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From Mandatory Exposure to Guided Engagement: Investigating the Structured Integration of Generative AI in Higher Education

Emese Belényesi [1], Marta Katalin Korpics [1,*], Tamás Méhes [1] and Andrea Győrfyné Kukoda [2]

[1] Department of Human Resources, Faculty of Public Governance and International Studies, Ludovika University of Public Service, 2 Ludovika tér, 1083 Budapest, Hungary; belenyesi.emese@uni-nke.hu (E.B.)
[2] Department of Public Finance, Faculty of Public Governance and International Studies, Ludovika University of Public Service, 2 Ludovika tér, 1083 Budapest, Hungary; gyorfynekukoda.andrea@uni-nke.hu
* Correspondence: korpics.marta.katalin@uni-nke.hu

Abstract

The rapid institutionalization of generative artificial intelligence (GenAI) in higher education has created an urgent need for empirical evidence on how structured course-level integration relates to student engagement and perceptions of learning. This study examines a usefulness-centered conceptual framework combining elements of the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology (TAM/UTAUT) with the digital competence perspective of DigComp 2.2. A structured pedagogical pilot intervention requiring all students to use generative AI tools was implemented in an undergraduate Public Service Management course (n = 76). Students completed AI-supported group assignments and an immediate post-intervention questionnaire comprising 19 Likert-scale items, four demographic questions, and four optional open-ended questions that are not analyzed in the present paper. Because most variables were non-normally distributed, non-parametric statistical methods were applied, including Spearman's rank correlations, Mann–Whitney U tests, and Kruskal–Wallis tests. Perceived learning usefulness was strongly and positively associated with both frequency of AI use and satisfaction with the learning process. Ethical attitudes were also positive, but more weakly associated with frequency of use. Demographic group differences were observed mainly in specific usage patterns rather than in general attitudes towards AI-supported learning. These exploratory findings suggest that perceived learning usefulness remains relevant in mandatory AI-integration contexts. Pedagogical scaffolding—including prompt literacy, verification practices, and reflective documentation—provides a structured framework for guided and responsible use of generative AI tools in higher education.

Keywords: generative AI; higher education; perceived learning usefulness; DigComp 2.2; mandatory AI integration; pedagogical scaffolding

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1. Introduction

The emergence of generative artificial intelligence (GenAI) has initiated a structural transformation in higher education. The integration of generative AI is not merely a technological issue; it also reshapes pedagogical approaches to learning, teaching, and assessment. Accelerated digitalization during the COVID-19 pandemic opened the door to AI-based solutions and highlighted the importance of the adaptability of education systems [1,2,3]. The information technology revolution has fundamentally transformed learning processes, changing student expectations and learning habits [4,5].

Unlike previous digital tools, generative AI systems actively participate in knowledge production, thereby reshaping pedagogical roles, assessment practices, and digital competence requirements. While numerous studies have examined voluntary AI use among students, less attention has been devoted to structured, mandatory integration of generative AI within formal course design.

Existing research typically focuses on either technology acceptance or digital competence development. However, the intersection of these perspectives remains underexplored. The DigComp 2.2 framework provides a normative model of AI-related digital competences, whereas the Technology Acceptance Model (TAM) explains behavioral adoption through perceived usefulness and ease of use. Yet few empirical studies integrate these frameworks within an intervention-based design.

Furthermore, ethical concerns, including academic integrity, dependency, and cognitive outsourcing, raise questions about the sustainability of AI-supported learning. While students often report high perceived usefulness, the relationship between ethical awareness and actual patterns of AI use remains unclear.

To address these gaps, the present study examines a structured pilot intervention in which generative AI tools were mandatorily embedded into a public service management course. The research examines (1) acceptance-related associations, (2) competence-related perceptions, (3) ethical considerations, and (4) demographic group differences within a standardized AI-supported learning environment. By combining competence-based and acceptance-based frameworks, the study aims to contribute to the growing body of literature on responsible and pedagogically grounded AI integration in higher education.

To clarify the theoretical alignment of the study, Figure 1 presents the integrated conceptual framework underpinning the empirical analysis. The model synthesizes competence-based (DigComp 2.2) and acceptance-based (TAM/UTAUT) perspectives within a structured pedagogical intervention context.

The framework treats structured AI integration as the instructional context within which perceived learning usefulness, frequency of AI use, and learning experience and satisfaction are examined. Perceived learning usefulness is conceptualized as a central construct associated with frequency of use and learning-related perceptions. Ethical attitudes are examined through correlational analysis, whereas demographic characteristics are treated as contextual variables explored through group comparisons. DigComp 2.2 provides a normative interpretive framework and is not operationalized as a directly measured outcome variable.

Unlike previous studies that focus on the ‘if’ and ‘when’ of voluntary AI adoption, this research focuses on the ‘how’ of structured integration. By examining a mandatory intervention, we provide a unique perspective on the quality of student engagement and the role of perceived usefulness in an environment where usage is no longer optional. This study contributes to the literature by bringing TAM/UTAUT and DigComp 2.2 into a shared conceptual framework for interpreting a real-world pedagogical intervention.

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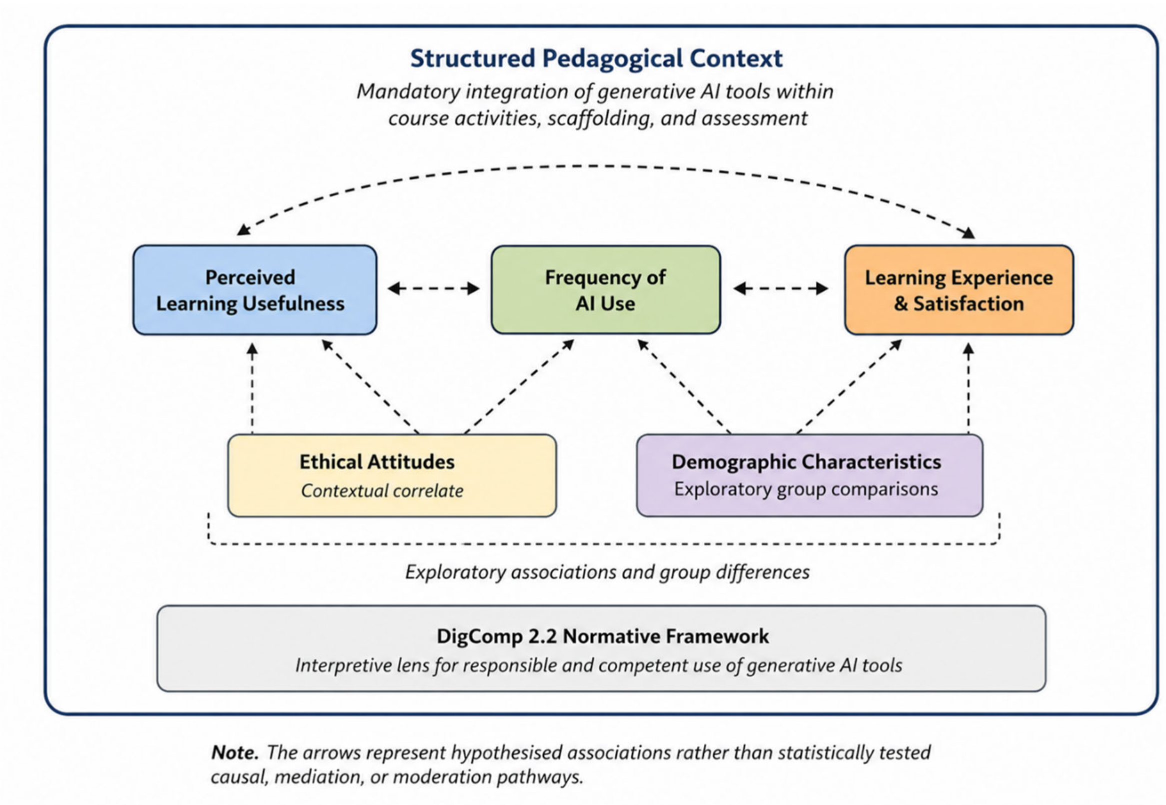

Figure 1. Integrated conceptual framework of structured AI integration in higher education. Dashed arrows indicate hypothesized associations and contextual links; colors distinguish conceptual components and do not represent quantitative values. Source: authors.

2. Literature Review

2.1. Digital and AI Competences in Higher Education

The rapid expansion of generative artificial intelligence (generative AI tools) has substantially reshaped expectations regarding digital competence in higher education. The primary normative framework of this study is DigComp 2.2, which defines the knowledge, skills, and attitudes required for critical, safe, and responsible engagement with AI technologies [6]. Building on earlier iterations of the framework [7,8,9], DigComp 2.2 explicitly incorporates AI-related competences, including the evaluation of AI-generated outputs, bias recognition, data awareness, and ethical use.

In the context of generative AI, digital competence extends beyond technical literacy toward reflective and critical engagement. The ability to interpret AI-generated content, validate outputs, and integrate machine-generated suggestions into domain-specific tasks represents a qualitative shift in higher education skill requirements [10]. Despite the normative clarity of DigComp 2.2, empirical evidence on competence-related changes during structured AI integration remains limited.

The conceptualization of digital competence can be further refined by frameworks that focus specifically on academic teaching practice. The HeDiCom framework, for instance, operationalizes higher education teachers' digital competencies across technological, pedagogical, ethical, and professional engagement dimensions, emphasizing that meaningful technology integration requires pedagogically grounded and ethically informed instructional design [11]. This perspective highlights that student experiences with AI-supported learning environments are not determined solely by access to technology, but by how educators translate digital competence into structured learning activities.

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2.2. Technology Acceptance and AI Use

While competence frameworks define normative expectations, actual AI use is strongly shaped by acceptance dynamics. The Technology Acceptance Model (TAM) posits that perceived usefulness (PU) and perceived ease of use (PEOU) are associated with technology adoption [12,13]. The Unified Theory of Acceptance and Use of Technology (UTAUT) further extends this perspective by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by demographic variables [14,15].

In higher education contexts, AI acceptance is typically associated with perceived performance benefits, efficiency gains, and accessibility [16,17,18,19]. These findings suggest that students' engagement with AI is predominantly pragmatic, with technologies being adopted when they demonstrably enhance task completion and academic performance.

Emerging evidence also indicates that pedagogical framing plays a critical role in shaping acceptance patterns. Intervention-based studies show that when AI use is embedded within structured assessment contexts rather than left as voluntary, perceived usefulness becomes more strongly aligned with actual behavioral engagement [20]. Nevertheless, empirical research examining mandatory, course-wide AI integration remains scarce. As highlighted in recent systematic reviews [21], there is a pressing need for studies that move beyond exploratory perceptions and instead investigate structured and pedagogically grounded implementations of generative AI in authentic educational settings.

2.3. Pedagogical Perspectives on AI-Supported Learning

Beyond acceptance models, AI integration must be interpreted within broader pedagogical frameworks. Cognitive load theory suggests that instructional design defines whether AI reduces extraneous cognitive load or contributes to superficial automation of learning processes [22]. In this respect, structured prompting strategies may help channel AI interaction toward deeper cognitive engagement.

Metacognitive theory further emphasizes the importance of learners' ability to monitor and regulate their own cognitive processes [23]. The requirement to critically evaluate AI-generated outputs may foster reflective awareness, particularly when such evaluation is embedded into assessment criteria.

From a motivational perspective, self-determination theory highlights autonomy, competence, and relatedness as key drivers of intrinsic motivation [24]. While generative AI tools may enhance perceived competence and efficiency, their impact on intrinsic motivation depends largely on how they are integrated into learning design. As emphasized in a recent systematic review, the effective use of generative AI tools in higher education depends not only on technological affordances but on the pedagogical "why" and "how" guiding its implementation [25].

Within this pedagogical landscape, generative AI also shows strong potential to support self-regulated learning (SRL). Chiu [26], drawing on self-determination theory, demonstrates how generative AI chatbots can scaffold autonomy, competence, and relatedness by supporting goal setting, monitoring, and reflection. These findings position generative AI not merely as an information source, but as a metacognitive partner that can enhance learners' regulatory capacities. However, the effectiveness of such support is contingent upon structured and guided use, as unregulated interaction may lead to surface-level engagement rather than deep learning.

2.4. Benefits, Risks, and Ethical Considerations

AI applications in higher education span a wide range of domains, including personalized learning, automated assessment, content generation, and administrative optimization [27,28,29]. These developments highlight the transformative potential of AI to reshape educational processes.

At the same time, generative AI introduces significant risks, including hallucinated outputs, data protection concerns, and challenges to academic integrity [30,31]. Addressing these risks requires more than restrictive policies; as Airaj [32] argues, institutions must embed ethical AI literacy and transparency directly into teaching and learning practices.

Student behavior further complicates this landscape. Learners increasingly rely on generative AI for tasks such as essay writing, problem solving, and exam preparation [33,30], often without a deep understanding of the underlying mechanisms. This may have implications for critical thinking and creativity. Empirical studies suggest that while students tend to express higher levels of trust in AI systems than educators, they often demonstrate lower levels of ethical reflexivity [34,35].

Cultural and institutional contexts also shape perceptions of AI. Comparative studies reveal differences in the relative emphasis placed on benefits and risks across educational systems [36,37], while broader analyses highlight both the transformative potential of AI and its capacity to exacerbate existing inequalities [38].

Empirical evidence on AI-supported learning environments further reinforces these considerations. Lee et al. [39] found that the use of an AI-based chatbot significantly improved students' academic performance, self-efficacy, learning attitudes, and motivation. These results suggest that AI can positively influence both cognitive and affective dimensions of learning when embedded within structured pedagogical designs. Importantly, this underscores a central argument of the present study: the educational value of AI lies not in the technology itself, but in how it is pedagogically integrated.

2.5. Synthesis and Research Gap

Taken together, the literature suggests that the educational potential of generative AI is closely tied to three interrelated factors: (1) the digital competence of educators, (2) the pedagogical design of AI-supported learning environments, and (3) the extent to which generative AI tools support self-regulated learning processes.

While existing studies provide valuable insights into each of these areas, there remains a need for integrative research that examines how they interact in practice. In particular, limited attention has been paid to how structured educational interventions involving generative AI influence students' learning experiences within specific disciplinary contexts.

Accordingly, the present study aims to address this gap by investigating how guided use of generative AI tools affects students' learning processes and perceptions in higher education. By situating AI use within a structured pedagogical framework, the study seeks to contribute to a more nuanced understanding of how generative technologies can be effectively integrated into teaching and learning.

3. Conceptual Framework

3.1. Integrated Theoretical Framework and Research Positioning

The literature converges around three central insights. First, DigComp 2.2 provides a structured normative framework for interpreting AI-related competences in higher education, defining the knowledge, skills, and attitudes required for responsible and critical engagement with generative AI. Second, technology acceptance models (TAM/UTAUT)

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explain behavioral engagement primarily through perceived usefulness and performance expectancy. Third, pedagogical framing and ethical regulation shape whether AI integration supports meaningful learning processes or results in superficial automation.

Despite the rapidly expanding discourse on AI in higher education, empirical studies examining structured, mandatory AI integration within authentic course contexts remain limited. Most existing research focuses either on voluntary adoption patterns or on normative competence expectations, rarely combining these perspectives within an intervention-based design.

This study positions structured AI integration at the intersection of competence frameworks, acceptance theory, and pedagogical design. Rather than treating competence development, technology acceptance, and instructional structuring as separate domains, the study conceptualizes them as complementary perspectives within a standardized educational environment. Within this framework, the structured embedding of AI provides the instructional context for examining students' perceived learning usefulness, frequency of use, and learning-related perceptions. Perceived learning usefulness is treated as a central construct associated with frequency of use and satisfaction, while ethical attitudes and demographic characteristics are examined as contextual factors.

By combining a normative competence framework (DigComp 2.2) with empirically operationalized acceptance constructs (TAM/UTAUT), the study provides a theoretically integrated basis for analyzing how structured pedagogical embedding relates to perceived usefulness, behavioral engagement, ethical considerations, and learning experience. This integrated model underpins the research questions and hypotheses tested in the empirical section.

3.2. Research Questions and Objectives

Building on the integrated framework of digital competence (DigComp 2.2) and technology acceptance theory (TAM/UTAUT), the study examines AI integration primarily through perceived usefulness and behavioral engagement within a structured pedagogical context.

The research addresses the following questions:

- RQ1. How does perceived learning usefulness relate to the frequency of AI use in a mandatory, structured course environment?
- RQ2. To what extent are ethical attitudes associated with actual AI usage intensity?
- RQ3. How is AI usage related to students' perceived learning experience and satisfaction?
- RQ4. How do patterns of AI use and overall acceptance differ across demographic groups?

Rather than measuring objective competence development, the study interprets findings within the normative framework of DigComp 2.2, focusing on competence-related perceptions.

3.3. Hypotheses

Drawing on technology acceptance theory and competence-oriented digital pedagogy, the following exploratory hypotheses were formulated:

- *Hypothesis 1 (H1). The perceived learning usefulness of generative AI tools is positively associated with frequency of AI use*. This hypothesis is grounded in TAM, which identifies perceived usefulness as being associated with behavioral engagement.

- *Hypothesis 2 (H2). Ethical concerns are less strongly associated with AI usage intensity than perceived learning usefulness.* This reflects the assumption that pragmatic performance expectations outweigh normative concerns in shaping everyday academic practices.
- *Hypothesis 3 (H3). Frequency of AI use is positively associated with perceived learning experience and satisfaction. Based* on self-determination theory, structured AI integration is expected to reinforce perceived competence and experiential engagement rather than directly enhance intrinsic motivation.
- *Hypothesis 4 (H4). Demographic groups differ in specific patterns of AI use, while their overall acceptance levels remain broadly similar.* In line with UTAUT, demographic characteristics function as moderating rather than primary explanatory variables.

The study does not test objective competence gains; instead, findings are interpreted in light of the DigComp 2.2 framework as a normative reference point.

4. Research Design and Methodology

4.1. Description of the Pilot Project

The pilot intervention was implemented within an undergraduate course entitled Public Service Management. The primary aim was not merely pedagogical innovation, but the creation of a structured and standardized AI-integrated learning environment suitable for examining students' perceptions, usage patterns, and competence-related self-assessments.

The intervention embedded the use of generative AI tools into the course's core assessment structure. Rather than allowing voluntary or incidental AI use, all students were required to complete the final group project using predefined generative AI applications. This mandatory integration ensured comparable exposure to AI-supported task completion among participants and reduced variability due to unequal access or self-selection.

4.2. Standardization and Instructional Control

The course concluded with a group-based project in which students (in groups of four) analyzed a selected public service or public administration organization using theoretical models covered in the course (e.g., organizational strategy, structure, and culture). While the disciplinary content followed standard curricular requirements, the AI-related component was strictly standardized:

- All project deliverables had to incorporate documented use of predefined generative AI tools.
- Predefined platforms were specified for each output format (presentation, video, visual narrative, quiz, and reflective documentation).
- AI-assisted content generation, prompting, and validation were explicitly required.
- Students were instructed to document their AI use within the reflective component.

This design created a controlled AI-supported environment in which the mode of technological engagement was structurally embedded into the assessment criteria.

4.3. The Pedagogical Intervention and Task Design

To ensure a standardized 'mandatory exposure', the intervention followed a structured, four-phase human-in-the-loop (HITL) methodology. This framework integrated the practical steps of the project implementation with the development of AI literacy and critical thinking (as illustrated in Figure 2).

Phase 1: Conceptual Foundation and Project Initiation (Week 1): This phase focused on establishing a baseline level of 'AI Readiness' and organizational setup.

- Methodological Focus: Students received a 90 min workshop on the ethical use of generative AI tools and basic prompt engineering (Role–Context–Task–Constraint framework) to minimize technical barriers.
- Practical Implementation: Simultaneously, students formed groups of four and selected a public service organization to be the subject of their semester-long analysis.

Phase 2: Theoretical Framework and AI-Supported Execution (Weeks 2–5): In this phase, students transitioned from theory to application, using predefined generative AI platforms to analyze their chosen organization.

- Methodological Focus: The mandatory requirement was to use AI for *Information synthesis* (summarizing organizational documents), ideation (developing solutions for organizational challenges), and structural optimization of the project outputs.
- Practical Implementation: Students defined their theoretical frameworks based on the models taught in the course and collected primary data (websites, organizational charts). They then used generative AI tools to transform these data into multimodal content, including presentations, videos, storybooks, and quizzes.

Phase 3: Critical Verification and Guided Engagement (Week 6): This phase acted as the core pedagogical 'scaffolding', ensuring students did not become passive users.

- Methodological Focus: A crucial element was the 'Verification Log', aligned with the DigComp 2.2 'Information and Data Literacy' competency.
- Practical Implementation: Students were required to manually verify AI-generated facts and citations against library databases and official documents, correcting hallucinations and ensuring academic integrity.

Phase 4: Reflection, Submission, and Presentation (Final Stage): The final phase focused on the synthesis of the learning experience and peer evaluation.

- Methodological Focus: Students submitted a Reflective Portfolio, which included the original AI-generated raw outputs (as an appendix to ensure accountability), the human-corrected final version, and a 300-word reflection on how the use of generative AI tools had influenced their approach to and understanding of the topic.
- Practical Implementation: The intervention concluded with a *group presentation* (evaluation by instructor and audience), where students demonstrated their final analysis and shared their experiences regarding group dynamics and AI-assisted collaboration.

Figure 2 illustrates the synchronization between the four theoretical phases (Phases 1–4) and the practical project implementation steps. It depicts the progression from conceptual foundation and group formation through AI-assisted execution and critical verification, culminating in reflective submission and peer presentation.

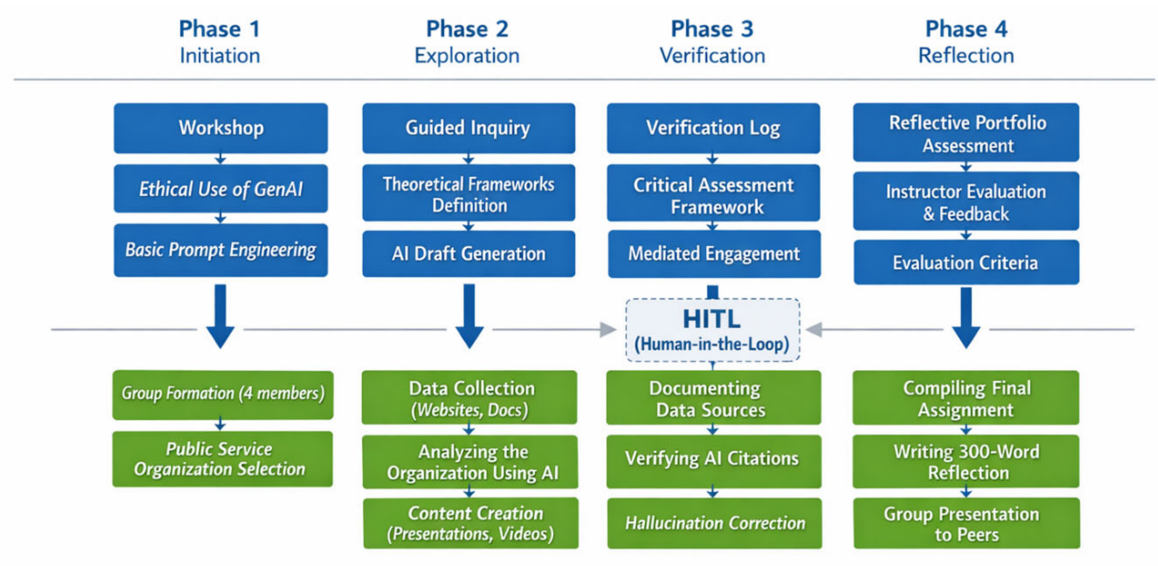

Figure 2. Integrated workflow of the AI-supported pedagogical intervention. Blue boxes denote instructional and methodological elements, green boxes denote student implementation activities, and arrows indicate progression and integration across the four phases through the human-in-the-loop (HITL) process. Source: authors.

4.4. Standardized Intervention Design and Analytical Scope

Although the study did not include a control group or a pre-intervention baseline, the instructional procedures were standardized across participants. First, AI exposure was mandatory and uniform across participants, limiting self-selection bias in technology use. Second, the instructional framework, assessment criteria, and AI platforms were identical for all groups, ensuring a high degree of procedural consistency. Third, data collection occurred immediately after completion of the structured AI-based project, capturing perceptions grounded in a shared and recent learning experience.

The project required students to analyze organizational documents and structures and to synthesize their findings using AI-generated outputs. However, the detailed disciplinary elements of the assignment primarily served as a contextual vehicle for standardized AI integration rather than as independent pedagogical variables within the research design.

While the absence of a control group limits causal inference, the standardized intervention design allows for consistent comparison of student perceptions within a shared and standardized instructional setting. No formal mediation or moderation analyses were conducted because of the exploratory pilot design and sample size.

4.4.1. Research Function of the Pilot Intervention

Within the research design, the project functioned as a structured intervention context rather than merely a course assignment. It provided:

– Uniform exposure to AI-supported task completion;
– Comparable conditions of AI-guided content creation;
– Embedded reflective elements concerning AI use.

The post-intervention questionnaire was administered immediately after project completion, ensuring that responses reflected direct and authentic engagement with AI-supported tools under controlled instructional conditions.

Thus, the pilot project created a standardized pedagogical environment that enabled the exploratory examination of perceived usefulness, usage intensity, ethical attitudes, and satisfaction within a mandatory AI-integrated framework.

4.4.2. The Questionnaire

The questionnaire entitled "Artificial Intelligence in Higher Education" was developed to examine students' perceptions, usage patterns, and attitudes related to the structured integration of generative AI tools in higher education. The instrument aimed to measure frequency of AI use, perceived learning usefulness, ethical attitudes, and learning experience and satisfaction within the mandatory AI-integrated course context. The complete questionnaire is provided in Appendix A.

4.4.3. Structure and Measurement Scales

The questionnaire comprised 19 Likert-scale items, four demographic questions, and four optional open-ended questions. The open-ended responses are not analyzed in the present paper. The closed-ended items were organized into four multi-item thematic scales:

- Frequency of AI use (FT)—5 items;
- Perceived learning usefulness (H)—5 items;
- Ethical attitudes (D)—4 items;
- Learning experience and satisfaction (ST)—5 items.

All attitudinal items were measured using a *5*-point Likert scale (1 = strongly disagree/not typical at all, 5 = strongly agree/completely typical). Scale anchors were adapted to the content of each block (e.g., frequency-based or agreement-based wording). In addition, the questionnaire included demographic questions covering gender, age group, type of training (full-time/part-time), and employment status. Four optional open-ended questions allowed students to elaborate on their experiences, perceived advantages and risks of AI use, and suggestions for future integration.

4.4.4. Instrument Development and Pre-Test

The initial version of the questionnaire was constructed based on the theoretical framework of the study, drawing on constructs derived from technology acceptance theory (perceived usefulness, behavioral engagement), ethical considerations in AI use, and competence-related perceptions interpreted within the DigComp 2.2 framework.

A preliminary version was pre-tested with *10 undergraduate students* who were not part of the final sample. The pre-test aimed at assessing:

- Clarity and comprehensibility of item wording;
- Appropriateness and balance of response categories;
- Logical flow and estimated completion time;
- Overall user experience in the online format.

Based on the feedback, several modifications were implemented:

- Ambiguous or overly broad open-ended questions were reformulated or converted into closed-ended Likert-scale items to improve quantifiability and scale reliability.
- Certain items were reworded to eliminate double-barreled phrasing and enhance conceptual clarity.
- Demographic variables were clarified and expanded (e.g., refined age categories, inclusion of employment status).

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– Minor adjustments were made to scale anchors to ensure consistency across thematic blocks.

The instrument demonstrated satisfactory face and content validity, as items were derived from established theoretical constructs and refined through pilot testing. The finalized instrument was implemented in Google Forms and administered online immediately after completion of the AI-based project tasks. This timing ensured that responses were grounded in recent, structured AI use experiences within a standardized instructional context.

All procedures involving human participants were conducted in accordance with institutional ethical standards and the 1964 Helsinki Declaration and its later amendments. Ethical approval for this study was granted by the Institutional Ethics Committee of Ludovika University of Public Service; protocol code 112/2021 (XI. 24.), approved on 24 November 2021. Before data collection, students were informed of the study's scope, voluntary nature, and complete anonymity via an electronic consent form. To eliminate potential coercion in this mandatory course context, students were explicitly assured that participation in the survey was entirely decoupled from course assessment and grading. Survey responses were collected anonymously via Google Forms with no IP address tracking.

5. Results

5.1. Sample Characteristics

The final sample consisted of $n = 76$ higher education students enrolled in a course at a single institution. The majority of respondents were full-time students (73.7%), while 26.3% participated in part-time education. The gender distribution of the sample was relatively balanced (52.6% male, 47.4% female). Most participants were under 25 years of age (81.6%), reflecting the typical demographic composition of undergraduate cohorts. In addition, 64.5% of the students reported being employed alongside their studies, indicating that a substantial proportion of the sample combined academic and professional commitments. Given the pilot nature of the study and the single-institution sampling frame, the findings should be interpreted primarily as exploratory insights into emerging patterns of AI-supported learning practices among higher education students.

5.2. Analysis of Responses to Questions Measured on a Likert Scale

Prior to hypothesis testing, the reliability and internal consistency of the questionnaire constructs were examined. Internal consistency of the constructs was assessed using Cronbach's alpha coefficients. All measured scales exceeded the commonly recommended threshold of $\alpha = 0.70$, indicating acceptable to excellent reliability for exploratory research.

Reliability of Scales: The various statement blocks in the questionnaire form attitude and opinion dimensions that can be evaluated on a Likert scale (1–5). All of the multi-item scales used in the study showed adequate or excellent internal reliability. Cronbach's alpha values ranged from 0.77 to 0.85 in the dimensions of AI usage frequency, perceived learning usefulness, ethical attitudes, and learning experience and satisfaction, which supports the applicability of the scales for exploratory analyses (Table 1).

Table 1. Descriptive statistics and internal consistency of the study scales ($n = 76$). Source: authors.

Question Block	No. of Items	Mean	SD	Cronbach's Alpha
Frequency of AI use (FT)	5	4.06	1.25	0.769
Perceived learning usefulness (H)	5	3.82	1.13	0.852
Ethical attitudes (D)	4	3.22	1.31	0.784
Learning experience and satisfaction (ST)	5	3.78	1.13	0.841

Patterns of AI use and perceived learning usefulness: Based on the descriptive statistics of the responses to questions assessing attitudes towards AI use, artificial intelligence tools have become an integral part of students' learning practices, particularly due to their learning-supporting and time-saving functions. Although ethical concerns were moderately present in the responses, students showed an open and positive attitude towards the integration of AI into their studies.

According to the responses to the thematic block questions on the frequency of use of generative artificial intelligence (GenAI) tools, the most common forms of use were interpreting and summarizing course material and generating ideas, while exam preparation showed a slightly lower but still high level of use. Overall, AI applications appear primarily as functional, goal-oriented learning support (Table 2).

Frequency of use was rated on a Likert scale of 1 to 5 (1 = not at all typical, 5 = completely typical).

Table 2. Descriptive statistics for frequency-of-use items. Source: authors.

Variable	Mean	SD
FT1: Use of ChatGPT for course assignments	4.04	1.37
FT2: Using other generative AI (e.g., Copilot, Gemini)	4.21	1.15
FT3: Use for exam preparation	3.88	1.34
FT4: Use for idea generation and creative tasks	3.97	1.26
FT5: Explaining and summarizing teaching material	4.18	1.15

According to the perceived learning usefulness ratings, students primarily view AI as a time-saving and learning-supporting tool. The strongest agreement was related to time efficiency and faster task completion, while the assessment of the stress-reducing effect was more restrained. This suggests that AI functions primarily as a pragmatic learning tool rather than as emotional or motivational support (Table 3).

Table 3. Descriptive statistics for perceived learning usefulness items. Source: authors.

Statement	Mean	SD
H1: Helped to complete studies more quickly	4.10	1.03
H2: I understood the course material better	4.08	1.04
H3: The quality of my assignments improved	3.55	1.14
H4: Reduced stress associated with learning	3.16	1.43
H5: Saved me time	4.24	1.03

Ethical Considerations and Attitudes: Ethical concerns related to the use of AI appeared at a moderate level. Students perceived the risks of dependency and assessment integrity to a certain extent but considered the need for institutional regulation to be less important. The findings indicate that ethical considerations are present in this exploratory sample, but do not dominate the use of AI for learning purposes (Table 4).

Table 4. Descriptive statistics for ethical-attitude items. Source: authors.

Statement	Mean	SD
D1: May compromise academic integrity	3.25	1.17
D2: Excessive reliance on generative AI tools may result in dependency	3.42	1.40
D3: University regulation is necessary	2.91	1.36
D4: Evaluating AI-assisted assignments is challenging for instructors	3.28	1.30

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In line with hypothesis H2, the relationship between ethical concerns and actual AI use proved to be weaker than the perceived learning usefulness, which points to the pragmatic nature of students' AI use.

According to the findings of the Learning Experience and Satisfaction thematic block, the integration of AI-assisted systems into courses resulted in a high level of satisfaction among students, the majority of whom would be willing to use them in other subjects as well. The use of AI moderately increased the respondents' motivation level while clearly improving their learning experience (Table 5).

Table 5. Descriptive statistics for learning experience, motivation, and satisfaction items. Source: authors.

Statement	Mean	SD
ST1: Increased my learning motivation	3.38	1.17
ST2: Made learning more engaging	3.67	1.19
ST3: I am satisfied with the integration of AI.	4.12	1.01
ST4: I would use it in other subjects	4.03	1.08
ST5: I would have had more difficulties without them	3.71	1.20

In line with hypothesis H3, frequency of AI use showed a stronger association with perceived learning experience and satisfaction than with increased learning motivation.

Figure 3 presents the average scores for individual survey items (on a 1–5 Likert scale), illustrating students' reported frequency of AI use, perceived learning usefulness, ethical attitudes, and overall satisfaction within the pilot AI-integrated course.

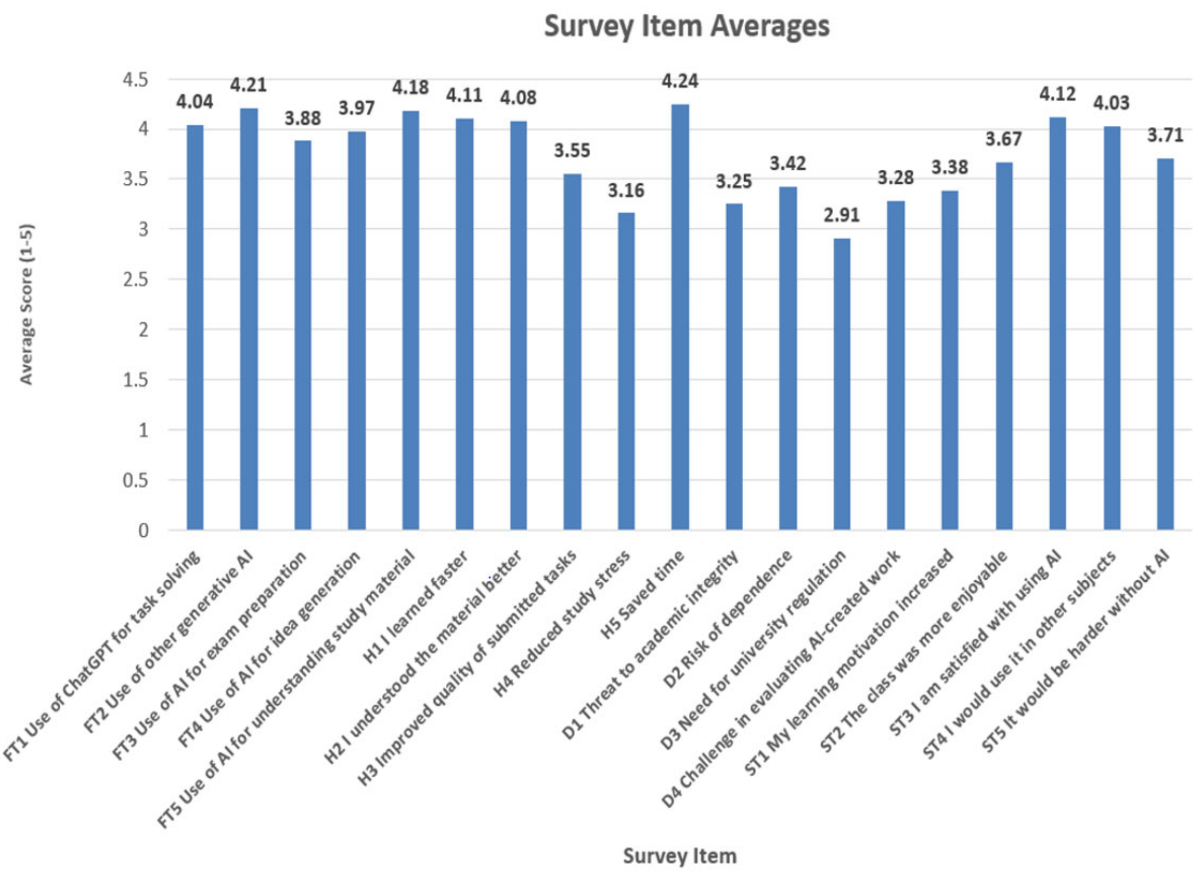

Figure 3. Mean scores for questionnaire items across the four study dimensions. Source: authors.

5.3. Associations Between AI Use, Perceived Learning Usefulness, Ethical Attitudes, and Satisfaction

The research aimed to explore the statistical correlations between the individual attitude scales and the experiences and opinions of AI use. Shapiro–Wilk tests indicated that the majority of variables significantly deviated from normal distribution ($p < 0.05$); therefore, non-parametric statistical procedures (Spearman's rank correlation, Mann–Whitney U test, Kruskal–Wallis test) were applied in the subsequent analyses. The complete Shapiro–Wilk test is provided in Appendix B, Figure A1.

Spearman's rank correlations showed positive associations among the four composite scales, with the strongest association observed between perceived learning usefulness and learning experience and satisfaction (Table 6).

Spearman's correlation matrix examining the relationships between the four main thematic dimensions:

Table 6. Spearman's rank correlation matrix for the study scales. Note. Values are Spearman's ϱ. * *p* < 0.05. ** *p* < 0.01. Source: authors.

Scales	Frequency of AI Use (FT)	Perceived Learning Usefulness (H)	Ethical Attitudes (D)	Learning Experience and Satisfaction (ST)
Frequency of AI Use (FT)	1.00			
Perceived Learning Usefulness (H)	0.62 **	1.00		
Ethical Attitudes (D)	0.38 *	0.51 **	1.00	
Learning Experience and Satisfaction (ST)	0.54 **	0.67 **	0.49 *	1.00

Overall, perceived learning usefulness was positively associated with both frequency of AI use ($\varrho = 0.62$, $p < 0.01$) and learning experience and satisfaction ($\varrho = 0.67$, $p < 0.01$). Ethical attitudes were also positively associated with frequency of use, although the relationship was weaker ($\varrho = 0.38$, $p < 0.05$). These findings describe a pattern of associations among the measured constructs but do not establish a causal pathway or mediation effect. The Spearman Correlation Heatmap is provided in Appendix B Figure A2.

In line with hypothesis *H1*, the findings show that the perceived learning usefulness of generative AI systems are closely related to frequency of use, especially in the case of functional, study-related applications.

5.4. Group Differences (Exploratory Analyses)

The research also explored, through non-parametric difference tests, whether different patterns emerge in terms of attitudes and experiences with AI applications based on the demographic characteristics of the respondents (gender, age, employment status, type of training).

The Mann–Whitney U test was used to compare two independent groups formed along the variables of gender, employment status, and full-time/part-time education, while the Kruskal–Wallis test was used to compare the five age groups. Although an independent-samples t-test was also run in IBM SPSS 31.0 Statistics the results of this parametric test cannot be considered reliable due to the violation of normality and the ordinal measurement level, so the interpretation is based solely on non-parametric tests.

Non-parametric difference tests identified several significant differences in demographic and educational background variables (Mann–Whitney U Test, Figure 4). In the comparison by *type of training*, the Mann–Whitney U test indicated a significant difference for a single variable. In the case of AI use for explaining the curriculum (FT5), full-time students reported a higher frequency of use than part-time students ($U = 376.00$; $Z = -2.414$;

https://doi.org/10.3390/higheredu5030076

p = 0.016; mean rank: full-time = 41.79; part-time = 29.30). The calculated effect size was r = −0.28, indicating a small-to-moderate effect. This result suggests that full-time students in the sample integrate generative AI tools to a greater extent into their learning processes that support the interpretation of the curriculum. In the other dimensions examined—perceived learning usefulness, ethical judgement, satisfaction, and learning experience—there were no statistically significant differences between the two forms of education (p > 0.05), which suggests that the general attitude towards AI applications and their acceptance is fundamentally similar among full-time and part-time students in the sample.

When comparing participants by gender, the Mann–Whitney U test indicated a statistically significant difference for two variables. In the case of the use of alternative generative AI tools (FT2) and the use of AI for exams (FT3), female students reported more frequent use for study purposes (FT2: U = 467.00; Z = −2.951; p = 0.003; FT3: U = 467.00; Z = −2.796; p = 0.005). Effect size calculations indicated small-to-moderate effects (r = −0.34 and r = −0.32). For the other variables examined—such as ethical concerns, the enjoyment value of AI use, and the perception of time savings—there were no statistically significant differences between male and female students (p > 0.05), suggesting that general attitudes towards AI use are similar across genders.

When comparing the students participating in the study according to their employment status, actively working students reported lower levels of concern about the risk of dependence on AI use (D2) than their unemployed peers (U = 441.5; Z = 2.457; p = 0.014). The corresponding effect size (r = 0.28) indicates a small-to-moderate practical effect. No statistically significant differences were observed regarding the remaining variables.

Overall, the analyses suggest that although the acceptance of AI-supported tools is generally positive among students, different usage patterns emerge along certain demographic characteristics. These differences are primarily evident in the frequency of AI use for study purposes, while basic attitudes and perceptions show a high degree of similarity across the groups studied.

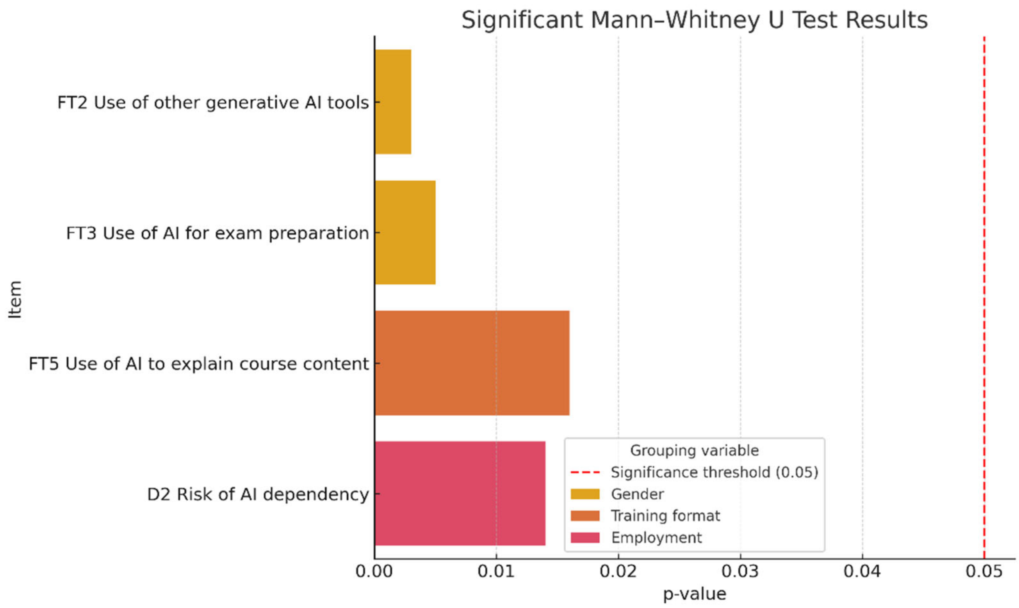

Figure 4. Statistically significant Mann–Whitney U-test results by grouping variable. Source: authors.

When examining the students' responses by *age* group, the analysis indicated statistically significant differences in four variables: the use of alternative generative AI tools

(FT2), the use of AI for idea generation (FT4), the use of AI for interpreting course material (FT5), and satisfaction with AI use (ST3) (Kruskal–Wallis Test, Figure 5).

The findings indicate different usage patterns: older students used AI-assisted systems other than ChatGPT less frequently, but their satisfaction was higher. AI was used primarily by younger students to explain course material, while the oldest age group tended to use it for idea generation. No statistically significant age differences were found for the other variables examined ($p > 0.05$).

Overall, the findings suggest that the use and perception of generative AI tools may differ depending on age: younger students typically reported more frequent and versatile use, while older students reported higher satisfaction in some cases.

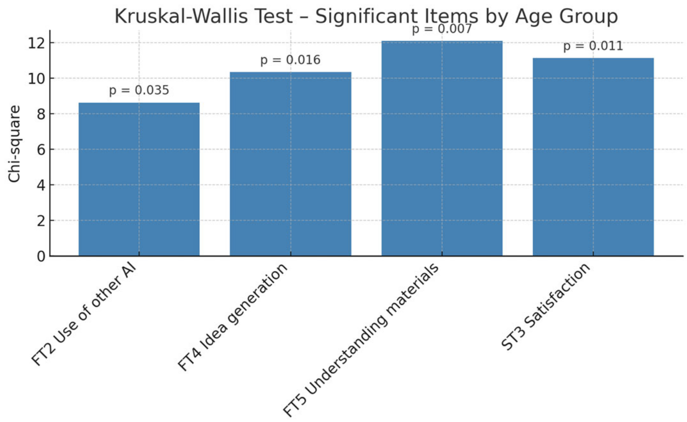

Figure 5. Kruskal–Wallis test showing significant age-group differences. Source: authors.

In line with hypothesis H4, the demographic differences identified were primarily evident in the manner and purposes of AI use, while the basic attitudes towards AI-based learning remained largely similar across the groups.

Given the exploratory nature of the item-level group comparisons, *p*-values were not adjusted for multiple testing and should therefore be interpreted cautiously. Due to the sample size and pilot nature of the study, these findings do not indicate stable group effects, but rather different usage trends.

5.5. Summary of Quantitative Findings

Based on the findings, the use of generative AI tools for study purposes is widespread among students and is generally viewed positively. Students primarily integrate AI into their learning processes in a pragmatic, task-oriented manner, with a particular emphasis on time savings, support for understanding the subject matter, and performance-related benefits. The use of AI is closely linked to perceived learning usefulness and satisfaction, while ethical considerations, although present in students' thinking, do not represent a significant limiting factor in the development of actual usage patterns.

The demographic differences identified are primarily reflected in the manner and intensity of AI use, rather than in basic attitudes, suggesting that AI-based learning is heterogeneous but fundamentally accepted. It should also be noted that the pedagogical integration of AI-supported tools is more strongly associated with an increase in learning experience and satisfaction than with an increase in learning motivation. Despite the pilot nature of the study, the findings paint a coherent picture of student adaptation to AI-based learning and confirm the need for further hypothesis-driven research on a larger sample.

5.6. Summary Evaluation of Hypotheses

The hypotheses formulated during the research were tested in an exploratory manner, taking into account the pilot nature of the study and the limited size of the sample. Overall, the empirical findings support the relevance of the theoretical frameworks behind the hypotheses but show varying degrees of confirmation for each hypothesis.

H1, which concerned the positive relationship between the perceived learning usefulness of generative AI tools and the frequency of use, was supported. The results were consistent with this: perceived learning usefulness was positively and significantly associated with frequency of AI use. This pattern is compatible with the TAM-based proposition that perceived usefulness is relevant to technology-related behavior; however, the correlational design does not establish predictive or causal effects.

H2, which states that ethical concerns are less strongly related to actual usage intensity than perceived learning usefulness, was also supported. The results were also consistent with H2. Ethical attitudes were positive but more weakly associated with frequency of AI use than perceived learning usefulness was. This suggests that perceived learning usefulness was more closely related to reported use than ethical attitudes, without implying that students lacked ethical awareness.

H3, which examined the relationship between frequency of AI use and perceived learning experience and satisfaction, was supported. The results were consistent with H3, as frequency of AI use was positively associated with learning experience and satisfaction. The descriptive results also indicated higher ratings for satisfaction than for increased learning motivation.

H4 received partial exploratory support. The non-parametric group comparisons identified differences in selected usage patterns across gender, age, mode of study, and employment-status groups, whereas overall attitudes and acceptance were broadly similar. These findings represent group differences rather than statistically tested moderation effects.

Overall, the exploratory analyses were consistent with H1–H3 and provided partial support for H4. Perceived learning usefulness showed the strongest associations with frequency of use and satisfaction, while ethical attitudes and demographic group differences were less prominent. These findings should be interpreted as exploratory associations rather than as evidence of prediction, moderation, or causal effects.

6. Discussion

The findings of this pilot study provide exploratory insights into students' perceptions of mandatory, course-level integration of generative AI. By moving beyond voluntary adoption models, this research highlights how structured exposure appears to reshape the relationship between technology perception and actual engagement.

Rather than interpreting the findings in isolation, the following discussion compares the results with existing theoretical and empirical research on technology acceptance, digital competence, and pedagogically integrated AI in higher education.

6.1. Beyond Adoption: The Role of Perceived Usefulness in Mandatory Contexts

Traditional technology acceptance research, heavily influenced by the Technology Acceptance Model (TAM) and UTAUT, primarily focuses on "behavioral intention to use" as the ultimate dependent variable. However, in our study, the use of generative AI tools was not a choice but a pedagogical requirement. Venkatesh et al. [14] argued that in mandatory settings, Social Influence (the pressure to comply with institutional expectations) often overrides individual attitudes.

Because perceived ease of use was not measured, the present study cannot determine whether its role becomes secondary in a mandatory instructional context. The results nevertheless show that perceived learning usefulness was positively associated with both frequency of use and satisfaction. This suggests that perceived value remains relevant even when initial exposure is compulsory, shifting attention from the decision to adopt the technology towards variations in how students use and evaluate it.

These findings are broadly consistent with the Technology Acceptance Model proposed by Davis [12], which identifies perceived usefulness as a central determinant of technology-related behavior. However, our results extend this perspective by suggesting that perceived usefulness remains highly relevant even when AI use is institutionally required rather than voluntary. This observation is also compatible with the UTAUT framework [14], which recognizes the influence of contextual conditions on technology use. Furthermore, our findings complement the conclusions of Bhullar et al. [21], who highlighted the need for empirical studies examining structured pedagogical implementations of generative AI instead of focusing exclusively on students' intentions or general attitudes toward AI adoption.

6.2. DigComp 2.2 and the Competence-Oriented Interpretation of the Intervention

The intervention incorporated activities aligned with several dimensions of the DigComp 2.2 framework. Our intervention required students to move beyond simple prompt-engineering (technical skill) into the domains of Information and Data Literacy and Problem Solving. Specifically, students had to evaluate the credibility of AI-generated outputs and cognitively steer the AI to solve complex administrative cases.

Connecting to the DigComp 2.2 Framework: The findings suggest that structured, mandatory exposure may encourage students to engage in higher-level digital practices aligned with DigComp 2.2 domains, such as critical verification and content evaluation. While students frequently used AI for information synthesis ($M = 4.18$, aligning with DigComp Area 1), the intervention required students to verify AI-generated information and document corrections; however, the study did not measure change in verification competence directly.

Because all students received the same mandatory exposure and no pre-intervention measure of digital competence was collected, the study cannot determine whether the intervention reduced a digital divide. The design did, however, provide a common baseline of access, instruction, and guided practice. Whether such standardization reduces competence-related inequalities should be examined in future controlled and longitudinal studies.

These findings should not be interpreted as evidence of measurable competence development; rather, they are consistent with the competence domains described in DigComp 2.2 [6]. In particular, the emphasis placed on critical verification and responsible AI use reflects the framework's focus on information literacy, critical evaluation, and ethical engagement. Likewise, the pedagogical scaffolding applied in the intervention aligns with the HeDiCom framework [11], which emphasizes that meaningful digital competence emerges through well-designed instructional practices rather than through technology access alone.

6.3. Pedagogical Structuring and Learning Experience

The findings are consistent with the view that pedagogical design is relevant to students' experiences of generative AI. However, trust and mediation were not measured directly in the present study. The positive associations between perceived learning usefulness and satisfaction should therefore be interpreted as relationships among students' perceptions rather than as evidence of a tested mediating process.

The structured nature of the project—including milestones, instructor guidance, verification requirements, and reflective documentation—provided a shared pedagogical context for AI use. This interpretation is consistent with previous studies emphasizing the importance of purposeful instructional design, but the present results do not establish that the task design caused higher trust or satisfaction.

The present findings are consistent with previous research emphasizing that the educational value of AI depends largely on pedagogical design rather than on technological capabilities alone. Viberg et al. [37] similarly argued that trust in AI develops through meaningful educational experiences, while Lee et al. [39] demonstrated that AI-supported learning environments can positively influence students' learning experiences when embedded within structured instructional activities. Our results also support the conclusions of Ma et al. [25], who argued that the effectiveness of generative AI depends primarily on how and why it is integrated into teaching rather than on the technology itself.

6.4. Ethical Pragmatism

The ethical-attitude scale was positively and significantly, but more weakly, associated with frequency of AI use ($\varrho = 0.38$, $p < 0.05$) than perceived learning usefulness was ($\varrho = 0.62$, $p < 0.01$). This pattern is consistent with the exploratory interpretation that perceived learning usefulness was more closely related to reported use than ethical attitudes. It does not, however, demonstrate that students disregarded ethical concerns or that academic benefits outweighed such concerns. This pattern may be relevant to institutional policy and pedagogical practice.

The relatively weak association between ethical concerns and actual AI use is broadly consistent with previous studies reporting that students often recognize ethical risks while continuing to use generative AI because of its perceived academic benefits [35]. Similarly, Bond et al. [38] concluded that the successful implementation of AI in higher education requires balancing educational opportunities with ethical challenges rather than treating them as opposing goals. In this respect, our findings also support Airaj's [32] argument that ethical AI literacy should be integrated into authentic teaching practices instead of relying solely on institutional regulations.

6.5. Theoretical Implications and Contributions

Beyond its empirical findings, this study offers several theoretical contributions to the emerging literature on generative AI in higher education.

First, it extends the technology acceptance literature by examining mandatory rather than voluntary AI adoption. While most previous studies have investigated students' intentions to use generative AI under optional conditions, the present study explores technology acceptance within a structured pedagogical environment in which AI use formed an integral part of course assessment. This perspective broadens current understanding of AI acceptance beyond behavioral intention and highlights the importance of instructional context.

Second, the study provides an integrated conceptual perspective by combining technology acceptance theory (TAM/UTAUT) with the competence-oriented framework of DigComp 2.2. Rather than treating these approaches as competing explanations, the proposed framework positions them as complementary perspectives for interpreting AI-supported learning in higher education.

Third, the findings suggest that perceived usefulness remains a central explanatory construct even in mandatory learning environments. Although the exploratory design does not permit formal mediation testing, the observed pattern of associations indicates that perceived usefulness consistently accompanies AI usage intensity and learning satisfaction, supporting its continued relevance within structured pedagogical interventions.

Finally, the study contributes exploratory evidence from an authentic classroom implementation of generative AI. By analyzing a real course-level intervention rather than hypothetical scenarios or intention-based surveys, the research complements the growing body of literature with findings grounded in actual educational practice.

6.6. Pedagogical Implications

From a practical perspective, the results suggest several implications for the design of AI-supported higher education environments. First, the strong relationship between perceived usefulness and engagement highlights the importance of designing assignments that clearly demonstrate the academic value of generative AI tools. When students perceive AI as meaningfully contributing to learning outcomes, engagement appears to increase.

Second, the findings suggest that structured and transparent integration of generative AI tools may reduce uncertainty about their appropriate use. By embedding AI within clearly defined academic tasks, instructors can shift the focus from whether AI should be used to how it can be used productively and responsibly.

Third, the coexistence of ethical awareness and continued usage indicates that ethical guidance should accompany AI integration rather than function solely as a restrictive framework. Pedagogical approaches that combine practical use with critical reflection may therefore be particularly effective in supporting responsible AI literacy.

Overall, the findings suggest that assignments should make the intended academic value and responsible use of generative AI tools explicit. Because perceived learning usefulness was associated with both frequency of use and satisfaction, instructional design should combine functional relevance with verification, transparency, and critical reflection.

6.7. Limitations and Future Research

As a pilot study, this research has several limitations. First, the single-institution, single-course sample limits generalizability across disciplines and institutional contexts. Second, the absence of a control group and a pre-intervention baseline prevents causal attribution and the assessment of change over time. Third, the cross-sectional, self-reported data may be affected by social desirability, recall bias, and common-method variance. Fourth, the item-level demographic comparisons were exploratory and should be interpreted cautiously, particularly if no adjustment for multiple testing was applied.

Future research could build on the proposed framework (or updated versions of the framework, such as DigComp 3.0 [40]) by employing larger samples and longitudinal designs to examine how perceptions of AI usefulness and engagement evolve. Future adequately powered studies could use formal mediation analysis to examine whether perceived learning usefulness plays an intermediary role in the relationship between pedagogical design and student engagement.

Furthermore, future studies may benefit from combining survey data with behavioral learning analytics to capture more detailed patterns of AI-supported learning behavior. Such approaches could help clarify how students integrate generative AI tools into different stages of the learning process and how pedagogical design influences these patterns.

Overall, the correlational pattern indicates that perceived learning usefulness is associated with both frequency of AI use and satisfaction. The present design does not establish a causal pathway or mediation effect between instructional scaffolding, perceived usefulness, and engagement. Future research combining longitudinal surveys, behavioral usage data, and controlled designs could examine these relationships more directly.

7. Conclusions

The findings of this exploratory pilot study suggest that perceived learning usefulness is an important correlate of students' use and evaluation of generative AI tools in a mandatory, pedagogically scaffolded course context. Perceived learning usefulness was positively associated with both frequency of AI use and satisfaction, whereas ethical attitudes showed a weaker positive association with use. Demographic group differences were limited mainly to selected usage patterns.

Students reported stronger positive perceptions of satisfaction and functional learning benefits than of increased intrinsic motivation. This pattern suggests that, in the present sample, generative AI tools were evaluated primarily in terms of their instrumental and experiential value. These results are based on self-reported, cross-sectional data and should not be interpreted as evidence of objective learning improvement or competence development.

From an instructional perspective, the study highlights the potential value of structured AI integration that combines authentic academic tasks with verification, transparency, and reflection. The findings are consistent with the view that competence-oriented pedagogical design and technology-acceptance perspectives can complement one another, although this relationship requires further testing in larger and more diverse samples.

From a policy and instructional perspective, the findings underline the importance of structured and guided AI integration rather than laissez-faire adoption. When AI use is standardized, scaffolded, and embedded in authentic academic tasks, the findings are consistent with the assumption that competence-oriented instructional design and technology acceptance can complement each other.

Although exploratory, the study offers a theoretically integrated and empirically grounded contribution towards understanding students' perceptions of structured generative AI integration in higher education. As generative AI technologies continue to evolve, further research must move beyond descriptive adoption studies toward model-driven investigations of structured, competence-oriented integration.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Ethics Committee of Ludovika University of Public Service (protocol code 112/2021 (XI. 24.), approved on 24 November 2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy and ethical restrictions related to anonymous student survey data.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Artificial Intelligence in Higher Education Questionnaire

Dear Participant,

This survey investigates university students' adoption, experiences, perceived learning usefulness, and ethical perceptions regarding the use of generative artificial intelligence (GenAI) tools (e.g., ChatGPT, Microsoft Copilot, Google Gemini) in higher education. The survey is anonymous, participation is voluntary, and all responses will be used exclusively for scientific research. There are no right or wrong answers; please respond according to your own experience. Completion requires approximately 8–10 min.

Section I. Demographic Information

1. Gender

☐ Female
☐ Male
☐ Prefer not to say

2. Age

☐ ≤25
☐ 26–35
☐ 36–45
☐ 46–55
☐ ≥56

3. Program

☐ Master of Arts in Political Science (Full-time)
☐ Master of Arts in Political Science (Part-time)

4. Employment status

☐ Employed
☐ Not employed

Section II. AI Adoption

5. Frequency of AI Use

Please indicate how well each statement describes your own study practices.

1 = Not at all characteristic 2 3 4 5 = Completely characteristic

I use ChatGPT when completing coursework or assignments.

☐1 ☐2 ☐3 ☐4 ☐5

I use other generative AI applications (e.g., Microsoft Copilot, Google Gemini) during my studies.

☐1 ☐2 ☐3 ☐4 ☐5

I use generative AI tools when preparing for examinations.

☐1 ☐2 ☐3 ☐4 ☐5

I use generative AI tools for brainstorming, idea generation, or creative tasks.

☐1 ☐2 ☐3 ☐4 ☐5

I use generative AI tools to explain, clarify, or summarize learning materials.

☐1 ☐2 ☐3 ☐4 ☐5

Section III. Perceived Usefulness

6. Perceived Educational Benefits

Please indicate your level of agreement with each statement.

1 = Strongly disagree 2 3 4 5 = Strongly agree

Using generative AI tools enables me to complete academic tasks more efficiently.

☐1 ☐2 ☐3 ☐4 ☐5

Generative AI tools improve my understanding of course content.

☐1 ☐2 ☐3 ☐4 ☐5

Generative AI tools improve the quality of my academic work.

☐1 ☐2 ☐3 ☐4 ☐5

Generative AI tools reduce the stress associated with studying.

https://doi.org/10.3390/higheredu5030076

☐1 ☐2 ☐3 ☐4 ☐5

Generative AI tools help me manage my study time more effectively.

☐1 ☐2 ☐3 ☐4 ☐5

Section IV. Ethics and Academic Integrity

7. Ethical Perceptions

Please indicate your level of agreement.

1 = Strongly disagree 2 3 4 5 = Strongly agree

The use of generative AI tools may threaten academic integrity (e.g., plagiarism or unauthorized assistance).

☐1 ☐2 ☐3 ☐4 ☐5

Excessive reliance on generative AI tools may result in dependency.

☐1 ☐2 ☐3 ☐4 ☐5

Higher education institutions should establish clear policies for the responsible use of AI.

☐1 ☐2 ☐3 ☐4 ☐5

Evaluating AI-assisted assignments is challenging for instructors.

☐1 ☐2 ☐3 ☐4 ☐5

Section V. Learning Experience and Satisfaction

8. Learning Experience

Please indicate your level of agreement.

1 = Strongly disagree 2 3 4 5 = Strongly agree

Using generative AI tools has increased my motivation to learn.

☐1 ☐2 ☐3 ☐4 ☐5

Generative AI tools have made learning more engaging.

☐1 ☐2 ☐3 ☐4 ☐5

I am satisfied with the integration of generative AI tools into university teaching.

☐1 ☐2 ☐3 ☐4 ☐5

I would like generative AI tools to be incorporated into other university courses.

☐1 ☐2 ☐3 ☐4 ☐5

Without generative AI tools, I would have experienced greater difficulty completing course requirements.

☐1 ☐2 ☐3 ☐4 ☐5

Section VI. Open-ended Questions

9. What have been the most valuable benefits of using generative AI tools in your studies?

____

10. What have been the main disadvantages or challenges of using generative AI tools?

____

11. How should universities regulate the responsible use of generative AI tools?

____

12. What recommendations would you make for integrating generative AI tools more effectively into higher education?

____

Appendix B. Supplementary Statistical Figures

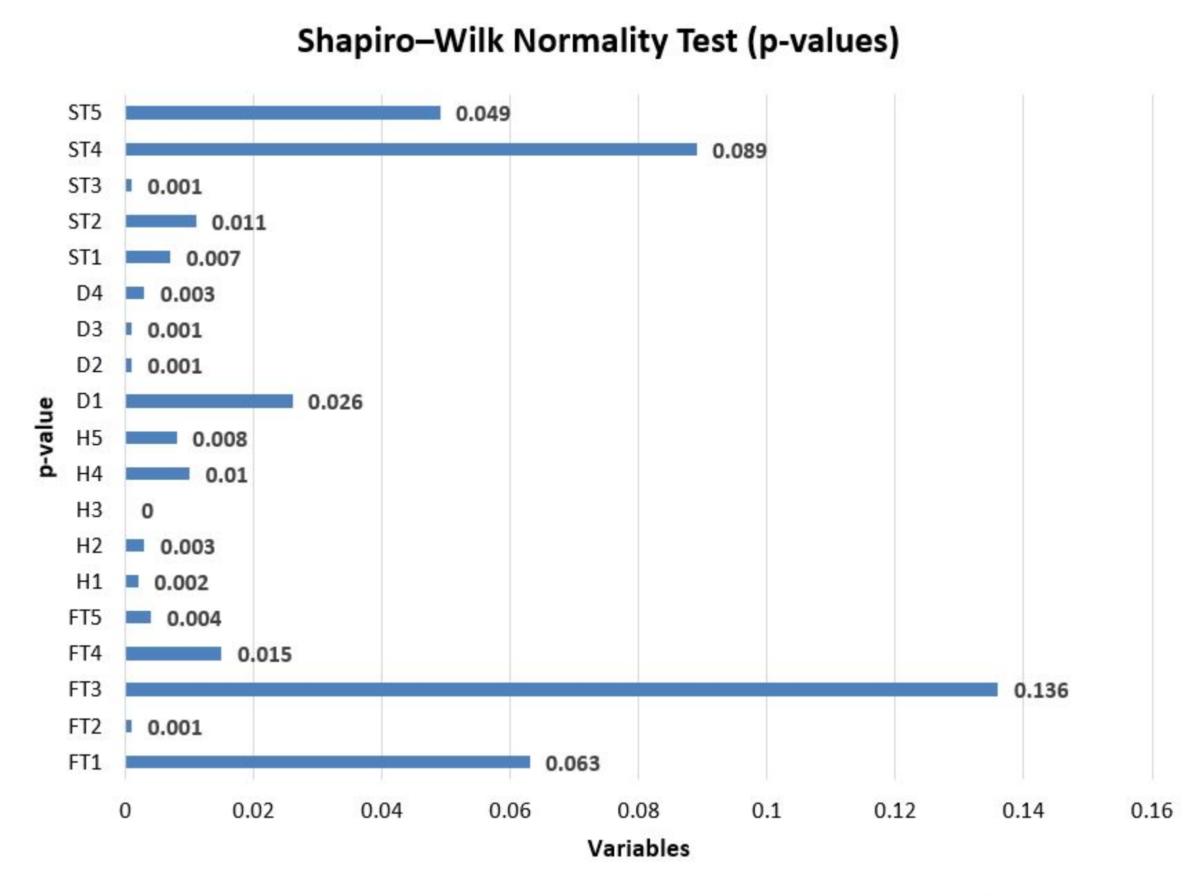

Figure A1. Shapiro–Wilk test *p*-values for questionnaire items. Source: authors.

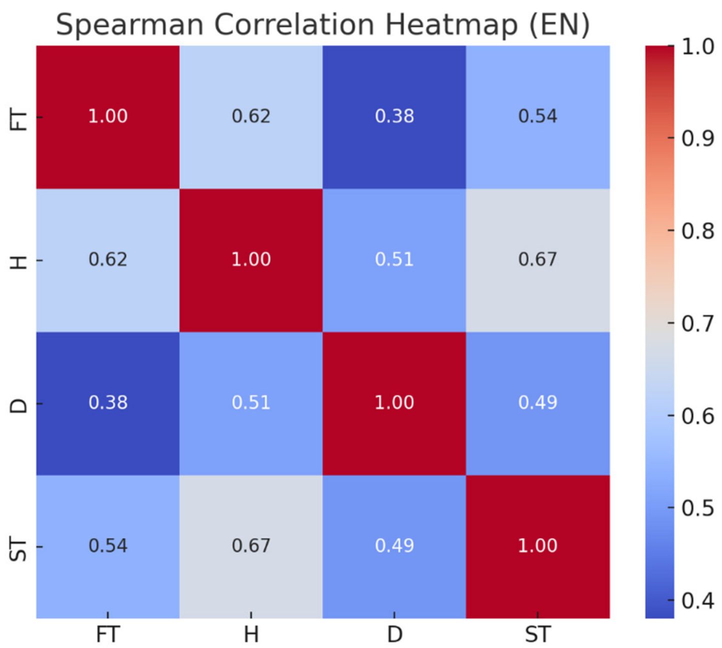

Figure A2. Spearman's rank correlation matrix for the study scales. Source: authors.

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