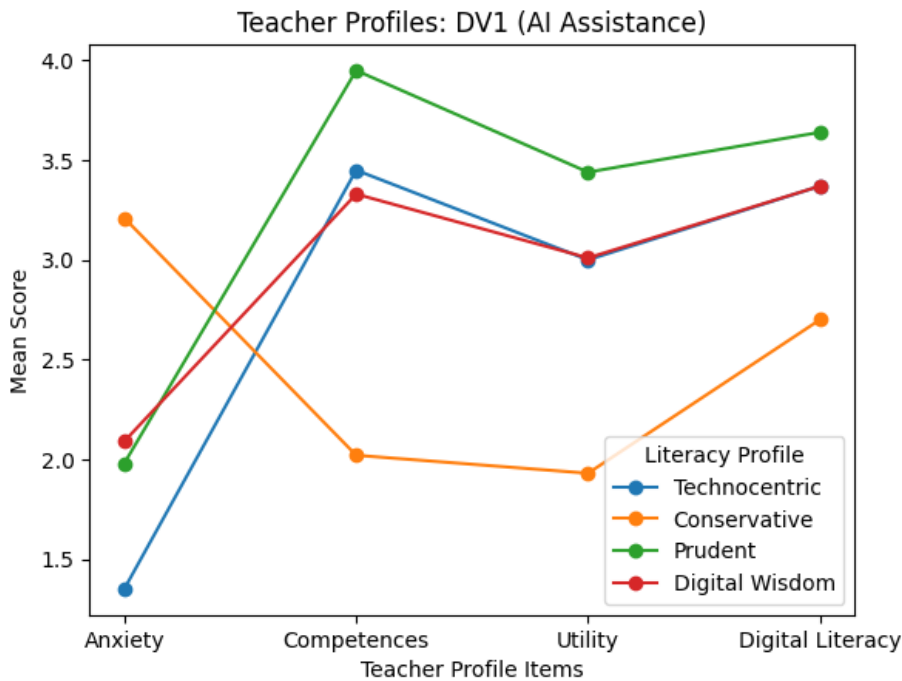
Table 76: Multiple comparison for first model

Dependent Variable	(I) 1ST SCENARIO	(J) 1ST SCENARIO	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
ANXIETY	total delegation	total refusal	-1,86	0,59	0,01	-3,40	-0,31
		use for drafts	-0,63	0,54	0,65	-2,04	0,79
		brainstorming	-0,74	0,55	0,54	-2,19	0,71
		total delegation	1,86	0,59	0,01	0,31	3,40

UTIL	total	use for drafts	1,23	0,29	0,00	0,47	1,98	
	refusal	Brainstorming	1,12	0,31	0,00	0,29	1,94	
	use for drafts	total delegation	0,63	0,54	0,65	-0,79	2,04	
		total refusal	-1,23	0,29	0,00	-1,98	-0,47	
		Brainstorming	-0,11	0,21	0,95	-0,65	0,43	
	Brainstorming	total delegation	0,74	0,55	0,54	-0,71	2,19	
		total refusal	-1,12	0,31	0,00	-1,94	-0,29	
		use for drafts	0,11	0,21	0,95	-0,43	0,65	
	total delegation	total refusal	1,06	0,51	0,17	-0,29	2,41	
		use for drafts	-0,45	0,47	0,78	-1,69	0,79	
		Brainstorming	-0,02	0,48	1,00	-1,29	1,25	
	total refusal	total delegation	-1,06	0,51	0,17	-2,41	0,29	
		use for drafts	-1,51	0,25	0,00	-2,17	-0,85	
		Brainstorming	-1,08	0,27	0,00	-1,80	-0,36	
	use for drafts	total delegation	0,45	0,47	0,78	-0,79	1,69	
		total refusal	1,51	0,25	0,00	0,85	2,17	
		Brainstorming	0,43	0,18	0,09	-0,04	0,90	
	Brainstorming	total delegation	0,02	0,48	1,00	-1,25	1,29	
		total refusal	1,08	0,27	0,00	0,36	1,80	
		use for drafts	-0,43	0,18	0,09	-0,90	0,04	
	COMP	total delegation	total refusal	1,43	0,47	0,02	0,18	2,68
			use for drafts	-0,50	0,43	0,66	-1,65	0,64
			Brainstorming	0,12	0,45	0,99	-1,05	1,30
		total refusal	total delegation	-1,43	0,47	0,02	-2,68	-0,18
use for drafts			-1,94	0,23	0,00	-2,55	-1,32	
Brainstorming			-1,31	0,25	0,00	-1,97	-0,64	
use for drafts		total delegation	0,50	0,43	0,66	-0,64	1,65	
		total refusal	1,94	0,23	0,00	1,32	2,55	
		Brainstorming	0,63	0,17	0,00	0,19	1,07	
Brainstorming		total delegation	-0,12	0,45	0,99	-1,30	1,05	
		total refusal	1,31	0,25	0,00	0,64	1,97	
		use for drafts	-0,63	0,17	0,00	-1,07	-0,19	
total delegation		total refusal	0,67	0,50	0,55	-0,66	2,00	
		use for drafts	-0,27	0,46	0,94	-1,48	0,95	
		Brainstorming	0,00	0,47	1,00	-1,25	1,25	
total refusal		total delegation	-0,67	0,50	0,55	-2,00	0,66	
		use for drafts	-0,94	0,25	0,00	-1,59	-0,29	
		Brainstorming	-0,67	0,27	0,07	-1,38	0,04	
DIGITAL LITERACY		use for drafts	total delegation	0,27	0,46	0,94	-0,95	1,48
			total refusal	0,94	0,25	0,00	0,29	1,59
			Brainstorming	0,27	0,18	0,43	-0,20	0,73
		Brainstorming	total delegation	0,00	0,47	1,00	-1,25	1,25
			total refusal	0,67	0,27	0,07	-0,04	1,38
			use for drafts	-0,27	0,18	0,43	-0,73	0,20

. The mean difference is significant at the 0.05 level.

The graph that follows optically verifies that conservative teachers (who totally refuse AI assistance) report significantly higher anxiety than all other groups, report significantly less competences, find AI less useful and report less digital literacy.



Graph: Differences in the first model

Second scenario

The table that follows presents the means and standard deviations for each dimension based on the second scenario of an AI tutor that leads to reduced personal connection between teacher and student. Teachers present different scores in the dimensions of competences and utilities.

Table 77: Comparison of second model

Scenario	Level	Anxiety	Competences	Utility	Digital Literacy
2ND SCENARIO (AI Tutor)	Technocentric	1.92 (1.11)	4.40 (.25)	3.41 (1.06)	3.62 (1.06)
	Conservative	2.30 (1.03)	2.97 (1.16)	2.43 (.99)	3.34 (.93)
	Prudent	2.27 (.81)	3.34 (.90)	3.01 (.72)	3.32 (.65)
	Digital Wisdom	1.97 (.78)	3.86 (.54)	3.45 (.66)	3.45 (.69)
	p-value (Sig.)	.483	.005	.007	.447

Teachers scored differently in the utility dimension, based on their preferences on the second scenario. Post-hoc comparisons showed that conservatives who advise against the AI tutor ($M=2.43$, $SD=.99$) scored significantly lower in perceived utility compared to the digitally wise group that prefers the active method ($M=3.45$, $SD=.66$), $F(3,67)=4.656$, $p=.005$. The technocentric (pure performance) and prudent (limited use) groups did not differ significantly from any of the other groups on utility. Teachers scored differently in the competences dimension, based to their preferences on the second scenario with post-hoc tests indicating that conservatives who advise against the AI tutor ($M=2.97$, $SD=1.16$) reported significantly lower competences than the digitally wise group that prefers the active method ($M=3.86$, $SD=.54$), $F(3,67)=4.449$, $p=.007$.

Unlike the first scenario, there were no significant differences among the groups regarding anxiety, $F(3, 67)=.828$, $p=.483$, or digital literacy, $F(3, 67)=.898$, $p=.447$.

Table 78: Significance on second model

		Sum Squares	of df	Mean Square	F	Sig.
ANXIE TY	Between Groups	1,730	3	,577	,828	,483
	Within Groups	46,655	67	,696		
	Total	48,385	70			
UTIL	Between Groups	7,602	3	2,534	4,656	,005
	Within Groups	36,462	67	,544		
	Total	44,064	70			
COMP	Between Groups	8,429	3	2,810	4,449	,007
	Within Groups	42,315	67	,632		
	Total	50,744	70			
DIGITA L LITERA CY	Between Groups	1,290	3	,430	,898	,447
	Within Groups	32,083	67	,479		
	Total	33,373	70			

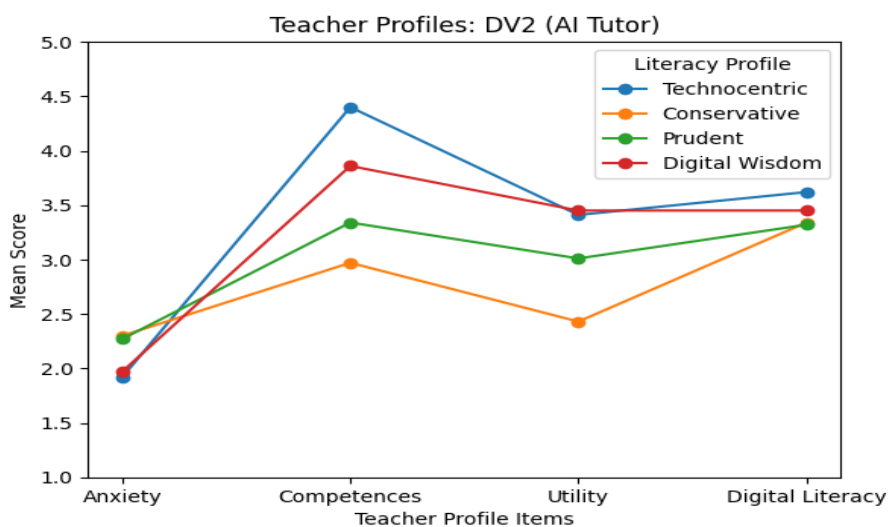
In the following table, post-hoc comparisons become available. Regarding the utility dimension, post-hoc comparisons showed that conservatives who advise against the AI tutor ($M=2.43$, $SD=.99$) scored significantly lower in perceived utility compared to the digitally wise group that prefers the active method ($M=3.45$, $SD=.66$). The technocentric (pure performance) ($M=3.41$, $SD=1.06$) and prudent (limited use) ($M=3.01$, $SD=.72$) groups did not differ significantly from any of the other groups on utility. Regarding the competences dimension, post-hoc tests indicated that conservatives who advise against the AI tutor ($M=2.97$, $SD=1.16$) reported significantly lower competences than the digitally wise group that prefers the active method ($M=3.86$, $SD=.54$), $p=.032$. The technocentric group ($M=4.40$, $SD=.25$) and prudent group ($M=3.34$, $SD=.90$) did not differ significantly from any of the other groups on competences.

Table 79: Multiple comparisons and second model

Dependent Variable	(I) 2ND SCENARIO	(J) 2ND SCENARIO	Mean Differenc e (I-J)	Std. Error	Sig.	95% Interval Lower Bound	Confidence Upper Bound
UTIL	I advise against it	I advise against it	-0,33	0,33	0,75	-1,20	0,54
		limited use	-0,30	0,21	0,49	-0,87	0,26
		pure performanc e					
	pure performanc e	I advise against it	0,98	0,58	0,34	-0,56	2,52
		limited use	0,41	0,54	0,88	-1,01	1,83
		active method	-0,03	0,54	1,00	-1,45	1,38
	I advise against it	pure performance	-0,98	0,58	0,34	-2,52	0,56
		limited use	-0,57	0,29	0,22	-1,35	0,20
		active method	-1,01	0,29	0,01	-1,78	-0,24
	limited use	pure performance	-0,41	0,54	0,88	-1,83	1,01
		I advise against it	0,57	0,29	0,22	-0,20	1,35
		active method	-0,44	0,19	0,10	-0,94	0,06

COMP	active method	pure performance	0,03	0,54	1,00	-1,38	1,45
		I advise against it	1,01	0,29	0,01	0,24	1,78
		limited use	0,44	0,19	0,10	-0,06	0,94
		I advise against it	1,43	0,63	0,11	-0,22	3,09
	pure performance	limited use	1,07	0,58	0,26	-0,46	2,60
		active method	0,55	0,58	0,78	-0,98	2,07
		I advise against it	-1,43	0,63	0,11	-3,09	0,22
	I advise against it	limited use	-0,36	0,32	0,66	-1,20	0,47
		active method	-0,88	0,32	0,03	-1,72	-0,05
		pure performance	-1,07	0,58	0,26	-2,60	0,46
	limited use	I advise against it	0,36	0,32	0,66	-0,47	1,20
		active method	-0,52	0,20	0,06	-1,06	0,02
		pure performance	-0,55	0,58	0,78	-2,07	0,98
	active method	I advise against it	0,88	0,32	0,03	0,05	1,72
		limited use	0,52	0,20	0,06	-0,02	1,06
		pure performance	0,03	0,54	1,00	-1,38	1,45

. The mean difference is significant at the 0.05 level.



Graph: Differences of second model

Third scenario

The table that follows presents the means and standad deviations for each dimension based on the third scenario of a student that presents an essay including AI generated text. Teachers present different scores only on anxiety, as indicated by p value.

Table 80: Differences of third model

Scenario	Level	Anxiety	Competences	Utility	Digital Literacy
3D SCENARIO (AI Essay)	Technocentric	2.00 (1.02)	3.50 (1.09)	3.04 (1.14)	3.50 (1.44)

Conservative	2.49 (.95)	3.24 (.78)	2.93 (.95)	3.27 (.61)
Prudent	2.10 (.86)	3.65 (.98)	3.19 (.85)	3.74 (.63)
Digital Wisdom	1.84 (.52)	3.78 (.73)	3.33 (.64)	3.43 (.62)
p-value (Sig.)	<.001	.362	.150	.197

Teachers scored differently in the anxiety dimension based on their preferences for the third scenario, $F(3, 67)=2.775$, $p=.048$. There were no significant differences among the groups regarding competences, $F(3, 67)=1.832$, $p=.150$, utility, $F(3, 67)=1.085$, $p=.362$, or digital literacy, $F(3, 67)=1.604$, $p=.197$.

Table 81: Significance of third model

		Sum Squares	df	Mean Square	F	Sig.
ANXIETY	Between Groups	5,347	3	1,782	2,775	,048
	Within Groups	43,038	67	,642		
	Total	48,385	70			
UTIL	Between Groups	2,041	3	,680	1,085	,362
	Within Groups	42,023	67	,627		
	Total	44,064	70			
COMP	Between Groups	3,847	3	1,282	1,832	,150
	Within Groups	46,896	67	,700		
	Total	50,744	70			
DIGITAL LITERACY	Between Groups	2,236	3	,745	1,604	,197
	Within Groups	31,137	67	,465		
	Total	33,373	70			

Multiple Comparisons

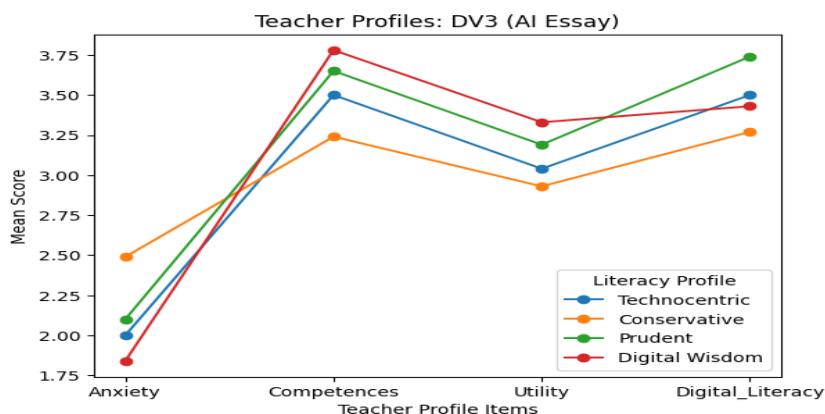
In the following table, post-hoc comparisons become available. Regarding the anxiety dimension, post-hoc comparisons showed that conservatives who ask students to redo the essay without AI ($M=2.49$, $SD=.95$) scored significantly higher in anxiety compared to the digitally wise group that promotes co-creation ($M=1.84$, $SD=.52$), $p=.029$. The technocentric group (Plagiarism) ($M=2.00$, $SD=1.02$) and prudent group (Penalty) ($M=2.10$, $SD=.86$) did not differ significantly from any of the other groups on anxiety.

Table 82: Multiple comparisons of third model

(I) 3D SCENARIO	(J) 3D SCENARIO	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound Upper Bound	
Plagiarism	redo without AI	-0,49	0,43	0,67	-1,63	0,65
	Penalty	-0,11	0,45	1,00	-1,28	1,06
	co-creation	0,15	0,43	0,98	-0,98	1,29
redo without AI	Plagiarism	0,49	0,43	0,67	-0,65	1,63
	Penalty	0,38	0,25	0,44	-0,28	1,05
	co-creation	0,65	0,23	0,03	0,05	1,25

Penalty	Plagiarism	0,11	0,45	1,00	-1,06	1,28
	redo without					
	AI	-0,38	0,25	0,44	-1,05	0,28
	co-creation	0,26	0,25	0,72	-0,40	0,92
co-creation	Plagiarism	-0,15	0,43	0,98	-1,29	0,98
	redo without					
	AI	-0,65	0,23	0,03	-1,25	-0,05
	Penalty	-0,26	0,25	0,72	-0,92	0,40

. The mean difference is significant at the 0.05 level.



Graph: Differences of third model

The four core dimensions failed to predict any of the three scenario with non significant regression models. But anovas, regarding the first scenario showed that technocentric reported least anxiety and conservative the highest anxiety. Prudent reported highest competences and digital literacy and conservative the lowest competences and digital literacy. Prudent find the highest utility in AI and conservative the lowest.

In the second scenario technocentric reported highest competences and conservative the lowest. Digitally wise find the highest utility in AI and conservative the lowest. Regarding anxiety and digital literacy there were no differences.

In the third scenario digitally wise reported lowest anxiety and conservative the highest. No differences were found in the rest three core dimensions. Next table demonstrates the findings for the research hypothesis (for the teachers' sample).

STUDENTS

Descriptive Statistics

Means and standard deviations

Regarding the item AILQ_IM01 sample s mean was $M=3.19$, $SD=1.15$, demonstrating neutral stance (neither disagree, either agree). Similarly, students demonstrated a neutral stance with most items with M between 2.50 – 3.50 (Lindner & Lindner (2024). Students rather disagreed with AILQ_IMO3 , ($M=2.44$, $SD=1.23$), AILQ_EN02 ($M=2.45$, $SD=1.28$), and AILQ_SI03 ($M=2.28$, $SD=1.33$). Lastly, students agreed with AILQ_BI01 , ($M=3.74$, $SD=1.24$), AILQ_KU02 , ($M=3.84$, $SD=1.29$), AILQ_AIE02 , ($M=3.69$, $SD=1.32$), AILQ_AIE08 ($M=3.65$, $SD=1.28$), and AILQ_AIE10 ($M=3.56$, $SD=1.31$). Students agreed that they will use AI in the future, that they know how to use AI apps, that the bad use of AI can lead to problems for humanity, that AI should benefit everybody independently from physical abilities and gender and that AI users should be informed about the system s goal and what are the limitations.

Table 83: Means for students questionnaire

ITEMS	N	Minimum	Maximum	Mean	SD
AILQ_IM01	350	1,00	5,00	3,19	1,16
AILQ_IM02	350	1,00	5,00	3,10	1,23
AILQ_IM03	350	1,00	5,00	2,45	1,23
AILQ_IM04	350	1,00	5,00	2,94	1,32
AILQ_SE01	350	1,00	5,00	3,24	1,18
AILQ_SE02	350	1,00	5,00	3,31	1,20
AILQ_SE03	350	1,00	5,00	2,97	1,20
AILQ_SE04	350	1,00	5,00	3,33	1,19
AILQ_CL01	350	1,00	5,00	3,23	1,12
AILQ_CL03	350	1,00	5,00	3,32	1,19
AILQ_BI01	350	1,00	5,00	3,74	1,24
AILQ_BI02	350	1,00	5,00	3,01	1,30
AILQ_BI03	350	1,00	5,00	2,61	1,30
AILQ_EN01	350	1,00	5,00	2,72	1,30
AILQ_EN02	350	1,00	5,00	2,46	1,28
AILQ_SI01	350	1,00	5,00	2,52	1,38
AILQ_SI02	350	1,00	5,00	3,07	1,30
AILQ_SI03	350	1,00	5,00	2,28	1,33
AILQ_KU01	350	1,00	5,00	3,08	1,30
AILQ_KU02	350	1,00	5,00	3,84	1,30
AILQ_KU05	350	1,00	5,00	3,18	1,25
AILQ_EC01	350	1,00	5,00	3,19	1,25
AILQ_EC03	350	1,00	5,00	3,05	1,31
AILQ_EC04	350	1,00	5,00	3,04	1,17
AILQ_AIE02	350	1,00	5,00	3,70	1,33
AILQ_AIE05	350	1,00	5,00	3,50	1,25
AILQ_AIE07	350	1,00	5,00	3,33	1,21
AILQ_AIE08	350	1,00	5,00	3,66	1,29
AILQ_AIE10	350	1,00	5,00	3,56	1,31
AILQ_AIE11	350	1,00	5,00	3,27	1,19
AILQ_AIE12	350	1,00	5,00	3,43	1,31
AILQ_AIE13	350	1,00	5,00	3,47	1,23
DIG_INF11	350	1,00	5,00	3,48	1,23
DIFINF12	350	1,000	5,000	3,41	1,25
DIGCOM	350	1,00	5,00	3,37	1,22
DIGCRE	350	1,00	5,00	3,30	1,14
DIG_SAF41	350	1,00	5,00	3,38	1,24
DIG_SAF42	350	1,00	5,00	3,43	1,25
DIG_SAF43	350	1,00	5,00	3,33	1,18
DIG_SAF44	350	1,00	5,00	3,15	1,20
DIG_SAF45	350	1,00	5,00	3,20	1,16
DIG_SAF46	350	1,00	5,00	3,11	1,32
DIGPRO53	350	1,00	5,00	3,28	1,15
DIGPRO54	350	1,00	5,00	3,21	1,11
AIEASAUT06	350	1,00	5,00	3,50	1,30
N (listwise)	350				

Frequencies

N analysis for item AILQ_IM01 revealed that while the largest concentration of respondents maintained a neutral position (39.1%, N=137), the distribution leaned toward a positive sentiment.

Specifically, the combined agreement (36.3%)—consisting of Agree (19.7%) and Totally Agree (16.6%)—notably outweighed the combined disagreement (24.6%). The same approach applies for the rest.

Table 84: Distributions for students sample

Items	Scale	Count	Layer Column N %
AILQ_IM01	totally disagree	31	8,9%
	Disagree	55	15,7%
	Neutral	137	39,1%
	Agree	69	19,7%
	totally agree	58	16,6%
AILQ_IM02	totally disagree	37	10,6%
	Disagree	75	21,4%
	Neutral	117	33,4%
	Agree	59	16,9%
	totally agree	62	17,7%
AILQ_IM03	totally disagree	99	28,3%
	disagree	89	25,4%
	neutral	96	27,4%
	agree	38	10,9%
	totally agree	28	8,0%
AILQ_IM04	totally disagree	58	16,6%
	disagree	81	23,1%
	neutral	92	26,3%
	agree	61	17,4%
	totally agree	58	16,6%
AILQ_SE01	totally disagree	30	8,6%
	disagree	59	16,9%
	neutral	120	34,3%
	agree	80	22,9%
	totally agree	61	17,4%
AILQ_SE02	totally disagree	30	8,6%
	disagree	60	17,1%
	neutral	98	28,0%
	agree	97	27,7%
	totally agree	65	18,6%
AILQ_SE03	totally disagree	45	12,9%
	disagree	74	21,1%
	neutral	124	35,4%
	agree	59	16,9%
	totally agree	48	13,7%
AILQ_SE04	totally disagree	27	7,7%
	disagree	55	15,7%
	neutral	114	32,6%
	agree	83	23,7%
	totally agree	71	20,3%
AILQ_CL01	totally disagree	24	6,9%
	disagree	61	17,4%
	neutral	129	36,9%
	agree	82	23,4%
AILQ_CL03	totally agree	54	15,4%
	totally disagree	33	9,4%
	disagree	42	12,0%

AILQ_BI01	neutral	126	36,0%
	agree	79	22,6%
	totally agree	70	20,0%
	totally disagree	21	6,0%
	disagree	39	11,1%
AILQ_BI02	neutral	83	23,7%
	agree	74	21,1%
	totally agree	133	38,0%
	totally disagree	57	16,3%
	disagree	64	18,3%
AILQ_BI03	neutral	103	29,4%
	agree	70	20,0%
	totally agree	56	16,0%
	totally disagree	89	25,4%
	disagree	85	24,3%
AILQ_EN01	neutral	90	25,7%
	agree	47	13,4%
	totally agree	39	11,1%
	totally disagree	77	22,0%
	disagree	83	23,7%
AILQ_EN02	neutral	97	27,7%
	agree	48	13,7%
	totally agree	45	12,9%
	totally disagree	103	29,4%
	disagree	90	25,7%
AILQ_SI01	neutral	86	24,6%
	agree	36	10,3%
	totally agree	35	10,0%
	totally disagree	113	32,3%
	disagree	75	21,4%
AILQ_SI02	neutral	72	20,6%
	agree	46	13,1%
	totally agree	44	12,6%
	totally disagree	50	14,3%
	disagree	69	19,7%
AILQ_SI03	neutral	98	28,0%
	agree	71	20,3%
	totally agree	62	17,7%
	totally disagree	136	38,9%
	disagree	82	23,4%
AILQ_KU01	neutral	67	19,1%
	agree	28	8,0%
	totally agree	37	10,6%
	totally disagree	46	13,1%
	disagree	75	21,4%
AILQ_KU02	neutral	104	29,7%
	agree	56	16,0%
	totally agree	69	19,7%
	totally disagree	27	7,7%
	disagree	32	9,1%
AILQ_KU05	neutral	68	19,4%
	agree	65	18,6%
	totally agree	158	45,1%
	totally disagree	41	11,7%
	disagree	58	16,6%

AILQ_EC01	neutral	113	32,3%
	agree	72	20,6%
	totally agree	66	18,9%
	totally disagree	39	11,1%
	disagree	59	16,9%
AILQ_EC03	neutral	117	33,4%
	agree	66	18,9%
	totally agree	69	19,7%
	totally disagree	51	14,6%
	disagree	75	21,4%
AILQ_EC04	neutral	97	27,7%
	agree	61	17,4%
	totally agree	66	18,9%
	totally disagree	33	9,4%
	disagree	83	23,7%
AILQ_AIE02	neutral	122	34,9%
	agree	62	17,7%
	totally agree	50	14,3%
	totally disagree	27	7,7%
	disagree	45	12,9%
AILQ_AIE05	neutral	79	22,6%
	agree	55	15,7%
	totally agree	144	41,1%
	totally disagree	24	6,9%
	disagree	50	14,3%
AILQ_AIE07	neutral	110	31,4%
	agree	60	17,1%
	totally agree	106	30,3%
	totally disagree	32	9,1%
	disagree	46	13,1%
AILQ_AIE08	neutral	120	34,3%
	agree	77	22,0%
	totally agree	75	21,4%
	totally disagree	33	9,4%
	disagree	25	7,1%
AILQ_AIE10	neutral	96	27,4%
	agree	71	20,3%
	totally agree	125	35,7%
	totally disagree	32	9,1%
	disagree	42	12,0%
AILQ_AIE11	neutral	93	26,6%
	agree	63	18,0%
	totally agree	120	34,3%
	totally disagree	31	8,9%
	disagree	52	14,9%
AILQ_AIE12	neutral	127	36,3%
	agree	72	20,6%
	totally agree	68	19,4%
	totally disagree	37	10,6%
	disagree	44	12,6%
AILQ_AIE13	neutral	104	29,7%
	agree	63	18,0%
	totally agree	102	29,1%
	totally disagree	29	8,3%
	disagree	44	12,6%

	neutral	99	28,3%
	agree	88	25,1%
	totally agree	90	25,7%
	not able	29	8,3%
	rather not able	41	11,7%
DIG_INF11	neutral	107	30,6%
	rather able	80	22,9%
	very able	93	26,6%
	not able	34	9,7%
	rather not able	47	13,4%
DIFINF12	neutral	93	26,6%
	rather able	94	26,9%
	very able	82	23,4%
	not at all	31	8,9%
	not so much	46	13,1%
DIGCOM	neutral	118	33,7%
	much	74	21,1%
	very much	81	23,1%
	not at all	26	7,4%
	not so much	52	14,9%
DIGCRE	neutral	124	35,4%
	much	87	24,9%
	very much	61	17,4%
	not able	30	8,6%
	rather not able	56	16,0%
DIG_SAF41	neutral	93	26,6%
	rather able	92	26,3%
	very able	79	22,6%
	not able	34	9,7%
	rather not able	41	11,7%
DIG_SAF42	neutral	101	28,9%
	rather able	89	25,4%
	very able	85	24,3%
	not able	30	8,6%
	rather not able	48	13,7%
DIG_SAF43	neutral	115	32,9%
	rather able	91	26,0%
	very able	66	18,9%
	not informed	37	10,6%
	rather not informed	63	18,0%
DIG_SAF44	neutral	116	33,1%
	rather informed	80	22,9%
	very informed	54	15,4%
	not able	29	8,3%
	rather not able	66	18,9%
DIG_SAF45	neutral	118	33,7%
	rather able	81	23,1%
	very able	56	16,0%
	not informed	53	15,1%
	rather not informed	59	16,9%
DIG_SAF46	neutral	103	29,4%
	rather informed	65	18,6%
	very informed	70	20,0%

DIGPRO53	not able	30	8,6%
	rather not able	43	12,3%
	neutral	136	38,9%
	rather able	80	22,9%
	very able	61	17,4%
	not informed	26	7,4%
DIGPRO54	rather not informed	56	16,0%
	neutral	135	38,6%
	rather informed	83	23,7%
	very informed	50	14,3%
	totally disagree	29	8,3%
	disagree	51	14,6%
AIEASAUT06	neutral	100	28,6%
	agree	55	15,7%
	totally agree	115	32,9%
	blind trust	71	20,3%
SD04	generic text	164	46,9%
	deletion	79	22,6%
	integrityTime	36	10,3%
	acceptance	82	23,4%
SD05	use delete	37	10,6%
	false data	98	28,0%
	ethical refusal	133	38,0%
	A New model	102	29,1%
SD06	D Inertia	38	10,9%
	C Refurbished	81	23,1%
	B Maintenance	129	36,9%

Correlations

A Pearson correlation analysis was conducted to examine the relationships among the five core digital literacy dimensions (Affective, Behavioural, Cognitive, Ethical, and Safety) and the three decision-making scenarios (SD04, SD05, and SD06) for the student sample (N=350). The five core variables (Affective, Behavioural, Cognitive, Ethical, and Safety) demonstrated strong, positive, and highly significant internal relationships (all $p < .01$). The strongest correlation was observed between the Affective and Behavioural dimensions ($r = .763$), followed by Affective and Cognitive ($r = .650$), and Cognitive and Behavioural ($r = .648$).

Relationships Among the Scenarios:

First Scenario (SD04 - AI Essay): No statistically significant correlations were found between the first scenario and any of the five core literacy dimensions (all $p > .05$).

Second Scenario (SD05 - Privacy): The second scenario showed a significant negative correlation with the Behavioural dimension ($r = -.119$, $p = .026$) and a significant positive correlation with the Ethical dimension ($r = .107$, $p = .045$).

Third Scenario (SD06 - Sustainability): The third scenario demonstrated significant negative correlations with both the Behavioural dimension ($r = -.161$, $p = .003$) and the Cognitive dimension ($r = -.115$, $p = .032$).

Table 85: Correlations (students sample)

	SD 05	SD 06	AFF ECTI VE	BEHA VIOUR AL	COG NITI VE	ET HIC AL	SA FE TY
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SD04	,125*	,067	-,081	-,083	-,006	,052	,023
SD05		,172**	-,051	-,119*	-,048	,107*	,050
SD06			-,044	-,161**	-,115*	,015	,005
AFFECTIVE				,763**	,650**	,436**	,571**
BEHAVIOURAL					,648**	,339**	,497**
COGNITIVE						,528**	,643**
ETHICAL							,618**

Comparisons

gender

The table that follows presents the means and standard deviations for the measured dimensions based on the gender of the students (boys: n=147, girls: n=178, no reply: n=25). A preliminary review of the mean scores reveals a consistent numerical trend where boys report higher mean scores across the Affective, Behavioural, Cognitive, and Safety dimensions compared to girls and those who preferred not to reply.

Table 86: Means based on gender (students sample)

Variables	Gender groups	N	Mean	SD
AFFECTIVE	boy	147	3,29	,834
	girl	178	2,98	,699
	no reply	25	2,93	,975
	Total	350	3,10	,793
BEHAVIOURAL	boy	147	3,02	,949
	girl	178	2,62	,784
	no reply	25	2,70	,981
	Total	350	2,80	,890
COGNITIVE	boy	147	3,37	,871
	girl	178	3,12	,819

SAFETY	no reply	25	3,10	1,028
	Total	350	3,22	,864
	boy	147	3,44	,785
	girl	178	3,19	,729
	no reply	25	3,24	,876
	Total	350	3,30	,771

The analysis revealed significant main effects of gender on four of the five core digital literacy dimensions: the Affective dimension, $F(2, 347) = 7.131$, $p = .001$; the Behavioural dimension, $F(2, 347) = 8.548$, $p < .001$; the Cognitive dimension, $F(2, 347) = 3.899$, $p = .021$; and the Safety dimension, $F(2, 347) = 4.265$, $p = .015$. However, gender did not have a statistically significant effect on the Ethical dimension ($p = .161$) or on any of the three decision-making scenarios (SD04, SD05, and SD06; all $p > .05$).

Table 87: Significance and gender (students sample)

Variables		Sum of Squares	Df	Mean Square	F	Sig.
SD04	Between Groups	3,541	2	1,770	2,257	,106
	Within Groups	272,174	347	,784		
	Total	275,714	349			
SD05	Between Groups	3,643	2	1,822	1,314	,270
	Within Groups	481,145	347	1,387		
	Total	484,789	349			
SD06	Between Groups	1,524	2	,762	,492	,612
	Within Groups	536,993	347	1,548		
	Total	538,517	349			
AFFECTIVE	Between Groups	8,680	2	4,340	7,131	,001
	Within Groups	211,197	347	,609		
	Total	219,878	349			
BEHAVIOURAL	Between Groups	12,992	2	6,496	8,548	,000
	Within Groups	263,704	347	,760		
	Total	276,696	349			
COGNITIVE	Between Groups	5,731	2	2,865	3,899	,021
	Within Groups	254,998	347	,735		
	Total	260,728	349			
ETHICAL	Between Groups	2,933	2	1,467	1,837	,161
	Within Groups	277,076	347	,798		
	Total	280,009	349			
SAFETY	Between Groups	4,987	2	2,494	4,265	,015
	Within Groups	202,888	347	,585		
	Total	207,875	349			

In the following table, post-hoc tests indicated that boys scored significantly higher than girls in the Affective dimension ($p = .001$), the Behavioural dimension ($p < .001$), the Cognitive dimension ($p =$

.020), and the Safety dimension ($p = .011$) than girls. There were no statistically significant differences between the no reply group and either boys or girls across any of the measured variables.

Table 88 Multiple Comparisons and gender (students sample)

Variable	(I) gender	(J) gender	Mean Difference (I-J)	Std. Error	Sig.
AFFECTIVE	Boy	Girl	0,31	0,09	,001
		no reply	0,36	0,17	,084
	Girl	Boy	-0,31	0,09	,001
		no reply	0,05	0,17	,955
	no reply	Boy	-0,36	0,17	,084
		Girl	-0,05	0,17	,955
BEHAVIOURAL	Boy	Girl	0,40	0,10	,000
		no reply	0,32	0,19	,205
	Girl	Boy	-0,40	0,10	,000
		no reply	-0,08	0,19	,911
	no reply	Boy	-0,32	0,19	,205
		Girl	0,08	0,19	,911
COGNITIVE	Boy	Girl	0,26	0,10	,020
		no reply	0,27	0,19	,305
	Girl	Boy	-0,26	0,10	,020
		no reply	0,02	0,18	,996
	no reply	Boy	-0,27	0,19	,305
		Girl	-0,02	0,18	,996
SAFETY	Boy	Girl	0,25	0,09	,011
		no reply	0,20	0,17	,461
	Girl	Boy	-0,25	0,09	,011
		no reply	-0,05	0,16	,950
	no reply	Boy	-0,20	0,17	,461
		Girl	0,05	0,16	,950

Age

The analysis revealed that age had a statistically significant main effect only on the Ethical dimension, $F(8, 341) = 3.030$, $p = .003$. Age did not yield statistically significant differences for any of the other core dimensions (Affective, Behavioural, Cognitive, Safety) or the three decision-making scenarios (SD04, SD05, SD06), with all corresponding p -values exceeding the .05 threshold.

Table 89: Means based on age (students sample)

Variables		Sum of Squares	df	Mean Square	F	Sig.
SD04	Between Groups	2,805	8	,351	,438	,898
	Within Groups	272,910	341	,800		
	Total	275,714	349			
SD05	Between Groups	17,909	8	2,239	1,635	,114
	Within Groups	466,880	341	1,369		
	Total	484,789	349			
SD06	Between Groups	8,091	8	1,011	,650	,735
	Within Groups	530,426	341	1,556		

AFFECTIVE	Total	538,517	349			
	Between Groups	5,900	8	,738	1,175	,313
	Within Groups	213,978	341	,628		
BEHAVIOURAL	Total	219,878	349			
	Between Groups	6,269	8	,784	,988	,445
	Within Groups	270,427	341	,793		
COGNITIVE	Total	276,696	349			
	Between Groups	5,648	8	,706	,944	,480
	Within Groups	255,080	341	,748		
ETHICAL	Total	260,728	349			
	Between Groups	18,583	8	2,323	3,030	,003
	Within Groups	261,426	341	,767		
SAFETY	Total	280,009	349			
	Between Groups	3,647	8	,456	,761	,637
	Within Groups	204,229	341	,599		
	Total	207,875	349			

DESCRIPTIVES FOR ETHICAL DIMENSION

The descriptives table outlines the means and standard deviations for the Ethical dimension across the various age groups. A review of the scores indicates a general upward trend in ethical awareness as students progress from early adolescence (11 years old, $M=3.21$) through late adolescence, peaking at 18 years old ($M=4.18$). Conversely, the oldest cohort in the sample (20 years old) reported a sharp decline, recording the lowest ethical scores overall ($M=2.35$). However, interpretations regarding the oldest groups should remain cautious due to their notably small sample sizes ($n=5$ for 18-year-olds, $n=6$ for 20-year-olds).

Table 90: Means based on age for ethical dimension (students sample)

AGE	N	Mean	SD
11,00	7	3,21	1,10
12,00	21	3,61	0,69
13,00	45	3,44	0,80
14,00	33	3,24	0,92
15,00	101	3,38	0,86
16,00	94	3,67	0,84
17,00	38	3,67	1,01
18,00	5	4,18	0,50
20,00	6	2,35	1,53
Total	350	3,49	0,90

The results indicate that the significance is driven entirely by the sharp drop in scores from the 20-year-old cohort. Specifically, the 20-year-old students scored significantly lower in the Ethical dimension compared to the 16-year-olds ($p = .012$), the 17-year-olds ($p = .020$), and the 18-year-olds ($p = .019$). No other age group comparisons yielded statistically significant differences.

Table 91: Multiple comparisons for ethical dimension (students sample)

(I) age	(J) age	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
	11,00	-0,86	0,49	0,71	-2,38	0,66
	12,00	-1,25	0,41	0,06	-2,52	0,01
	13,00	-1,09	0,38	0,10	-2,28	0,10
20,00	14,00	-0,88	0,39	0,36	-2,10	0,33
	15,00	-1,03	0,37	0,12	-2,18	0,12
	16,00	-1,32	0,37	0,01	-2,47	-0,17
	17,00	-1,32	0,38	0,02	-2,52	-0,12
	18,00	-1,82	0,53	0,02	-3,48	-0,17

. The mean difference is significant at the 0.05 level.

USE OF AI

Next table presents the means and standard deviations according AI reported use among students.

Table 92: Means based on AI use (students sample)

Variables	N	Mean	SD
SD05	Never	26	1,42
	only out of curiosity	37	2,03
	sometimes for ideas	152	2,04
	Regularly	135	1,56
	Total	350	1,81
SD06	Never	26	1,31
	only out of curiosity	37	1,73
	sometimes for ideas	152	1,88
	Regularly	135	1,50
	Total	350	1,68
AFFECTIVE	Never	26	2,77
	only out of curiosity	37	2,74
	sometimes for ideas	152	3,10
	Regularly	135	3,27
	Total	350	3,10
BEHAVIOUR AL	Never	26	2,77
	only out of curiosity	37	2,52
	sometimes for ideas	152	2,70
	Regularly	135	2,98
	Total	350	2,80
COGNITIVE	Never	26	2,96
	only out of curiosity	37	3,04
	sometimes for ideas	152	3,18
	Regularly	135	3,37
	Total	350	3,22
ETHICAL	Never	26	2,85
	only out of curiosity	37	3,35
	sometimes for ideas	152	3,61
	Regularly	135	3,51
	Total	350	3,48

Unlike other demographic variables such as age, the Use of AI yielded highly statistically significant main effects across almost all measured dimensions. The one-way ANOVA confirmed significant differences for the second scenario (SD05), $F(3, 346) = 5.580$, $p = .001$; the third scenario (SD06), $F(3, 346) = 3.093$, $p = .027$; the Affective dimension, $F(3, 346) = 6.363$, $p < .001$; the Behavioural dimension, $F(3, 346) = 3.925$, $p = .009$; the Cognitive dimension, $F(3, 346) = 2.886$, $p = .036$; and the Ethical dimension, $F(3, 346) = 5.948$, $p = .001$. AI usage frequency did not have a statistically significant effect on the first scenario (SD04, $p = .405$) or the Safety dimension ($p = .081$).

Table 93: Significance based on AI use (students sample)

Variables		Sum of Squares	Df	Mean Square	F	Sig.
SD04	Between Groups	2,311	3	,770	,975	,405
	Within Groups	273,403	346	,790		
	Total	275,714	349			
SD05	Between Groups	22,373	3	7,458	5,580	,001
	Within Groups	462,416	346	1,336		
	Total	484,789	349			
SD06	Between Groups	14,065	3	4,688	3,093	,027
	Within Groups	524,452	346	1,516		
	Total	538,517	349			
AFFECTIVE	Between Groups	11,497	3	3,832	6,363	,000
	Within Groups	208,381	346	,602		
	Total	219,878	349			
BEHAVIOUR AL	Between Groups	9,108	3	3,036	3,925	,009
	Within Groups	267,589	346	,773		
	Total	276,696	349			
COGNITIVE	Between Groups	6,365	3	2,122	2,886	,036
	Within Groups	254,363	346	,735		
	Total	260,728	349			
ETHICAL	Between Groups	13,733	3	4,578	5,948	,001
	Within Groups	266,277	346	,770		
	Total	280,009	349			
SAFETY	Between Groups	4,000	3	1,333	2,263	,081
	Within Groups	203,875	346	,589		
	Total	207,875	349			

To specify where the statistically significant differences lie between the AI usage groups, post-hoc multiple comparisons were conducted. The results reveal a clear hierarchy and progression based on the depth of AI integration:

Affective Dimension: regular AI users scored significantly higher in positive affective attitudes compared to students who never use AI ($p = .016$) and those who use it only out of curiosity ($p = .002$).

Behavioural Dimension: Regular AI users exhibited significantly higher behavioural engagement than both students who use AI only out of curiosity ($p = .022$) and those who use it sometimes for ideas ($p = .034$).

Ethical Dimension: A strong distinction was observed regarding ethical awareness. Students who use AI sometimes for ideas and regularly demonstrated significantly higher scores compared to non-users ($p < .001$ and $p = .003$, respectively).

Cognitive Dimension: Although the initial ANOVA indicated a significant overall main effect for the cognitive dimension, the more conservative post-hoc multiple comparisons did not yield any statistically significant pairwise differences between the specific frequency groups (all $p > .05$).

Decision-Making Scenarios (SD05 & SD06): For both the privacy scenario (SD05) and the sustainability scenario (SD06), a distinct pattern emerged where moderate use peaked over frequent use. Students using AI sometimes for ideas scored significantly higher than regular users in both SD05 ($p = .003$) and SD06 ($p = .048$).

Table 94: Multiple comparisons and AI use (students sample)

Dependent Variable	(I) Aluse	(J) Aluse	Mean Difference (I-J)	Std. Error	Sig.
SD05	Never	only out of curiosity	-,604	,296	,175
		sometimes for ideas	-,616	,245	,060
		regularly	-,132	,248	,950
		never	,604	,296	,175
	only out of curiosity	sometimes for ideas	-,012	,212	1,000
		regularly	,471	,215	,126
		never	,616	,245	,060
	sometimes for ideas	only out of curiosity	,012	,212	1,000
		regularly	,484	,137	,003
		never	,132	,248	,950
	Regularly	only out of curiosity	-,471	,215	,126
		sometimes for ideas	-,484	,137	,003
SD06	Never	only out of curiosity	-,422	,315	,538
		sometimes for ideas	-,574	,261	,126
		regularly	-,196	,264	,879
		never	,422	,315	,538
	only out of curiosity	sometimes for ideas	-,152	,226	,907
		regularly	,226	,228	,756
		never	,574	,261	,126
	sometimes for ideas	only out of curiosity	,152	,226	,907
		regularly	,378	,146	,048
		never	,196	,264	,879
	Regularly	only out of curiosity	-,226	,228	,756
		sometimes for ideas	-,378	,146	,048
AFFECTIV E	Never	only out of curiosity	0,03	0,20	,998

BEHAVIOURAL	sometimes	sometimes			
		for ideas	-0,33	0,16	,191
		regularly	-0,50	0,17	,016
	only out of curiosity	never	-0,03	0,20	,998
		sometimes			
		for ideas	-0,36	0,14	,054
	sometimes for ideas	regularly	-0,53	0,14	,002
		never	0,33	0,16	,191
		only out of curiosity	0,36	0,14	,054
	Regularly	regularly	-0,17	0,09	,260
		never	0,50	0,17	,016
		only out of curiosity	0,53	0,14	,002
	Never	sometimes for ideas	0,17	0,09	,260
		only out of curiosity	0,25	0,23	,673
		sometimes for ideas	0,07	0,19	,984
	only out of curiosity	regularly	-0,22	0,19	,661
		never	-0,25	0,23	,673
		sometimes for ideas	-0,19	0,16	,656
	sometimes for ideas	regularly	-0,47	0,16	,022
		never	-0,07	0,19	,984
		only out of curiosity	0,19	0,16	,656
	regularly	regularly	-0,28	0,10	,034
		never	0,22	0,19	,661
		only out of curiosity	0,47	0,16	,022
	never	sometimes for ideas	0,28	0,10	,034
		only out of curiosity	-0,09	0,22	,978
		sometimes for ideas	-0,22	0,18	,605
COGNITIVE	only out of curiosity	regularly	-0,42	0,18	,106
		never	0,09	0,22	,978
		sometimes for ideas	-0,14	0,16	,820
	sometimes for ideas	regularly	-0,33	0,16	,165
		never	0,22	0,18	,605
		only out of curiosity	0,14	0,16	,820
	regularly	regularly	-0,19	0,10	,230
		never	0,42	0,18	,106
		only out of curiosity	0,33	0,16	,165
	never	sometimes for ideas	0,19	0,10	,230
		only out of curiosity	-0,50	0,22	,117
	ETHICAL				

	sometimes			
	for ideas	-0,76	0,19	,000
	regularly	-0,66	0,19	,003
	never	0,50	0,22	,117
only out of	sometimes			
curiosity	for ideas	-0,26	0,16	,360
	regularly	-0,16	0,16	,763
	never	0,76	0,19	,000
sometimes	only out of			
for ideas	curiosity	0,26	0,16	,360
	regularly	0,10	0,10	,747
	never	0,66	0,19	,003
regularly	only out of			
	curiosity	0,16	0,16	,763
	sometimes			
	for ideas	-0,10	0,10	,747

AI VALUE

The analysis confirmed significant main effects across four of the five core literacy dimensions: the Affective dimension, $F(3, 346) = 4.427$, $p = .005$; the Behavioural dimension, $F(3, 346) = 3.447$, $p = .017$; the Cognitive dimension, $F(3, 346) = 5.398$, $p = .001$; and the Ethical dimension, $F(3, 346) = 2.872$, $p = .036$. Students' perceived value of AI did not have a statistically significant effect on the Safety dimension ($p = .179$) or any of the three specific decision-making scenarios (SD04, $p = .414$; SD05, $p = .063$; SD06, $p = .764$).

Table 95: Significance and AI value (students' sample)

		Sum of Squares	Df	Mean Square	F	Sig.
SD04	Between Groups	2,266	3	,755	,956	,414
	Within Groups	273,448	346	,790		
	Total	275,714	349			
SD05	Between Groups	10,108	3	3,369	2,456	,063
	Within Groups	474,681	346	1,372		
	Total	484,789	349			
SD06	Between Groups	1,790	3	,597	,385	,764
	Within Groups	536,727	346	1,551		
	Total	538,517	349			
AFFECTIVE	Between Groups	8,127	3	2,709	4,427	,005
	Within Groups	211,751	346	,612		
	Total	219,878	349			
BEHAVIOURAL	Between Groups	8,029	3	2,676	3,447	,017
	Within Groups	268,667	346	,776		
	Total	276,696	349			
COGNITIVE	Between Groups	11,658	3	3,886	5,398	,001
	Within Groups	249,070	346	,720		
	Total	260,728	349			
ETHICAL	Between Groups	6,803	3	2,268	2,872	,036
	Within Groups					

SAFETY	Within Groups	273,206	346	,790		
	Total	280,009	349			
	Between Groups	2,917	3	,972	1,642	,179
	Within Groups	204,958	346	,592		
	Total	207,875	349			

In the following table it is demonstrated that students who hold the most positive view of AI (helps me learn) consistently reported the highest mean scores in the Affective (M=3.22), Behavioural (M=2.93), Cognitive (M=3.37), and Ethical (M=3.60) dimensions. Conversely, students holding the most negative view (it is like copying) reported the lowest mean scores across the Affective, Behavioural, and Cognitive dimensions.

Table 96: Means and AI value (students sample)

		N	Mean	SD
AFFECTIVE	it is like copying	60	2,79	,956
	helps, but i learn less	70	3,14	,801
	useful if you know how to use	95	3,13	,788
	helps me learn	125	3,23	,665
	Total	350	3,11	,793
BEHAVIOURAL	it is like copying	60	2,52	,992
	helps, but i learn less	70	2,89	,911
	useful if you know how to use	95	2,73	,879
	helps me learn	125	2,94	,805
	Total	350	2,80	,890
COGNITIVE	it is like copying	60	2,86	,934
	helps, but i learn less	70	3,17	,853
	useful if you know how to use	95	3,31	,839
	helps me learn	125	3,38	,809
	Total	350	3,23	,864
ETHICAL	it is like copying	60	3,39	1,032
	helps, but i learn less	70	3,26	,847
	useful if you know how to use	95	3,57	,920
	helps me learn	125	3,61	,805
	Total	350	3,49	,895

The results highlight a clear divide between students who view AI as a beneficial learning tool versus those who view it as a shortcut:

Affective Dimension: Students who view AI positively as something that helps me learn scored significantly higher in affective attitudes ($p = .002$) than those who view it as like copying. Similarly, students who view AI as useful if you know how to use it also scored significantly higher than the like copying group ($p = .040$).

Behavioural Dimension: Active behavioural engagement was significantly higher among students who believe AI helps me learn compared to those who equate it with copying ($p = .015$). No other pairwise comparisons were statistically significant for this dimension.

Cognitive Dimension: A strong distinction was observed in cognitive skills. Both the helps me learn group ($p = .001$) and the useful if you know how to use it group ($p = .008$) demonstrated significantly higher perceived cognitive competence than students who feel using AI is like copying.

Ethical Dimension: For the ethical dimension, the significant difference shifted slightly. Students who believe AI helps me learn demonstrated significantly higher ethical awareness compared to those who believe AI helps, but I learn less ($p = .041$).

Table 97: Multiple comparisons and AI value (students sample)

Dependent Variable	(I) Alvalue	(J) Alvalue	Mean Difference (I-J)	Std. Error	Sig.
AFFECTIVE	it is like copying	helps, but i learn less	-0,35	0,14	,055
		useful if you know how to use	-0,34	0,13	,040
		helps me learn it is like copying	-0,44	0,12	,002
		helps, but i learn less	0,35	0,14	,055
	helps, but i learn less	useful if you know how to use	0,01	0,12	1,000
		helps me learn it is like copying	-0,09	0,12	,861
		useful if you know how to use	0,34	0,13	,040
		helps, but i learn less	-0,01	0,12	1,000
	useful if you know how to use	helps me learn it is like copying	-0,10	0,11	,793
		helps, but i learn less	0,44	0,12	,002
		helps me learn it is like copying	0,09	0,12	,861
		useful if you know how to use	0,10	0,11	,793
	helps me learn	helps, but i learn less	-0,37	0,16	,084
		useful if you know how to use	-0,21	0,15	,483
		helps me learn it is like copying	-0,42	0,14	,015
		helps, but i learn less	0,37	0,16	,084
	it is like copying	useful if you know how to use	0,16	0,14	,653
		helps me learn it is like copying	-0,05	0,13	,984
		helps, but i learn less	0,21	0,15	,483
		helps me learn it is like copying	-0,16	0,14	,653
BEHAVIORAL	helps, but i learn less	useful if you know how to use	-0,21	0,12	,309
		helps me learn it is like copying	0,42	0,14	,015
		helps, but i learn less	0,05	0,13	,984
		useful if you know how to use	0,21	0,12	,309
	useful if you know how to use	helps, but i learn less	-0,30	0,15	,180
		helps me learn it is like copying			
		helps, but i learn less			
		useful if you know how to use			
COGNITIVE	it is like copying	helps, but i learn less			
		useful if you know how to use			

ETHICAL	helps, but i learn less	useful if you know how to use	-0,45	0,14	,008
		helps me learn	-0,51	0,13	,001
		it is like copying	0,30	0,15	,180
	useful if you know how to use	helps, but i learn less	-0,15	0,13	,688
		helps me learn	-0,21	0,13	,351
		it is like copying	0,45	0,14	,008
	helps me learn	helps, but i learn less	0,15	0,13	,688
		helps me learn	-0,06	0,12	,950
		it is like copying	0,51	0,13	,001
	it is like copying	helps, but i learn less	0,21	0,13	,351
		useful if you know how to use	0,06	0,12	,950
		helps, but i learn less	0,13	0,16	,826
	helps, but i learn less	useful if you know how to use	-0,18	0,15	,609
		helps me learn	-0,22	0,14	,400
		it is like copying	-0,13	0,16	,826
	useful if you know how to use	helps, but i learn less	-0,31	0,14	,113
		helps me learn	-0,35	0,13	,041
		it is like copying	0,18	0,15	,609
	helps me learn	helps, but i learn less	0,31	0,14	,113
		helps me learn	-0,04	0,12	,989
		it is like copying	0,22	0,14	,400
	useful if you know how to use	helps, but i learn less	0,35	0,13	,041
		useful if you know how to use	0,04	0,12	,989

REGRESSIONS

First scenario – students

R Square value was = .020, meaning that only 2.0% of the total variance in the students responses to the first scenario can be explained by this model. This is an extremely low explanatory power, indicating that factors outside of these five digital literacy dimensions are driving the students decisions in this specific scenario.

Table 98: First model (students sample)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,141a	,020	,006	,886
a. Predictors: (Constant), SAFETY, BEHAVIOURAL, ETHICAL, COGNITIVE, AFFECTIVE				

The overall regression model is not statistically significant, $F(5,344)=1.400$, $p=.224$. This confirms that the combination of Affective, Behavioural, Cognitive, Ethical, and Safety dimensions does not reliably predict how students will respond to the first scenario.

Table 99: Significance of first model (students sample)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	5,500	5	1,100	1,400	,224b
Residual	270,214	344	,786		
Total	275,714	349			
a. Dependent Variable: SD04					
b. Predictors: (Constant), SAFETY, BEHAVIOURAL, ETHICAL, COGNITIVE, AFFECTIVE					

None of the individual independent variables have a p-value less than .05. This means that not a single one of the five digital literacy dimensions serves as a statistically significant predictor for the first scenario when controlling for the others.

Table 100: Coefficients of first model (students sample)

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.
	B	Beta		
(Constant)	1,240		5,280	,000
AFFECTIVE	-,126	-,113	-1,258	,209
BEHAVIOURAL	-,076	-,077	-,877	,381
COGNITIVE	,048	,047	,566	,572
ETHICAL	,069	,070	,998	,319
SAFETY	,060	,052	,656	,513
a. Dependent Variable: SD04				

Second scenario - students

R Square value was = .44, meaning that only 4.4 % of the total variance in the students responses to the second scenario can be explained by this model.

Table 101: Second model (students sample)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
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1	,209a	,044	,030	1,161
a. Predictors: (Constant), SAFETY, BEHAVIOURAL, ETHICAL, COGNITIVE, AFFECTIVE				

The overall regression model is statistically significant, $F(95,344)=3.144$, $p=.009$.

Table 102: Significance of second model (students sample)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	21,188	5	4,238	3,144	,009b
Residual	463,601	344	1,348		
Total	484,789	349			

a. Dependent Variable: SD05
b. Predictors: (Constant), SAFETY, BEHAVIOURAL, ETHICAL, COGNITIVE, AFFECTIVE

The Ethical dimension was found to be a significant positive predictor of students' decisions in the privacy scenario ($B = .193$, $p = .035$). This suggests that students with higher levels of ethical awareness are significantly more likely to make informed or digitally wise decisions when faced with apps that compromise personal data.

Interestingly, the Behavioural dimension emerged as a significant negative predictor ($B = -.235$, $p = .040$). This indicates that students who report higher levels of active behavioural engagement with AI tools are statistically more likely to adopt passive or less cautious stances toward data privacy, perhaps due to a higher level of comfort or reliance on the technology.

The dimensions of Affective attitudes ($p = .787$), Cognitive skills ($p = .330$), and Safety awareness ($p = .274$) did not significantly contribute to the model. While these dimensions correlate with general AI literacy, they do not uniquely predict the specific choices students make regarding the privacy dilemma presented in this scenario.

Table 103: Coefficients of second model (students sample)

Model	Unstandardized Coefficients	Standardized Coefficients	T	Sig.
	B	Beta		
(Constant)	1,603		5,212	,000
AFFECTIVE	,036	,024	,271	,787
1 BEHAVIOURAL	-,235	-,178	-2,059	,040
COGNITIVE	-,110	-,080	-,976	,330
ETHICAL	,193	,146	2,116	,035
SAFETY	,131	,086	1,096	,274

a. Dependent Variable: SD05

Third scenario - students

R Square value was = .039, meaning that only 3.9% of the total variance in the students' responses to the third scenario can be explained by this model.

Table 104: Third model (students sample)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
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1	,230a	,053	,039	1,218
a. Predictors: (Constant), SAFETY, BEHAVIOURAL, ETHICAL, COGNITIVE, AFFECTIVE				

The overall regression model is statistically significant, $F(95,344)=3.844$, $p=.002$.

Table 105: Significance of third model (students sample)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	28,493	5	5,699	3,844	,002b
Residual	510,024	344	1,483		
Total	538,517	349			

a. Dependent Variable: SD06

b. Predictors: (Constant), SAFETY, BEHAVIOURAL, ETHICAL, COGNITIVE, AFFECTIVE

The Affective dimension was a significant positive predictor of students decisions ($B = .274$, $p = .048$). This suggests that students with higher positive emotional attitudes and perceived utility toward AI are more likely to align with the digitally wise or sustainable choice in this specific scenario. Similar to the second scenario, the Behavioural dimension acted as a strong and significant negative predictor ($B = -.371$, $p = .002$). This indicates that students with higher levels of active behavioural engagement and intention to use AI tools are significantly more likely to choose the technocentric option (buying a new phone unnecessarily) rather than the sustainable one. The Cognitive dimension approached significance ($p = .075$) but, along with Ethical awareness ($p = .564$) and Safety awareness ($p = .170$), did not uniquely predict the outcome for this scenario.

Table 106: Coefficients of third model (students sample)

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.
	B	Beta		
(Constant)	1,782		5,524	,000
AFFECTIVE	,274	,175	1,984	,048
1 BEHAVIOURAL	-,371	-,266	-3,098	,002
COGNITIVE	-,210	-,146	-1,785	,075
ETHICAL	,055	,040	,577	,564
SAFETY	,172	,107	1,377	,170

a. Dependent Variable: SD06

Scenaria comparisons

The table that follows presents the means and standad deviations for each dimension based on the first scenario regarding AI generated text in a school s essay. Students present different scores in the behavioural dimension.

Table 107: First scenario and profiles - means

Scenario	Level	Affective	Behavio ural	Cogniti ve	Ethical	Safety
SD04 (AI generate d text)	Technoce ntric	3.22 (.90)	3.03 (.97)	3.28 (1.01)	3.31 (1.06)	3.24 (.92)

Passive	3.15 (.71)	2.77 (.85)	3.23 (.79)	3.57 (.78)	3.32 (.71)
Prudent	2.90 (.79)	2.60 (.83)	3.11 (.84)	3.37 (.88)	3.26 (.73)
Wise	3.17 (3.17)	2.93 (.87)	3.39 (.85)	3.64 (.99)	3.36 (.80)
p-value (Sig.)	0.057	0.018	0.369	0.064	0.664

Students scored differently in the behavioural dimension, based to their preferences on the first scenario (how to reach in AI generated text for a school essay), with technocentric (M=3.03, SD=.97) scoring much higher than the prudent students (M=2.60, SD=.83), $F(3)=3.368$, $p=.019$.

Table 108: First scenario and profiles - differences

Variables		Sum Squares	of Df	Mean Square	F	Sig.
AFFECTIVE	Between Groups	4,701	3	1,567	2,520	,058
	Within Groups	215,177	346	,622		
	Total	219,878	349			
BEHAVIOURAL	Between Groups	7,851	3	2,617	3,368	,019
	Within Groups	268,846	346	,777		
	Total	276,696	349			
COGNITIVE	Between Groups	2,361	3	,787	1,054	,369
	Within Groups	258,368	346	,747		
	Total	260,728	349			
ETHICAL	Between Groups	5,473	3	1,824	2,299	,077
	Within Groups	274,536	346	,793		
	Total	280,009	349			
SAFETY	Between Groups	,779	3	,260	,434	,729
	Within Groups	207,096	346	,599		
	Total	207,875	349			

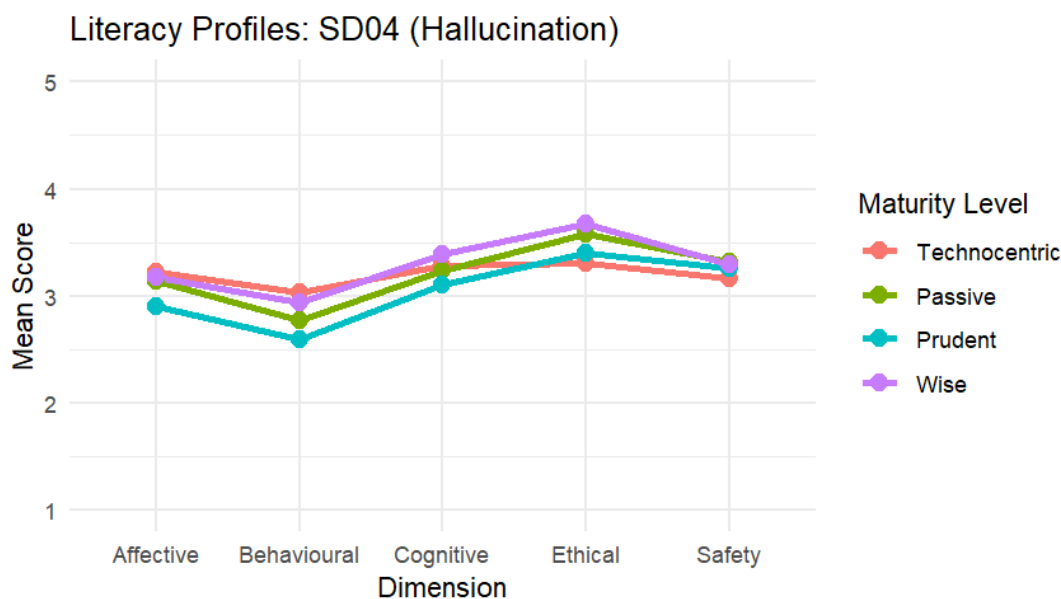
From the following table becomes obvious which two groups differ significantly on the behavioural dimension.

Table 109: Multiple Comparisons

(I) SD04	(J) SD04	Mean Difference (I-J)	Std. Error	Sig.
	generic text	,26516	,12523	,150
blind trust	deletion	,43377	,14415	,015
	integrityTi me	,09942	,18035	,946
generic text	blind trust	-,26516	,12523	,150
	deletion	,16861	,12072	,502
	integrityTi me	-,16574	,16224	,737
deletion	blind trust	-,43377	,14415	,015

	generic text	-,16861	,12072	,502
	integrityTime	-,33434	,17725	,236
	blind trust	-,09942	,18035	,946
integrityTime	generic text	,16574	,16224	,737
	deletion	,33434	,17725	,236

The graph that follows optically verifies that technocentric (blind trust in AI generated text) and prudent students (that delete all AI text) differ in the behavioural dimension (students proactivity/intention to use AI).



Second scenario

The table that follows presents the means and standard deviations for each dimension based on the second scenario of an app that compromises data privacy. Students present different scores in the behavioural dimension.

Table 110: Second scenario and profiles - means

Scenario	Level	Affective	Behavioural	Cognitive	Ethical	Safety
SD05 (Privacy)	Technocentric	3.10 (.90)	2.89 (.95)	3.26 (.91)	3.32 (1.05)	3.15 (.90)
	Passive	3.30 (.83)	3.16 (.95)	3.33 (.92)	3.54 (.92)	3.35 (.85)
	Prudent	3.17 (.74)	2.74 (.83)	3.26 (.81)	3.44 (.78)	3.34 (.65)
	Wise	3.02 (.74)	2.69 (.84)	3.16 (.85)	3.62 (.84)	3.28 (.73)
	p-value (Sig.)	0.2290	0.0231	0.6890	0.0992	0.4700

Students scored differently in the behavioural dimension, based to their preferences on the second scenario (on whether you use an app that compromises data privacy), with passive ($M=3.16$, $SD=.95$) scoring much higher than the digitally wise students ($M=2.69$, $SD=.84$), $F(3)=2.500$, $p=.023$.

Table 111: Second scenario and profiles - differences

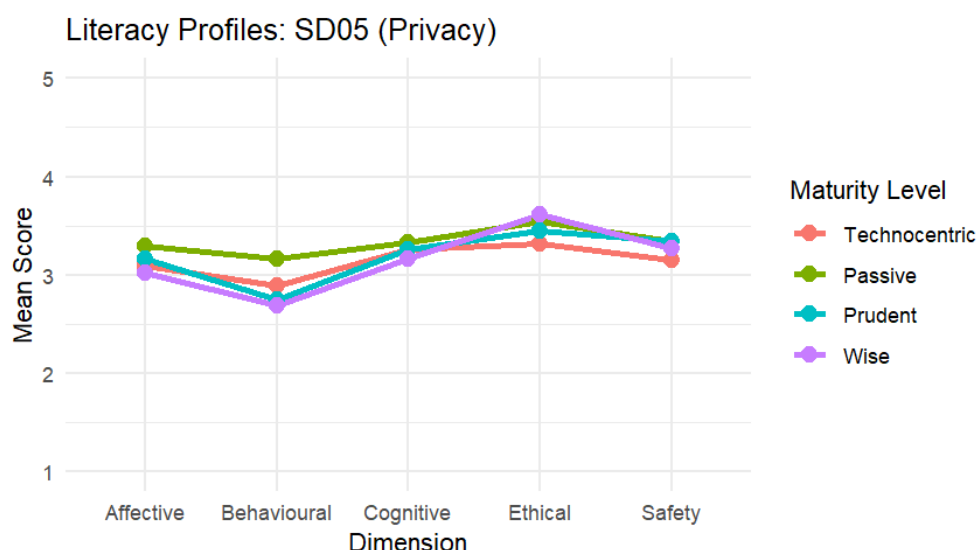
		Sum Squares	of Df	Mean Square	F	Sig.
AFFECTIVE	Between Groups	2,722	3	,907	1,446	,229
	Within Groups	217,155	346	,628		
	Total	219,878	349			
BEHAVIOUR AL	Between Groups	7,499	3	2,500	3,213	,023
	Within Groups	269,197	346	,778		
	Total	276,696	349			
COGNITIVE	Between Groups	1,105	3	,368	,491	,689
	Within Groups	259,623	346	,750		
	Total	260,728	349			
ETHICAL	Between Groups	4,167	3	1,389	1,742	,158
	Within Groups	275,842	346	,797		
	Total	280,009	349			
SAFETY	Between Groups	2,456	3	,819	1,379	,249
	Within Groups	205,420	346	,594		
	Total	207,875	349			

From the following table becomes obvious which two groups differ significantly on the behavioural dimension.

Table 112: Multiple Comparisons

(I) SD05	(J) SD05	Mean Difference (I-J)	Std. Error	Sig.
Acceptance	use delete	-,26549	,17469	,427
	false data	,14839	,13201	,675
	ethical			
	refusal	,20720	,12385	,340
use delete	Acceptance	,26549	,17469	,427
	false data	,41389	,17020	,073
	ethical			
	refusal	,47269	,16394	,022
false data	Acceptance	-,14839	,13201	,675
	use delete	-,41389	,17020	,073
	ethical			
	refusal	,05881	,11743	,959
ethical refusal	Acceptance	-,20720	,12385	,340
	use delete	-,47269	,16394	,022
	false data	-,05881	,11743	,959

The graph that follows optically verifies that passive (who use and delete) and digitally wise students (that ethically refuse) differ in the behavioural dimension (students proactivity/intention to use AI).



Third scenario

The table that follows presents the means and standard deviations for each dimension based on the third scenario of replacing a mobile device with a new one, even if not necessary. Students present different scores in the behavioural dimension.

Table 113: Third scenario and profiles - means

Scenario	Level	Affective	Behavioural	Cognitive	Ethical	Safety
SD06 (Sustainability)	Technocentric	3.20 (.82)	3.01 (.91)	3.36 (.93)	3.49 (.97)	3.24 (.83)
	Passive	3.03 (.84)	2.87 (1.00)	3.41 (.79)	3.31 (.99)	3.25 (.86)
	Prudent	3.04 (.78)	2.71 (.84)	3.12 (.82)	3.53 (.75)	3.29 (.69)
	Wise	3.10 (.75)	2.67 (.83)	3.15 (.83)	3.52 (.88)	3.29 (.73)
	p-value (Sig.)	0.5250	0.0238	0.0949	0.5600	0.9610

Students scored differently in the behavioural dimension, based to their preferences on the third scenario (on whether you buy a mobile phone although not necessary), with technocentric ($M=3.20$, $SD=.82$) scoring much higher than the digitally wise students ($M=2.67$, $SD=.83$), $F(3)=2.483$, $p=.024$.

Table 114: Third scenario and profiles - differences

		Sum of Squares	Df	Mean Square	F	Sig.
AFFECTIVE	Between Groups	1,413	3	,471	,746	,525
	Within Groups	218,465	346	,631		
	Total	219,878	349			
BEHAVIOURAL	Between Groups	7,450	3	2,483	3,191	,024
	Within Groups	269,246	346	,778		
	Total	276,696	349			
COGNITIVE	Between Groups	4,749	3	1,583	2,140	,095

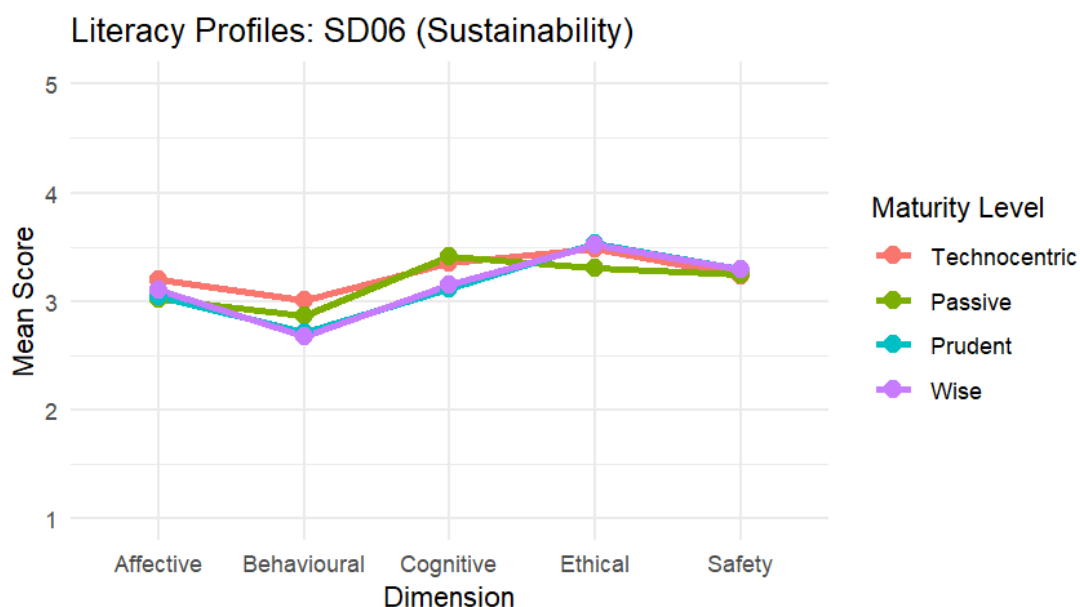
ETHICAL	Within Groups	255,979	346	,740		
	Total	260,728	349			
	Between Groups	1,908	3	,636	,791	,499
	Within Groups	278,101	346	,804		
	Total	280,009	349			
	Between Groups	,183	3	,061	,102	,959
SAFETY	Within Groups	207,692	346	,600		
	Total	207,875	349			

From the following table becomes obvious which two groups differ significantly on the behavioural dimension.

Table 115: Multiple Comparisons for the Behavioural dimension

(I) SD06	(J) SD06	Mean Difference (I-J)	Std. Error	Sig.
New model	Inertia	,13809	,16765	,843
	Refurbished	,29838	,13129	,106
	Maintenance	,33829	,11688	,021
Inertia	New model	-,13809	,16765	,843
	Refurbished	,16029	,17345	,792
	Maintenance	,20020	,16282	,608
Refurbished	New model	-,29838	,13129	,106
	Inertia	-,16029	,17345	,792
	Maintenance	,03991	,12506	,989
Maintenance	New model	-,33829	,11688	,021
	Inertia	-,20020	,16282	,608
	Refurbished	-,03991	,12506	,989

The graph that follows optically verifies that technocentric (who buy a new mobile phone) and digitally wise students (that maintain the device they have) differ in the behavioural dimension (students proactivity/intention to use AI).



ANNEX II

APPENDIX I

a) Qualitative Analysis: Interviews

Protocol for focus groups and semi-structured interviews - TEACHERS

1. Introduction and warm-up (10 min)
 - Brief presentation of the "Slow Tech Innovation" project objectives.
 - Informed consent and reassurance on data anonymity.
2. Perception of AI: resistances and opportunities (15 min)
 - Question 1: What are the main barriers or fears (e.g., "fear of replacement", lack of skills) that you encounter in the adoption of AI in your school?
 - Question 2: Conversely, in which specific areas do you believe AI can offer the greatest opportunities to improve teaching quality?
3. Ethical impact and well-being - Slow Tech paradigm (15 min)
 - Question 3: Considering the "Slow Tech" approach (which prioritizes human well-being over technological acceleration), what risks do you see in the daily use of AI for students' mental and cognitive health?
 - Question 4: Do you feel the need for clearer guidelines for ethical use? If so, on which specific aspects?
4. Guided discussion on ethical dilemmas - (20 min) (Present the scenarios to the participants to stimulate qualitative debate on the reasons for their choices)
 - Scenario A (Efficiency vs. Equity): Discussion on algorithmic bias in automated grading. Prompt: Is a discriminatory margin of error acceptable in exchange for significant time savings for the teacher?
 - Scenario B (Personalization vs. Privacy): Discussion on datafication. Prompt: What is the ethical limit in yielding students' behavioral data and emotions in exchange for hyper-personalized study paths?
 - Scenario C (Autonomy vs. Assistance): Discussion on human agency. Prompt: If a student uses AI to structure an essay but writes the content themselves, is it a future skill or plagiarism?
5. Closing and recommendations (10 min)
 - Question 5: What do you think should be the fundamental characteristics of an AI-based pedagogical model to be truly useful and sustainable for teachers?

APPENDIX II

Protocol for focus groups and semi-structured interviews - STUDENTS (WP2)

1. Introduction and warm-up (10 min)
 - Brief presentation of the "Slow Tech Innovation" project (language adapted to the target audience).
 - Informed consent (with possible reference to parental authorization) and reassurance of anonymity.
2. Perception of AI: habits and opportunities (15 min)
 - Question 1: For which school or personal study activities do you use AI the most? What difficulties or fears do you encounter (e.g., fear of getting false information, fear of being accused of cheating)?
 - Question 2: In which areas do you think AI is a valuable tool that helps you learn better, overcome blocks, or be more creative?
3. Ethical impact and well-being - Slow Tech paradigm (15 min)
 - Question 3: The "Slow Tech" approach centers on human well-being over the speed of technology. Using AI frequently for homework, do you fear it might make your critical thinking "lazy" or create anxiety/addiction?

- Question 4: Do you feel a lack of clear rules at school about what is "allowed" and what is not regarding the use of AI? Would you like more precise guidelines from teachers?
4. Guided discussion on ethical dilemmas (20 min) (Real scenarios adapted for qualitative debate)
- Scenario A (Academic Integrity & AI Hallucinations): (Read the scenario of the upcoming essay deadline with the AI-invented citation).
Prompt: Which decision would you make among the proposed options (submit, cut, generalize, ask for an extension) and why? How do you handle the pressure of grades when you realize that the AI might have "hallucinated" data?
 - Scenario B (Data Privacy vs. Social Pressure): (Read the scenario of the viral app requiring sensitive data to avoid being excluded from the group).
Prompt: What would you do and why? In your daily choices, how much does the fear of missing out (FOMO) weigh against the importance of protecting your personal data and photos?
 - Scenario C (Slow Tech & Planned Obsolescence): (Read the scenario of the two- year-old smartphone being slow compared to the new model with AI).
Prompt: Which option would you choose and why? How much do you feel the need to have the latest available technology at the expense of repair or reuse?
5. Closing and recommendations (10 min)
- Question 5: What is the most important thing you would like your teachers or the school to understand about how your generation experiences and uses Artificial Intelligence?



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Slow Tech Innovation
AI, Ethics and
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