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Balancing enthusiasm and engagement: The impact of AI chat tools on student learning habits and perceptions in higher education

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Abstract

This study investigates the shift in the use of AI-based chat tools in higher education focusing on changes in student engagement, learning behavior, and perceptions during a heavily AI-integrated semester. The research is based on pre- and post-semester surveys conducted among students from diverse demographic backgrounds and academic disciplines to assess their experiences and attitudes toward AI tools. The findings show that students initially enthusiastically embraced AI tools but their deep engagement diminished over time, indicating the importance of continuous support and structure for sustained usage. Although demographic factors such as age and academic discipline influenced initial openness, extended use reduced these differences. AI tools were most beneficial for understanding concepts and completing assignments, particularly in technical subjects like programming. Collaboration among classmates remained unaffected with AI use complementing rather than replacing traditional learning methods. AI tools enhance learning experiences by addressing individual needs and improving productivity. However, targeted integration and ongoing support are crucial to sustain long-term engagement. The study offers valuable insights for teachers, technologists, and policymakers to optimize AI integration in education, making it accessible, inclusive, and supportive of diverse learners globally.

Keywords: AI-based chat tools, Higher education, Instructional design, Learning habits, Longitudinal study, Openness to technology, Peer collaboration, Student engagement, Trust in AI.

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Contents

Contribution of this paper to the literature
This study significantly contributes to the literature on AI in education by offering a longitudinal analysis of student engagement and perceptions. It addresses gaps by tracking enthusiasm and sustained interaction across a semester revealing the nuanced impact of AI tools on diverse learners. The findings enrich understanding of AI integration's practical and theoretical implications.

1. Introduction

1.1. The Role of AI in Transforming Student Engagement and Learning Dynamics

In the past few years, artificial intelligence (AI) has made great progress in shifting entire industries with education being one of them. One of the most effective advances AI has made is the development of chat tools which AI is now capable of operating. These tools now aid in fundamentally changing how students approach learning, studying, and overall academic achievement.

This document closely analyzes the results of an educational study aimed and explaining the changing pattern of students' behavior, satisfaction, engagement levels, etc. AI is infused into the learning environments throughout a semester. Apart from semester-end surveys (see Table A1 in Appendix), there were pre-semester surveys employed aiming to analyze how students interact with tools empowered by AI and the role these tools play in their academic life at the university level in different subjects.

A primary focus of the study was how students accept new technological approaches and how embracing these changes influences their use of AI tools to transform their educational experience. This investigation could help determine whether participants view the AI tools as optional learning resources or essential aids within the learning dynamic. The survey also looked into students' readiness to change their learning routines a sign of the willingness for AI tools to meaningfully change their study habits. Questions about the frequency and length of AI tool usage were added to shed light on the magnitude and duration of the students' dependence on these tools for studying.

The survey focused on students' opinions about the efficiency of AI tools in different subjects like mathematics, programming, IT, engineering, sciences, economics, and humanities in relation to these cross-sectional areas. With this exploration, the study sought to answer in which academic areas AI tools are most needed. Another important part of the survey understood what particular tasks students use AI chat tools for. Tasks like grasping ideas, building up knowledge, preparing assignments, and preparing for examinations were pointed out to evaluate the level of support AI tools render to these academic activities. The survey also looked into the use of AI tools in cooperative learning environments.

Their research examined the frequency with which students use AI tools while studying with other classmates and whether these tools facilitate group work or promote autonomous, self-regulated learning. It also attempted to find out the particular motives that stimulated the use of AI tools by students. The goal of this part of the research problem was to understand what motives may underlie students' attempts to integrate AI into their learning processes like saving time, wanting to grasp challenging materials, trying to get good results or simply wanting to know something more. AI tools are optimally integrated into education when students' needs are met, and understanding these needs may help in determining the reasons behind the adoption of these technologies in education.

Across these domains, the research examined students' attitudes toward AI-based chat tools not only within the context of the study but as a replacement for more traditional resources such as textbooks or online databases. This was done to grasp how students value using AI tools compared to relying on conventional or other technological resources for learning. Alongside this issue, the survey aimed to measure the amount of belief students have in the answers, information, and assistance provided by AI-based chat systems. Trust is one of the most important factors for accepting and continually using a given technology, and knowing what level of trust these students have for the given tools offers useful information regarding the perceived and actual trustworthiness of such resources in education.

These aspects can be formulated into the following research questions organized into cohesive categories: The grouping of survey questions corresponding to the relevant research questions is summarized in Table A2 in the Appendix.

- RQ-1. How does students' openness to new technologies and methods with their willingness to develop new learning habits influence their engagement with AI-enhanced tools?
- RQ-2. To what extent do AI tools help students better connect with the curriculum and how do students perceive the usefulness of these tools across various subjects and specific academic tasks?
- RQ-3. What are the patterns of AI tool usage among students, including the frequency, duration, and application of these tools in individual and peer learning contexts?
- RQ-4. What are the key motivations driving students to use AI tools, and how do their preferences for AI as a primary resource and their trust in these tools affect their overall adoption and usage?

1.1.1. Research Questions' Alignment with the Constructs of Enthusiasm and Engagement

The study's research questions are grounded in broader concepts of educational psychology such as the dimensions of enthusiasm and engagement:

- RQ-1 captures enthusiasm by probing openness to new technologies and willingness to develop new habits, which are precursors to engagement. For instance, if students exhibit high enthusiasm, they are more likely to experiment with and incorporate AI tools into their routines.
- RQ-2 and RQ-3 focus on engagement by analyzing how students use AI tools to connect with the curriculum, the frequency of use, and applications in academic tasks. These behaviors can reflect sustained involvement and a deeper reliance on AI tools.

- RQ-4 bridges enthusiasm and engagement by investigating motivation and trust. Trust in AI tools' reliability often begins with enthusiasm but evolves into engagement as students integrate these tools into their academic processes.

In this study, survey responses grouped by research questions are analyzed directly rather than attempting to quantify enthusiasm and engagement as standalone metrics.

1.1.2. Interpreting Changes in Enthusiasm and Connection with Engagement

The difference in enthusiasm can be considered as the difference in answers provided by the participants in the pre-semester and post-semester phases. This method is consistent with the logic of the study and offers a clear method to analyze how enthusiasm changes over time. In addition, the differences can also be analyzed within the different components of engagement to deepen the understanding of student behavior and perceptions in an AI-enhanced learning environment.

1.1.3. Educational Theories Supporting the Analysis

To analyze the interactions of students with AI-based tools in educational settings, this research incorporates the following two foundational concepts: the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). These frameworks are helpful for understanding the relations between the constructs of enthusiasm and engagement which are the primary means through which students use and continually interact with AI-enhanced tools.

The Technology Acceptance Model (TAM) asserts that perceived usefulness and perceived ease of use are the foremost predictors of technology adoption (Davis, 1989). For this particular analysis, TAM is useful in examining how students perceive AI tools as aids for accomplishing academic tasks and as means for interacting with the curriculum more optimally. Enthusiasm which is an attitude towards new technologies corresponds with the positive perception ascribed to engagement in TAM. Students who appreciate the value of AI tools in performing daunting tasks or enhancing scholarly productivity are highly likely to adopt these tools as part of their routine. This theoretical viewpoint justifies the attention given to the survey questions aimed at the student's willingness to accept AI and their changing perceptions of its functions.

Self-determination theory (Ryan & Deci, 2000) supports TAM by adding sustained engagement to the intrinsic motivation, autonomy, competence, and relatedness factors. SDT explains for the motivations a student has for using AI tools like time-saving, understanding and enhancing, or goal-achieving. The motivating question items fit well with the intrinsic. For example, curiosity and interest, and extrinsic, like academic results, (motivation) focus of SDT. AI tools can motivate deeper engagement by enhancing intrinsic motivation through the adaptive feedback and tailored support offered which foster a sense of competence. Similarly, the way these tools empower students to learn at their own pace aligns with the core principles of SDT.

TAM and SDT offer strong theoretical underpinnings with regard to how enthusiasm acts as a gateway for engagement and how interaction with AI tools is governed by the perceptions of usefulness, motivation, and self-determination. Such frameworks are in close relation to the aims of the study which seek to explore the complex ways in which students engage with AI tools and the corresponding effects on their academic life. The study goes beyond explaining the patterns of enthusiasm and engagement toward understanding the reasons behind the elementary and cognitive aspects of technology integration within education with the application of these educational theories.

1.2. Rationale for Using Predefined Survey Categories

The study utilizes predetermined sets of survey questions for each research question instead of more complex approaches like Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis (CFA) which tries to abstract a relevant question from a set of questions mapped to latent factors. The chosen methodology balances both pragmatic and conceptual issues to guarantee that the results can reach many people and have meaning alongside the goals of the study.

This strategy facilitates the obtaining of the results. Applying basic descriptive statistical procedures and common hypothesis-testing procedures like t-tests and ANOVAs makes the results useful and understandable for educators and policymakers. Although construct validity is a vital issue for any research, especially that of educational research, factor analysis creates validity and reliability, it also creates an added dimension of subjectivity and interpretive ambiguity that requires a high level of expertise which makes it less ideal for studies whose emphasis is on practice.

In separate studies, we have analyzed and validated the latent dimensions of engagement using exploratory factor analysis and confirmatory factor analysis (Bognár et al., 2024; Bognár & Khine, 2025).

1.3. Addressing Research Gaps: Contributions to Understanding AI Integration in Education

Most studies done on AI-based tools in education focus on students' first impressions or general attitudes, and behavior patterns. This study attempts to fill important gaps in the literature using a longitudinal study design, tracking students' enthusiasm and engagement over the semester. Respondents' pre- and post-semester responses were analyzed to understand how curiosity-driven engagement morphs into sustained engagement patterns or gets abandoned due to unmet expectations.

2. Literature Review

2.1. The Transformative Potential of AI in Education

The use of artificial intelligence (AI) in education has the potential to revolutionize engagement, learning outcomes, and access (Nguyen, Kremantzis, Essien, Petrounias, & Hosseini, 2024b). It provides novel means to enhance education. The use of chatbots, virtual assistants, and generative AI (GenAI) systems which provide personalized feedback and dynamic content is crucial to the interaction of learners and teachers with curricula (Holmes & Tuomi, 2022; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). Chen, Jensen, Albert, Gupta, and

Lee (2023) note that personalization of curricula promotes the use of technology in education due to its multifaceted nature.

The history of AI in education begins with Intelligent Tutoring Systems (ITS) which delivered content and provided personalized teaching assistance to learners (VanLehn, 2011). However, ITS was not widely accepted because of its costs, limited usage and the lack of its incorporation into the already existing systems (Nguyen, 2022; Strobl et al., 2019).

Unlike earlier ITS, modern GenAI applications, such as ChatGPT respond promptly and allow the implementation of multiple forms of content. These tools facilitate active engagement and independent learning through real-time responses, content creation, and an adjustment to learners' preferences (Enriquez et al., 2023; Nguyen, Hong, Dang, & Huang, 2024a). Besides, AI has the potential to enhance collective learning through its ability to support group discussions which facilitates co-regulated learning (Järvelä, Nguyen, & Hadwin, 2023; Kasneci et al., 2023).

Notably, the integration of AI comes with important challenges. Issues regarding privacy, algorithmic discrimination, and access (Baker & Hawn, 2022; Crawford, Cowling, Ashton-Hay, Kelder, & Middleton, 2023) remain unsolved. There are also educational considerations. AI use may promote disengagement and neglect, which may impair critical thinking skills (Essien, Bukoye, O'Dea, & Kremantzis, 2024; Holmes et al., 2022). These challenges are addressed so that there is meaningful and thought-out AI integration into education as a practice.

2.2. AI Tools for Personalized and Adaptive Learning

Among the functions of AI, the ability to automate pedagogy for the specific learner remains one of the most powerful. AI technology can provide individualized learning opportunities for students through content and feedback modification practices depending on the individual learner's progress or preferences towards the tasks. The system enhances the learner's experience with the course and promotes his or her active participation.

Tools like ChatGPT can tailor tasks in such a way that they vary in level of difficulty, provide text, image as well as audio explanations of concepts and solve problems (Davenport & Mittal, 2022; Nguyen et al., 2024a). This flexibility fosters autonomy and self-regulation, fundamental attribution of intrinsic motivation (Enriquez et al., 2023; Ryan & Deci, 2000).

With AI tools access and inclusion are improved for that particular subset of students with disabilities and multilingual learners due to features such as automatic translation, voice recognition, and captioning. Their ease of use with other common tools makes it possible for greater adoption even in less wealthy environments (Grassini, 2023; Nguyen, Gardner, & Sheridan, 2018).

There are gaps with such advantages. Many AI systems rely on scant data sources with set parameters that disregard emotional and motivational aspects of learning (Crawford et al., 2023). There is also an overdependence on measurable results that suppress students' imagination and analytical skills. In addition, the "black box" problem of AI systems gives rise to issues of trust and responsibility (Cotton, Cotton, & Shipway, 2024).

In the future, efforts should be directed toward creating models that integrate behavioral, cognitive, and emotional data so that AI can provide more comprehensive assistance to learners (Järvelä et al., 2023). Cooperation between teachers, engineers, and legislators will be necessary to ensure that such tools are developed in a responsible and goal-oriented manner to combat the issue of biased AI tools.

2.3. The Role of AI in Student Engagement and Behavior

Artificial intelligence technologies have transformed student engagement, AI evolving from an emerging novelty to sustainers of academic effort. Initial engagement with AI stems, to a large extent, from interest in trying to either summarize using an AI tool or have it solve certain problems (Chen et al., 2023; Grassini, 2023) but continuing to use it hinges on effectiveness and usefulness to personal academic objectives (Montenegro-Rueda, Fernández-Cerero, Fernández-Batanero, & López-Meneses, 2023; Ryan & Deci, 2000).

This shift illustrates the Technology Acceptance Model (TAM) which argues that perceived user friendliness and utility are the most important factors that predict adoption (Davis, 1989; Holmes & Tuomi, 2022). Students who perceive AI as useful for time management or achieving better results are more likely to use it regularly.

However, AI does not guarantee that students will meaningfully engage with course content. The degree to which AI is integrated into the course design matters. There is greater engagement when the use of AI is incorporated into the required, collaborative, or problem-solving portions of assignments than when it is optional or unstructured (Glikson & Woolley, 2020; Guerra-Carrillo, Katovich, & Bunge, 2017).

Some obstacles persist. A few students do not have the necessary digital competencies to capitalize on AI, whereas some may rely on it too much which likely diminishes their ability to think critically. Teachers need to help them understand how to appropriately harness AI and create activities that require deep thinking, reflection, and decisiveness to solve this challenge (Grassini, 2023; Holmes et al., 2022). AI independence is an ethical concern due to the potential dangers of overuse stunting learning (Cotton et al., 2024).

Understanding how engagement changes over time with AI usage is essential to longitudinal research. According to Zimmerman (2008) the mere tracking of attitudes and usage creates trends that can be utilized for better instructional design. The incorporation of the emotional and social aspects of learning through AI-empowered SEL frameworks may further deepen the engagement (Järvelä et al., 2023).

Longitudinal studies promise valuable insights into how student engagement with AI tools evolves over time. Researchers can identify the factors that promote sustained and purposeful interaction with AI technologies by tracking patterns of use and shifts in attitudes (Zimmerman, 2008). Additionally, integrating social and emotional learning frameworks with AI tools can enhance emotional engagement, further enriching the learning experience (Järvelä et al., 2023).

2.4. Situating the Current Study in Broader Literature

In this paper, the discrepancies in how the use of AI tools results in different student learning behaviors are derived from enthusiasm which measures students' affective readiness associated with the adoption of new technologies, and engagement as a demonstrable characteristic of goal-directed behavior in which students interact with AI as part of academic activity. This enables us to track changes in these constructs over a semester in combination with a longitudinal study design.

2.4.1. Theoretical Foundations: Linking Enthusiasm and Engagement

This research is anchored on the Technology Acceptance Model (TAM), which connects the acceptance of technology with its perceived usefulness and ease of use (Davis, 1989; Holmes & Tuomi, 2022). Enthusiasm corresponds to early-stage acceptance which is often influenced by perceived usefulness. Self-Determination Theory (SDT) provides further scope by focusing on intrinsic motivation, self-governance, and mastery (Ryan & Deci, 2000). They all show how a positive disposition can transform into active participation when students recognize AI instruments as valuable and empowering.

2.4.2. Dynamic Interpretation of Enthusiasm

The study does not conceptualize enthusiasm as a fixed entity but considers it dynamic and thinks it can build through more exposure or decline through unmet expectations. Monitoring such changes over a period of time gives insight into shifts from curiosity-driven use to deep engagement or complete disengagement, capturing the complexities of students' relationships with AI tools over time.

2.4.3. Analysis Across Different Layers of Students

The research analyzes students' AI tool usage and perception across demographics and fields of study, which include economics, engineering, IT, social sciences, and teacher education. Similarly, it analyzes how students employ AI for concept comprehension, assignment completion, and exam preparation. Further, it investigates motivations such as time-saving, understanding, performance improvement, and the AI's contribution to peer and self-learning. These findings add to the understanding of the integration of AI tools into academic life in a more contextualized and practical way.

3. Survey Context and Data Collection

3.1. Sampling Method

The study employed a purposeful sampling approach, selecting teachers from a range of disciplines. These teachers were tasked with restructuring their courses to incorporate AI-enhanced teaching and learning methodologies. All students were required to enroll in these restructured courses as the older versions were no longer available. This ensured that every participant engaged with the AI-enhanced learning environment throughout the semester, providing consistent and comprehensive exposure to the new methods and tools.

Additionally, all students were required to complete a preparatory course on using AI chat tools to level out differences in AI familiarity. This preparatory course ensured that participants had a common baseline of knowledge, reducing variability in their ability to effectively use AI tools. Participation in the pre-and post-semester surveys was voluntary. Nevertheless, the high response rate minimized non-response bias, thereby enhancing the reliability of the findings.

Purposeful sampling was particularly appropriate for this study as it ensured that the findings were directly applicable to circumstances where courses have been intentionally restructured to embrace AI-enhanced environments. The study captures rich, context-specific insights that would not be possible with a broader and less targeted sampling approach by focusing on teachers and students actively involved in such redesigned courses.

However, potential biases were acknowledged, including the self-selection of students who responded to the surveys. These respondents may reflect a higher level of engagement or interest in AI tools compared to non-respondents. Despite this limitation, the targeted design of the sampling approach provides meaningful insights into the dynamics of AI adoption in restructured courses, offering a strong foundation for understanding the opportunities and challenges of integrating AI in education.

3.2. Responses

We conducted surveys at two pivotal points before the semester began and near its conclusion to explore the longitudinal effects of AI tools on student engagement. The pre-semester survey focused on assessing students' initial attitudes toward technology and their baseline levels of engagement before significant interaction with AI tools. In contrast, the post-semester survey, administered after students had thoroughly engaged with these tools, aimed to capture their experiences and any shifts in engagement. This approach allowed us to track changes in student engagement over time. The survey's paired questions, given before and after the semester are shown in Table A1 in the Appendix.

For some pairs of questions, it didn't make sense to ask the exact same question, as students in the pre-semester phase might not have been familiar with AI in the context of a certain subject. In these cases, we kept the intent of the questions but changed the wording. The meaning of the levels of possible responses is also indicated in this table.

Respondents represented a variety of disciplines, including economics, engineering, information technology, social sciences, and teacher education. The scope of the research required extensive collaboration among educators and authors to design and implement the necessary curriculum modifications. This diversity was essential for understanding the varied impacts of AI tools on student engagement across different fields of study.

The research involved students from two Hungarian universities: the University of Dunaújváros and Budapest Business University. Participation encompassed full-time and part-time students. The pre-semester survey received 908 responses of which 724 were valid after data cleaning. The post-semester survey garnered 716 responses with 642 valid entries remaining after similar data processing.

Responses were collected in both Hungarian and English with 697 Hungarian and 27 English responses in the pre-semester survey and 603 Hungarian and 39 English responses in the post-semester survey. English-speaking respondents were primarily international students participating in Hungary through programs like Erasmus or other scholarships, or as self-financed students. The respondents were diverse in nationality, including students from China, Turkey, Portugal, and other countries. Regarding gender, the pre-semester survey had 252 female and 466 male respondents, with 8 preferring not to disclose. The post-semester survey saw 223 female and 416 male respondents with 3 opting not to answer. The survey reached a broad age range, including mature students with the oldest respondent being 58.

A total of 12 teachers from various disciplines participated actively in the project. The demographic distribution of the students in the post-semester phase is illustrated in Figure 1. Data collection was conducted through Google Forms, and the subsequent data analysis was performed using IBM SPSS Statistics V29 and Minitab V22.

The pre-semester survey was administered during the first week of the semester while the post-semester survey took place towards the end of the term.

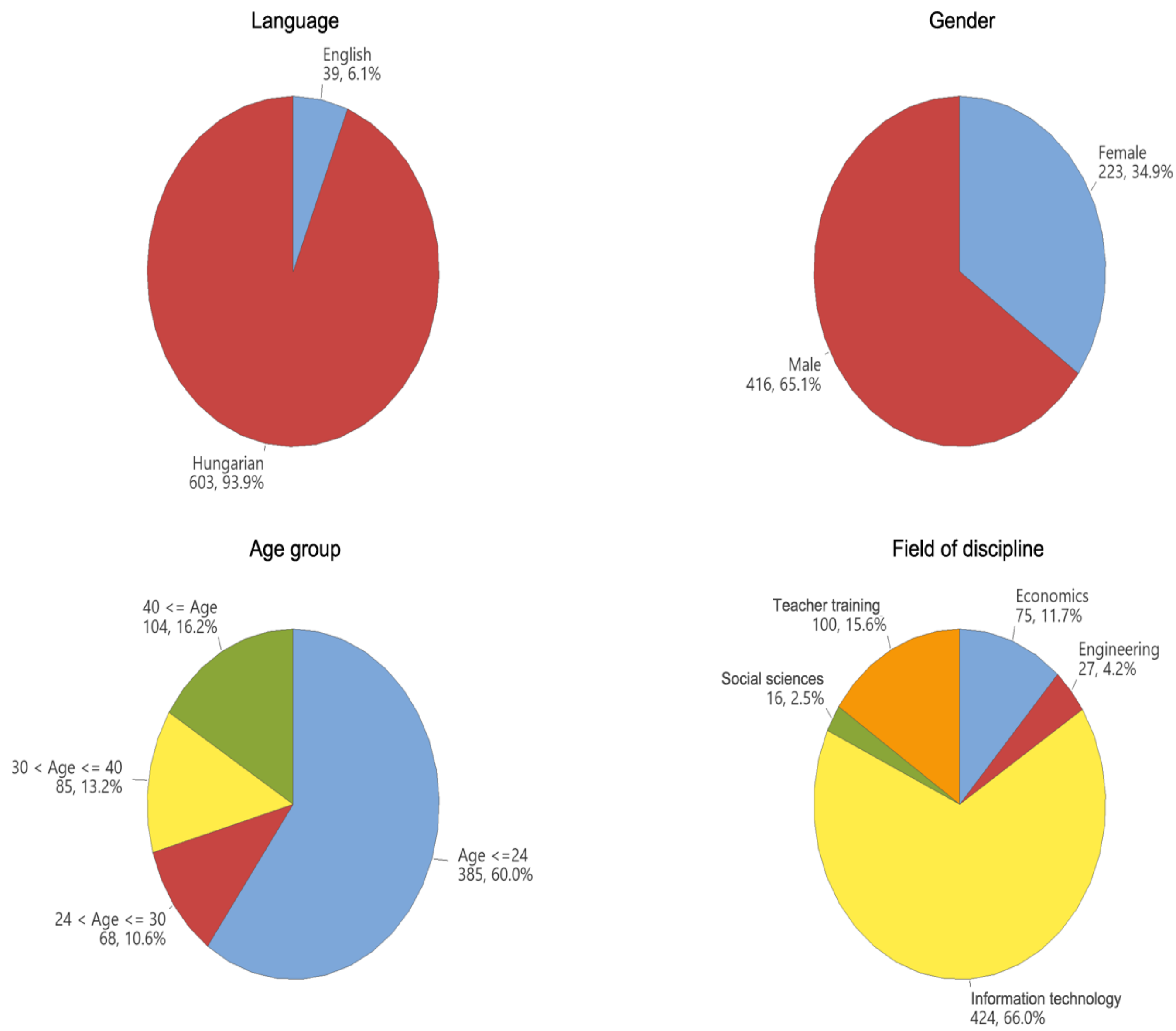

Figure 1. Demographic distribution of students in the post-semester phase.

4. Mitigating Response Bias and Ensuring Consistency

Several strategies were employed to ensure the consistency, objectivity, and relevance of AI tool integration throughout the courses to minimize response bias. A comprehensive teacher preparation program was implemented to standardize the introduction and use of AI tools with structured guidance provided to instructors. Teachers were trained to present the benefits and limitations of AI tools, setting clear and realistic expectations for students. Additionally, discipline-specific adjustments, consistent feedback loops, and carefully aligned survey items helped to further mitigate potential bias in student engagement reporting.

4.1. Reducing Variability Through Instructor and Student Training

Participating teachers were given comprehensive training and detailed guidelines to reduce variations in AI tool usage across courses. This training emphasized the uniform integration of AI tools throughout the semester. Teachers were encouraged to introduce AI-based tools such as chatbots and language models early in the term to allow students adequate time to become comfortable with the technology. These tools were incorporated regularly in classroom activities and homework assignments to give students consistent exposure. Teachers also provided balanced perspectives on the tools, discussing both their strengths and limitations, which helped set appropriate expectations.

All students were required to complete a preparatory course on using AI chat tools in addition to teacher training. The preparatory course minimized variability in their ability to effectively use AI tools and encouraged independent exploration by equipping students with essential skills and understanding.

4.2. Tailoring AI Integration to Discipline-Specific Needs

Teachers were encouraged to adapt AI integration strategies to fit their course objectives recognizing that students from different academic fields may use AI tools in different ways. For example, AI tools were used to aid with problem-solving, coding, and research tasks, utilizing AI for complex calculations or debugging in technical fields like engineering and computer science. In social science disciplines, AI tools were utilized for generating discussion prompts, synthesizing research findings, or conducting literature reviews, aligning with critical thinking and textual analysis. In teacher training, AI was used for brainstorming, creative writing, and summarizing dense materials, encouraging students to reflect on how AI can complement creative and analytical tasks.

This customized approach allowed students to use AI in ways that aligned with their course demands, helping to minimize disparities in engagement due to a one-size-fits-all approach.

4.3. Monitoring and Addressing Variability in AI Usage

To mitigate possible differences that may exist in the use of AI, several other actions were taken. Continuous feedback was sampled from students during the semester so that the teachers could know what problems the students had with AI and adjust accordingly. Information was gathered on the AI tools use frequency and the duration of time spent employing them, as well as the purposes for which students utilized these tools. A better picture of student activity was formed by combining survey answers with other data from the university's Learning Management System (LMS). While usage data of external platforms like ChatGPT could not be captured, interactions with the LMS were recorded to confirm the students' participation. Glaring discrepancies between reported engagement and actual concrete use of the system were marked and treated as outliers.

4.4. Ensuring Face Validity and Relevance

Face validity: Verification of the survey items included checking the relevant literature and obtaining feedback from educational psychologists to find out if it was clear and appropriate. A small pilot survey was administered to help ensure that questions were coherent to respondents; feedback was then used to refine vague questions prior to full data collection.

Relevance: The survey items focused on specific elements that pertain directly to the research questions of interest.

5. Reliability of the Survey Questions

In this case, reliability is the degree to which the survey questions designed to meet the research objectives are consistent and stable over time. In layman's terms, how dependable is the measurement of research questions asked within the parameters of a particular construct? In this study, we assessed the internal consistency of the survey questions using Cronbach's alpha which is a common measure for reliability in social science research. Generally, the higher the value of Cronbach's alpha, the more reliable the measurement. A value above 0.7 is considered acceptable.

The reliability statistics for each set of survey questions related to the RQ-1 – RQ-4 research questions are displayed in Table 1.

Table 1. The value of Cronbach's alpha.

Research questions	Cronbach's alpha
RQ-1 (Q1, Q2 and Q4)	0.706
RQ-2 (Q3, Q7 and Q8)	0.856
RQ-3 (Q5, Q6, Q9 and Q10)	0.770
RQ-4 (Q11, Q12 and Q13)	0.848

Within our survey, Cronbach's alpha calculated for all research questions is more than 0.7. In most cases, it is over 0.8 which implies they are reliable. This suggests that respondents can give answers to the survey questions that were structured within the constructs measuring the phenomena across varying situations. Such reliability is crucial in substantiating that the results of the study are valid representations of the actual student engagement dynamics in AI-enabled learning paradigms.

6. Findings and Discussions

6.1. Statistical Analyses

In the following sections, the average scores of students' responses will be compared across various respondent categories. Below is a brief explanation of how comparisons should be interpreted and which statistical concepts are being applied.

Three primary types of comparisons will be made.

Pre-Survey Comparisons: In this comparison, the average pre-survey scores of usually more than two groups (e.g., academic disciplines, age groups, or types of AI chat tools used by students) will be analyzed. This approach aims to identify statistically significant differences between group averages before the semester.

Post-survey Comparisons: This comparison mirrors the pre-survey analysis but focuses on post-survey data. The group averages from the post-survey will also be compared to determine which groups differ significantly.

A one-way ANOVA will be employed followed by post-hoc for pre- and post-survey comparisons. Tukey's method for pairwise comparisons at a 95% confidence level. In the descriptions of the findings from the various comparisons, the term *"significant"* will rigorously be used only for cases where the hypothesis tests yield p-values less than 0.05.

Pre- versus Post-survey Comparisons: In this case, the focus is on comparing two group averages, typically the pre- and post-semester scores. A two-sample t-test will be used to determine whether the changes between the pre- and post-semester averages are statistically significant. As with the previous comparisons, only those cases where the p-value is less than 0.05 will be designated as having *"significant"* differences.

Conditions for the Statistical Tests Used in the Study: In the context of this study, the use of one-way ANOVA for pre- and post-survey comparisons is particularly suited for our large sample size which enhances the robustness of the statistical analysis even when applied to Likert scale data. The analysis assumes that Likert scale responses can be treated as interval data—a common and accepted practice in educational research, particularly for large samples where the Central Limit Theorem ensures the approximation of normality for group means.

The ANOVA process includes verifying key assumptions, such as normality of residuals and homogeneity of variances. For large samples, the Central Limit Theorem reduces concerns about deviations from normality. Skewness and kurtosis values within the range of -2 to +2 are considered acceptable indicators of approximate normality. Levene's test is employed to confirm the equality of variances across groups. If the equality of variances does not hold, Welch's ANOVA test is performed which does not require this assumption. Once significant differences are detected by ANOVA, Tukey's or Games-Howell's post-hoc test is applied to identify which specific group pairs differ significantly ensuring that the results are interpretable and actionable.

To compare pre- and post-survey means, we employed an independent sample t-test as the conditions for its use were met within the context of this study. The responses in the pre-and post-survey groups were independent, with no overlap between the observations. The large sample size ensured that the data distribution approximated normality, satisfying the assumption of normality required for the t-test. Additionally, the equality of variances across the groups was tested using Levene's test confirming that the variances were sufficiently similar to justify the use of this method. In case of non-equal variances, the modified version of the t-test was applied. These conditions supported the appropriateness of the t-test for analyzing differences between pre-and post-survey means providing statistically valid and interpretable results.

Details of statistical analysis are described explicitly for the first comparison in Figure 2, " openness to new technologies, methods, and to develop new learning habits" as an illustrative example, with all subsequent analyses following the same rigorous methodological approach.

6.2. Students' Openness to New Topics, New Technologies and Methods and Their Willingness to Develop New Learning Habits

Figure 2 highlights the changes in students' openness to new topics, technologies and learning habits from before the semester began to near the end of the semester, during which AI tools were integrated into the curriculum. Table 2 summarizes the details of the statistical analyses.

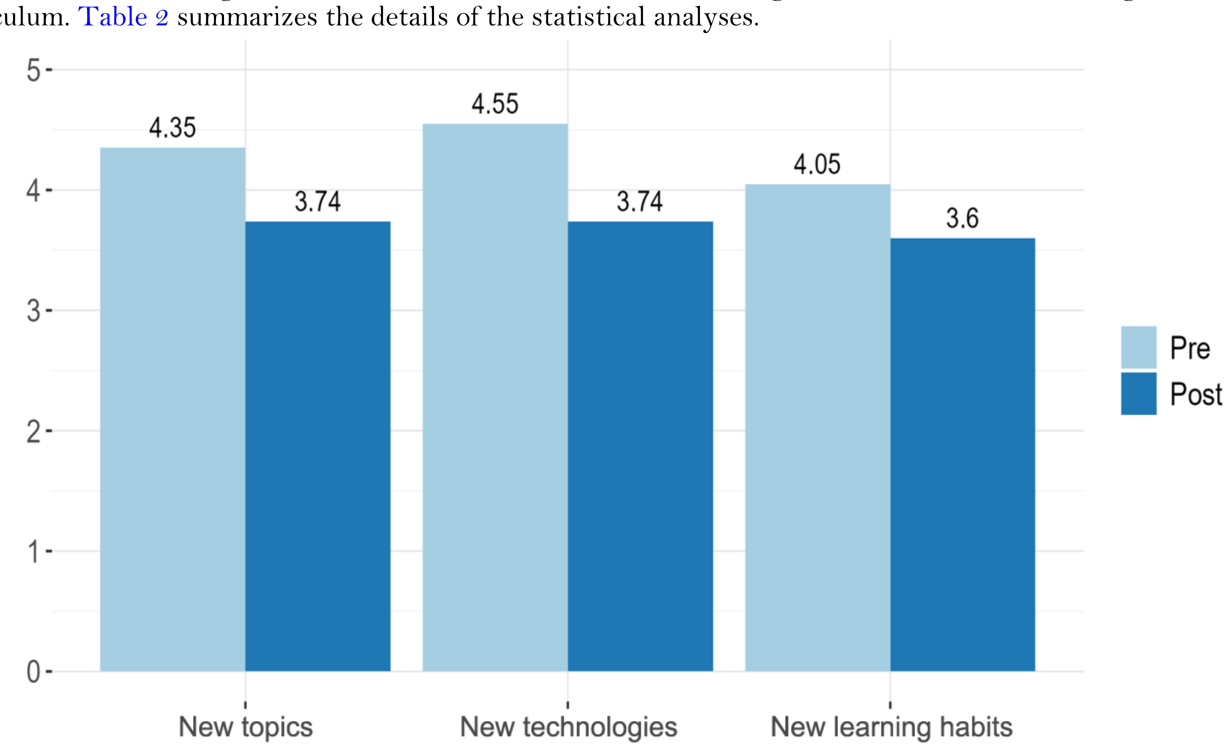

Figure 2. Openness to new technologies, and methods, and to develop new learning habits.

Initially, students were most open to new technologies with a pre-semester average of 4.55 indicating a strong enthusiasm for incorporating technological innovations into their learning. However, this category also experienced the steepest decline dropping to 3.74 by the end of the semester, bringing it in line with the other areas of openness.

When it comes to adopting new subjects, the pre-semester average was 4.35 and dropped to 3.74 signaling that students began to lose their willingness to engage with new topics over time. This implies that even though students showed a willingness to adopt new subjects, their lack of interest in them grew as they became accustomed to the functionalities and limitations of the AI systems.

The willingness to adopt new methodologies was the lowest yielding a score of 4.05 and dropped further after the semester to 3.60. This illustrates that even though students demonstrated the least willingness to accept new methodologies, their unwillingness did not increase as severely as the other two categories.

The post-semester data means are not despite the pre-semester averages for the three openness groups being significantly different. The data illustrates a significant general decline in enthusiasm across all categories. Openness to developing new learning habits remained the lowest both pre- and post-semesters. The most significant drop occurred in openness to new technologies while the least significant decline was observed in openness to new learning habits. This trend suggests that although students may initially embrace new tools and methods with enthusiasm, their willingness to engage deeply with these innovations tends to diminish over time.

Table 2. One-way ANOVA results for pre-survey comparison of student openness to new topics, technologies, and learning habits.

Details of the ANOVA test for pre-survey comparisons:

Factor information

Factors	**Levels**	**Values**
Factor	3	Q1 new topics, Q2 new technologies and Q4 new learning habits

Statistics

Variable	N	Mean	SE mean	St dev	Skewness	Kurtosis
Q1 new topics	724	4.34	0.026	0.720	-0.83	0.08
Q2 new technologies	724	4.54	0.024	0.666	-1.52	1.44
Q4 new learning habits	724	4.04	0.035	0.958	-0.92	0.42

Method

Null hypothesis	All means are equal.
Alternative hypothesis	Not all means are equal.
Significance level	$\alpha = 0.05$

Analysis of variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-value	P-value
Factor	2	91.78	6.30%	91.78	45.89	73.17	0.000
Error	2175	1364.15	93.70%	1364.15	0.627		
Total	2177	1455.93	100.00%				

Confidence intervals for the means

Factor	N	Mean	St dev	95% CI
Q1 new topics	724	4.34	0.720	(4.288 and 4.403)
Q2 new technologies	724	4.54	0.666	(4.491 and 4.607)
Q4 new learning habits	724	4.04	0.958	(3.991 and 4.107)

Grouping information using the Tukey method and 95% confidence

Factor	N	Mean	Grouping		
Q2 new technologies	724	4.54	A		
Q1 new topics	724	4.34		B	
Q4 new learning habits	724	4.04			C

Means that do not share a letter are significantly different.

Details of the two-sample t-test for pre- versus post-survey comparisons for "Q1 new topics"

Method

μ_1: Population mean of Q1 new topics when date of survey = Pre-survey

μ_2: Population mean of Q1 new topics when date of survey = Post survey

Difference: $\mu_1 - \mu_2$

Descriptive statistics: Q1 new topics

Date of survey	N	Mean	St dev	SE mean
Pre -survey	724	4.34	0.720	0.027
Post -survey	642	3.74	0.961	0.038

Confidence interval for the difference

Difference	Pooled St dev	95% CI for difference
0.606	0.841	(0.516 and 0.695)

Test

Null hypothesis	H_0: $\mu_1 - \mu_2 = 0$
Alternative hypothesis	H_1: $\mu_1 - \mu_2 \neq 0$

T-value	DF	P- value
13.29	1366	0.000

6.2.1. Demographic Groups

Figure 3 details the trends observed in students' openness to developing new learning habits across different demographic groups—language, gender, age, and academic discipline throughout the semester. Although it focuses specifically on this aspect, similar tendencies were also evident in students' openness to new technologies and topics.

English-speaking students who started with an openness score of 4.33 experienced a significant drop to 3.54 by the end of the semester. For Hungarian-speaking students the decline is also significant; they began with a slightly lower openness score of 4.04, declining to 3.60 post-semester indicating that while both groups experienced a decline, the drop was more pronounced among English speakers. However, the post-semester data do not show significant differences.

Gender differences also reveal significant pre- and post-response differences. Female students began the semester with an openness score of 4.17 which decreased sharply to 3.51. On the other hand, male students started with a slightly lower score of 3.99 but their decline was less severe dropping to 3.64. This suggests that female students initially embraced new learning habits more than male students but also experienced a more significant decline over time. At the same time, post-semester means are not statistically different.

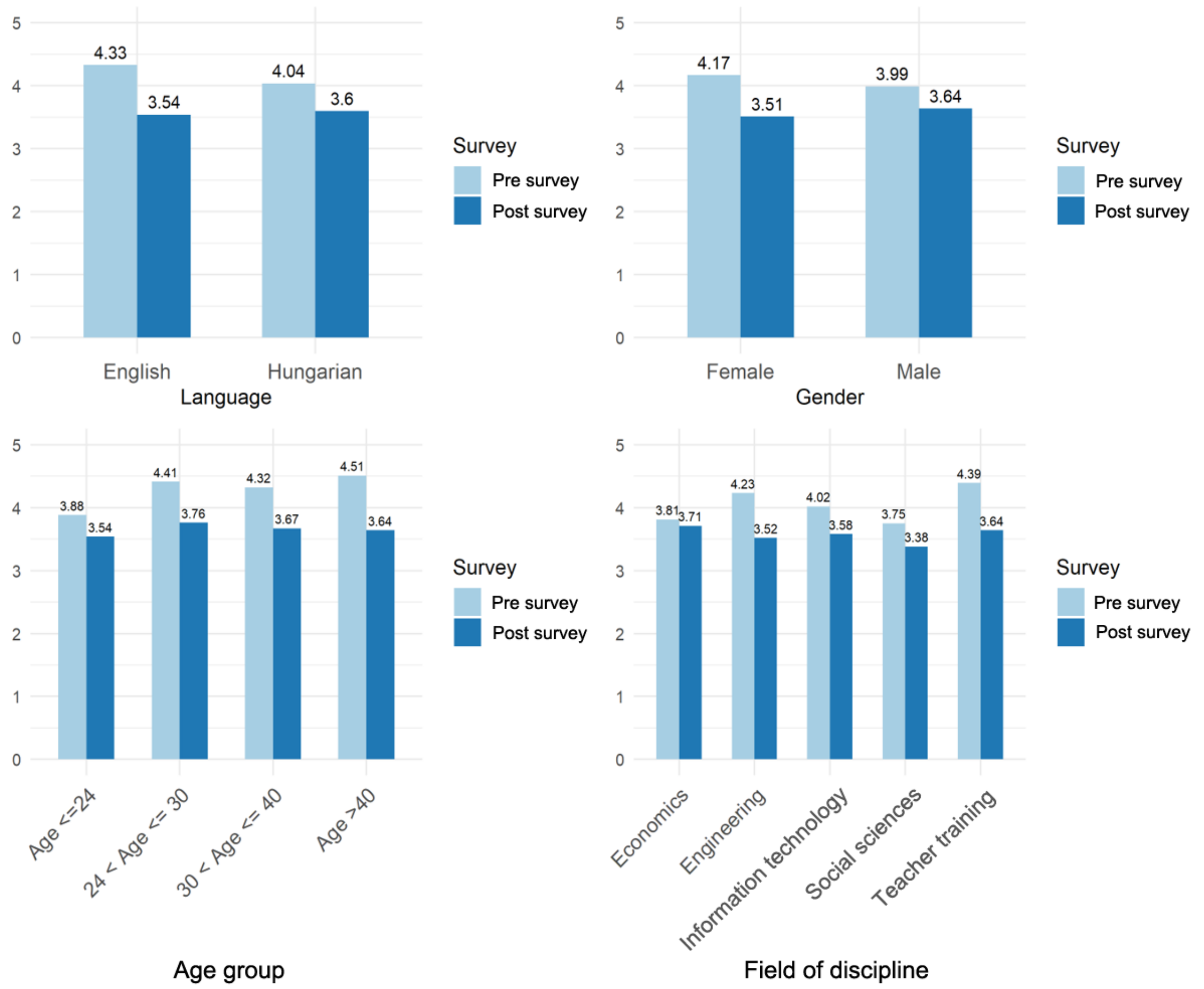

Figure 3. Openness to developing new learning habits across different demographic groups.

Age-related data shows that in all age group categories, the decline from pre- to post-semester is statistically significant. Older students, particularly those over 40, experienced the most significant decline in openness, starting from a high of 4.51 and dropping to 3.64. In contrast, younger students, especially those under 24, began with lower openness levels at 3.88 and saw a decline to 3.54. Students aged 24-30 exhibited high initial openness at 4.41, which decreased to 3.76 while those aged 30-40 followed a similar trend starting at 4.32 and falling to 3.67. Post-semester openness levels across all age groups became more balanced, suggesting that while older students experienced the steepest drop, their level ended up like the other categories despite the very different declines. Conducting a one-way ANOVA confirmed this uniformity of the post-semester mean scores across the different age groups, showing that at a 95% confidence level, no significant differences were found.

In terms of academic disciplines, students in teacher training started with the highest openness score of 4.39, which decreased to 3.64, reflecting a strong initial enthusiasm that waned over time. Engineering students, who began with an openness score of 4.23, saw a significant decline to 3.52. Information technology students started at 4.02 and dropped to 3.58. Only in these three cases was the decline statistically significant. This data highlights that while students across all disciplines experienced some decline in openness, the magnitude of this change varied. A one-way ANOVA confirmed the uniformity of the post-semester mean scores across the different disciplines, showing that, at a 95% confidence level, no significant differences were found.

Overall, the figures demonstrate a consistent decline in openness across all demographic groups with specific variations in the degree of this decline, highlighting the complex and evolving nature of student engagement with AI tools over the course of the semester. However, in all demographic groups, the post-semester data show that despite the initially large differences, by the end of the semester, these disparities diminish leveling out to practically uniform openness scores.

6.3. Students' Perceptions of the Usefulness of AI Tools

6.3.1. Usefulness of AI Tools for Different Subjects and the Curriculum in General

Figure 4 presents the pre- and post-semester evaluations of the perceived usefulness of AI tools across various academic contexts, including their overall contribution to connecting students with the curriculum and their effectiveness in specific subject areas such as mathematics, programming, other IT subjects, science, economics, and humanities.

Before the semester began, students generally rated the usefulness of AI tools in helping them connect with the curriculum at a high level (4.34). However, it's notable that none of the specific subject areas reached this level of perceived usefulness, with programming being rated the highest among them at 3.37 followed by other IT subjects (3.21), economics and humanities (2.90), science (2.80), and mathematics (2.56).

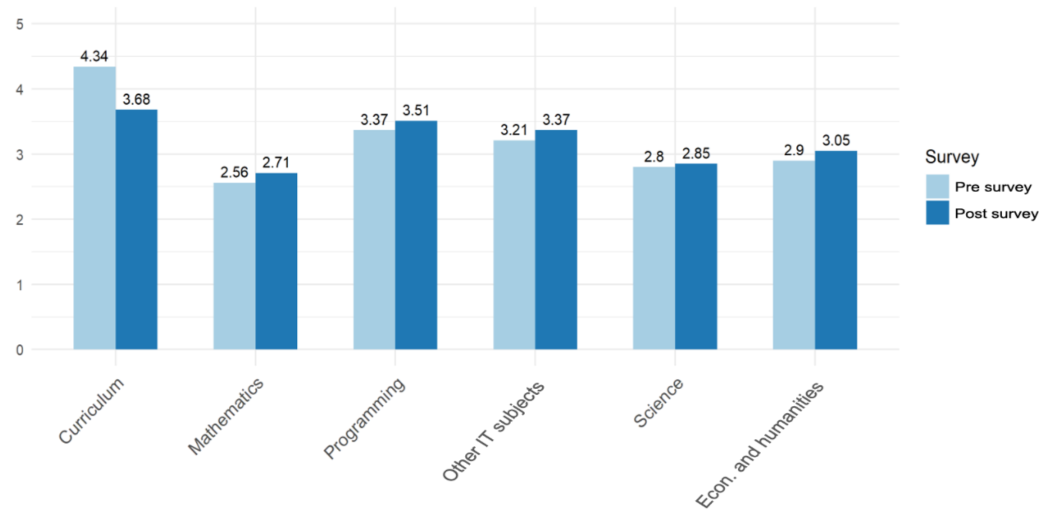

Figure 4. Perceived usefulness of AI tools across various academic subjects.

As the semester progressed and students had more exposure to AI tools integrated into their learning processes, there was a general, but statistically not significant, increase in the perceived usefulness across all subjects. In contrast, the overall usefulness of AI in connecting with the curriculum saw a significant decrease to 3.68, indicating that while students found AI helpful in individual subjects, this did not translate into a heightened perception of its usefulness in the broader curriculum context. The post-semester evaluations still showed programming and other IT subjects as leading in usefulness (3.51 and 3.37, respectively), but these ratings remained below the initial perception of AI's usefulness in connecting with the curriculum as a whole.

This disparity between the high perceived usefulness of AI in the curriculum and the lower rating in specific subjects highlights an oddity. It suggests that while students may recognize the general potential of AI tools to enhance their learning, this recognition does not consistently extend to their experiences in specific academic subjects. This could point to a gap between the anticipated benefits of AI and the practical realities of its application within individual subjects.

6.3.2. Usefulness of AI Tools Across Subjects by Students from Different Disciplines

One aspect of this oddity may stem from the fact that students in different fields of study use AI with varying intensity across specific subjects. To further explore this, let us examine how the perceived usefulness of AI varies in mathematics, programming , technical and science subjects, and economics and other humanities subjects among students from different academic disciplines, considering both pre-post changes and differences across fields of study. Scrutinizing the data shown in the four panels of Figure 5, we can confirm that this observed oddity can indeed be partially explained by this aspect.

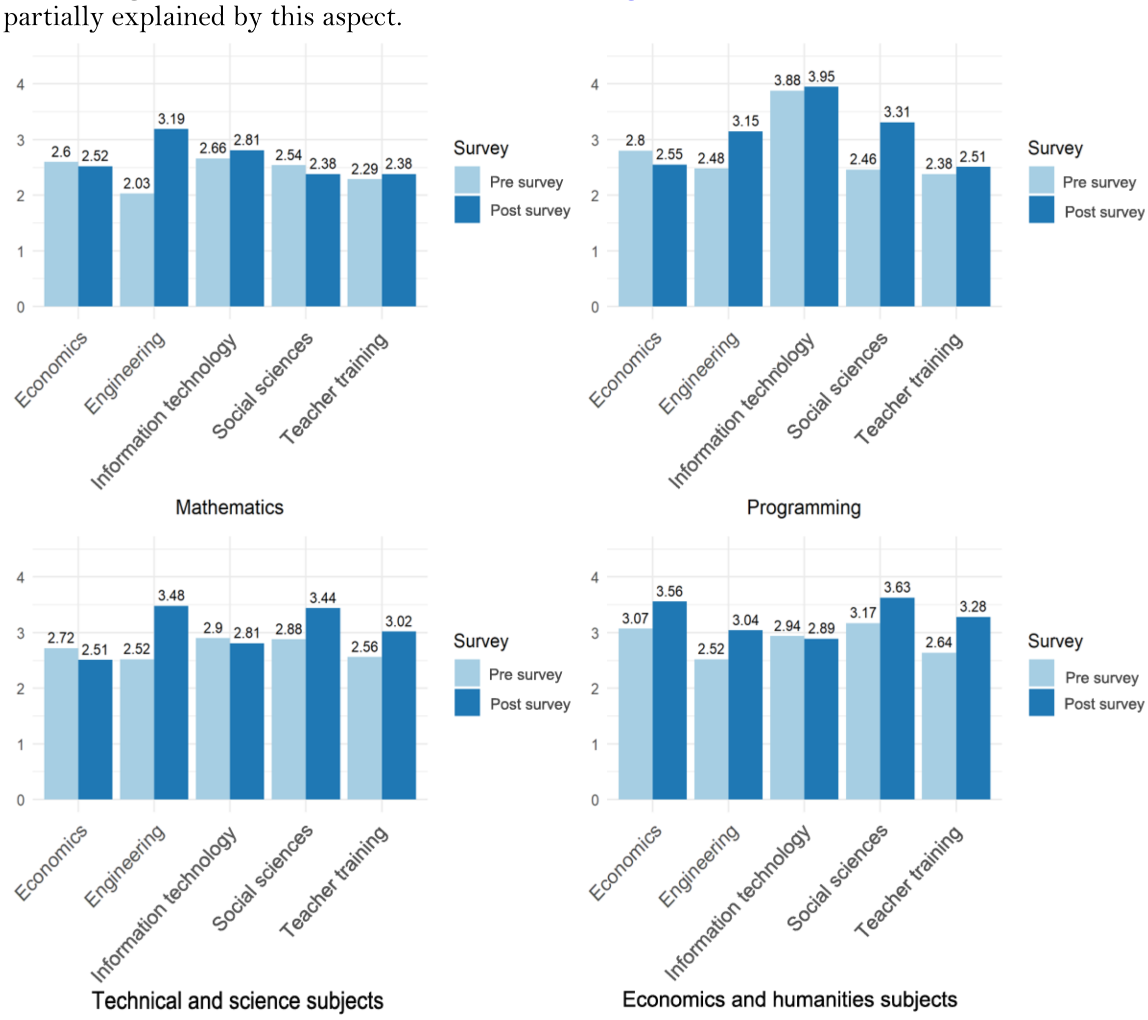

Figure 5. Perceived usefulness of AI tools across various subjects and fields of discipline.

In the mathematics, the perceived usefulness of AI varied widely across different disciplines. However, only in the case of engineering students did the pre- and post-semester mean scores show statistically significant differences. Their ratings rising from 2.03 pre-semester to 3.19 post-semester indicates that AI tools became significantly more valuable in their mathematical studies. Information technology students also experienced a modest increase from 2.66 to 2.81, reflecting a growing, albeit less pronounced, reliance on AI in mathematics. In contrast, students in economics, social sciences, and teacher training reported relatively stable ratings with slight decreases or minimal increases suggesting that AI tools had a more limited impact on their mathematical learning.

For programming, information technology students consistently rated the usefulness of AI highly with a slight increase from 3.88 pre-semester to 3.95 post-semester, reflecting their strong reliance on AI in programming. Only information technology students' mean scores were statistically significantly different from the other disciplines, emphasizing their unique engagement with AI in programming tasks. None of the pre-and post-semester means within each discipline field were statistically significantly different.

In technical and science subjects, engineering students showed the most significant increase in perceived usefulness of AI tools, with ratings rising from 2.52 to 3.48 post-semester. Surprisingly, social sciences students also reported a substantial, significant increase from 2.88 to 3.44, suggesting they found unexpected value in AI for these subjects. Conversely, information technology students who might be expected to benefit most from AI in technical areas showed a slight decrease in ratings from 2.90 to 2.81, perhaps reflecting unmet expectations or a more critical view over time. Economics and teacher training students reported lower and more stable ratings, indicating that AI tools were less impactful in technical subjects for these disciplines. Overall, these variations highlight how students' academic backgrounds influence their perception of AI's utility in technical subjects, with engineering and social sciences students seeing the most benefit.

Finally, in the economics and other humanities subjects category, social sciences students rated the usefulness of AI tools the highest, with a notable, significant increase from 3.17 pre-semester to 3.63 post-semester. This suggests that AI tools were increasingly integrated and valued in their humanities studies. Economics students also saw a significant rise in perceived usefulness, from 3.07 to 3.56 indicating a growing appreciation for AI in their field. Teacher training students' perceptions improved significantly from 2.64 to 3.28, while engineering students also showed a marked increase from 2.52 to 3.04. Interestingly, Information technology students saw a slight decrease in this area, from 2.94 to 2.89, possibly reflecting a more critical assessment as they became more familiar with AI tools.

Across all these figures, it becomes evident that the perceived usefulness of AI tools differs significantly not only before and after the semester but also across different academic disciplines. This diversity in perception could partially explain why, despite a high overall evaluation of AI's usefulness in the curriculum, no specific subject area reached the same level of endorsement.

6.3.3. Usefulness of AI Tools Across Different AI Platforms

The situation appears to be more complex when we examine the distribution of the types of AI chat tools used by students and analyze the usefulness of each type for different subjects.

In Figure 6, the pie chart illustrates the distribution of AI chat tools used by students in the post-semester phase with ChatGPT 3.5, a free version, being the most popular at 76.2%. This is followed by ChatGPT 4.0, a paid version, used by 10% of the students. Other AI tools, including Microsoft Copilot (5.9%), Gemini/Bard (4.5%), and GitHub Copilot (1.2%) as well as other miscellaneous tools (2.2%), account for the remaining usage. Despite the availability of various AI tools, the preference for the free version of ChatGPT is significantly higher. It's noteworthy that this distribution is relatively consistent across different academic disciplines, even though it's not explicitly shown here.

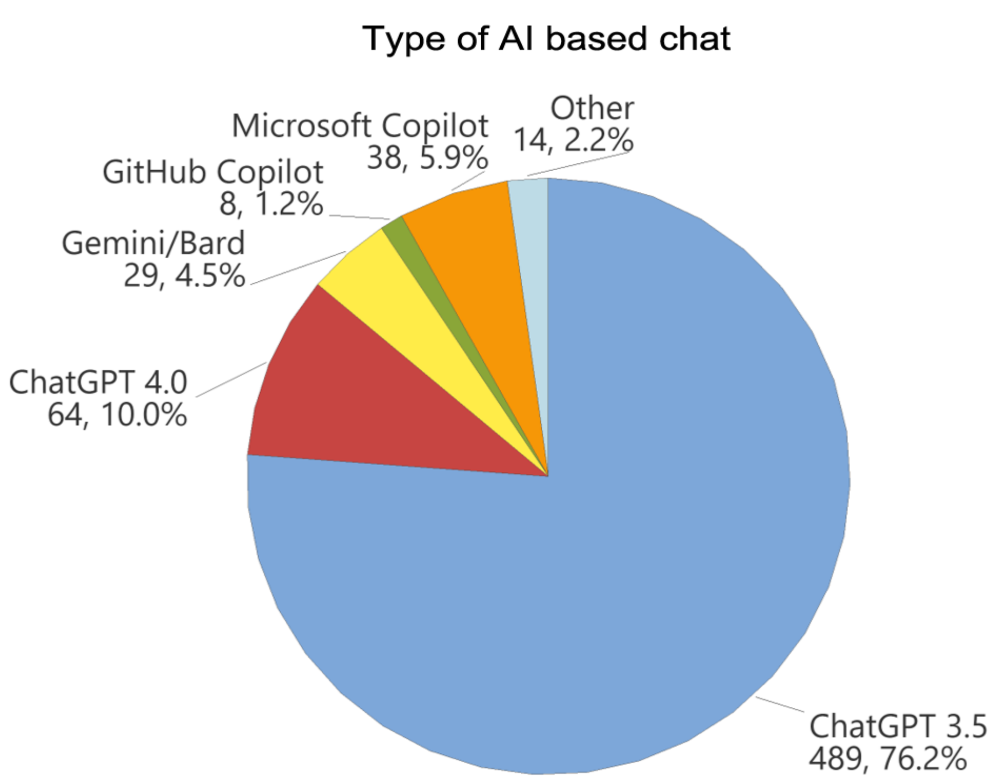

Figure 6. The distribution of AI tools used by students.

In Figure 7, the set of bar charts, the perceived usefulness of different AI tools across various subjects is depicted.

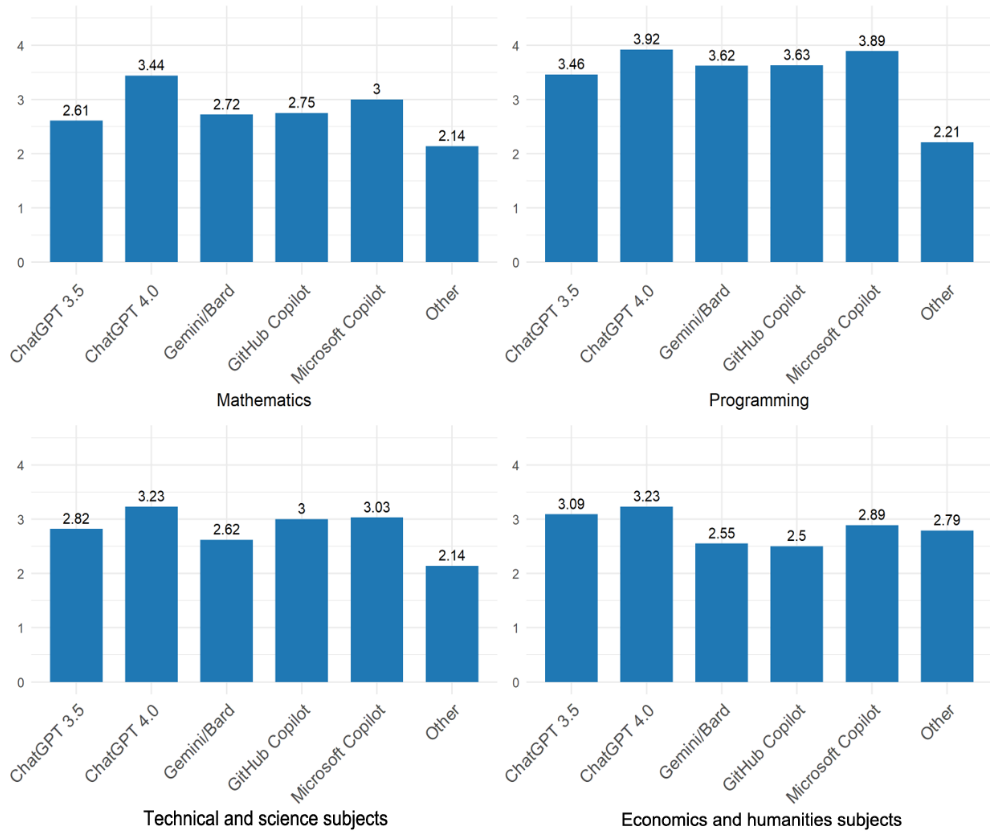

Figure 7. The perceived usefulness of different AI tools across various subjects.

The overall perceived usefulness of AI tools varies across different academic subjects with programming generally receiving the highest ratings. This suggests that students find AI tools particularly effective in this area, especially tools like ChatGPT 4.0 (3.92) and Microsoft Copilot (3.89). Mathematics, technical and science subjects also see relatively high ratings, particularly with ChatGPT 4.0 leading in usefulness (3.44 in mathematics and 3.23 in technical and science subjects).

The data indicates that AI tools are perceived as most useful in programming followed by mathematics and technical and science subjects. ChatGPT 4.0 consistently receives the highest ratings across subjects, particularly in technical fields, suggesting that students who use this paid version perceive significant benefits in their studies.

6.3.4. Usefulness of AI Tools for Various Academic Tasks

Figure 8 highlights the perceived usefulness of AI tools across different types of academic tasks.

"Understanding concepts" experienced the most significant increase in perceived usefulness rising from 3.29 pre-semester to 3.86 post-semester. This suggests that students found AI tools particularly helpful for grasping new concepts as they became more familiar with these technologies.

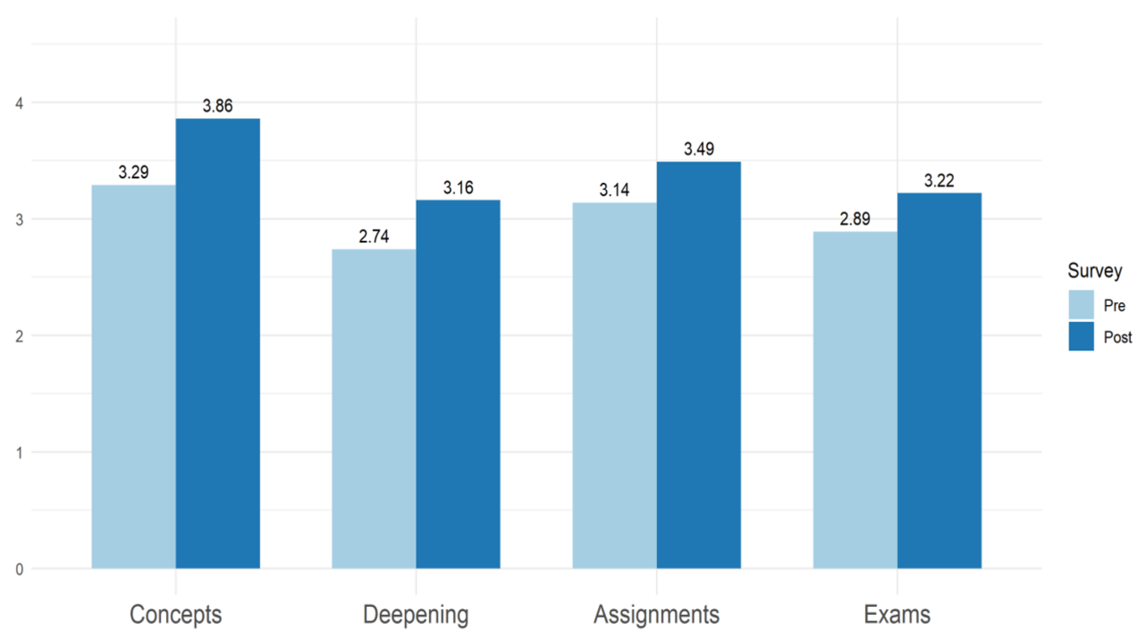

Figure 8. Perceived usefulness of AI tools across various types of tasks.

"Deepening what you have learned" had the lowest ratings among the tasks but showed a significant increase from 2.74 pre-semester to 3.16 post-semester. Although there was an improvement, this area remained where students found AI tools less effective for deeper, more reflective learning. "Preparation of assignments" also saw a significant increase in perceived usefulness, with ratings rising from 3.14 to 3.49. This indicates that students increasingly relied on AI tools for completing assignments as the semester progressed. " Preparing for exams" showed a significant increase in perceived usefulness moving from 2.89 to 3.22. While this task did not receive the highest ratings, the consistent increase suggests that AI tools have become a more integral part of students' exam preparation strategies.

Overall, the figure suggests that AI tools were increasingly valued for specific tasks; their perceived effectiveness varied depending on the type of academic activity.

Figure 9 reveals notable trends in students' perceptions of AI's usefulness across different academic tasks, comparing pre-semester and post-semester ratings as well as variations across different fields of discipline. In understanding concepts, there was a significant increase in the perceived usefulness of AI across all disciplines from pre- to post-semester. Information technology students rated AI the highest with a rise from 3.48 to 3.92. Economics students also showed a substantial increase from 3.31 to 3.87. Engineering, which started with a lower rating of 2.71 saw a notable increase to 3.67. Similarly, social sciences and teacher training both experienced increases with post-semester ratings of 3.69 and 3.68, respectively. This suggests that as students engaged more with AI throughout the semester, they found it increasingly valuable for grasping new concepts, particularly in technical and analytical fields.

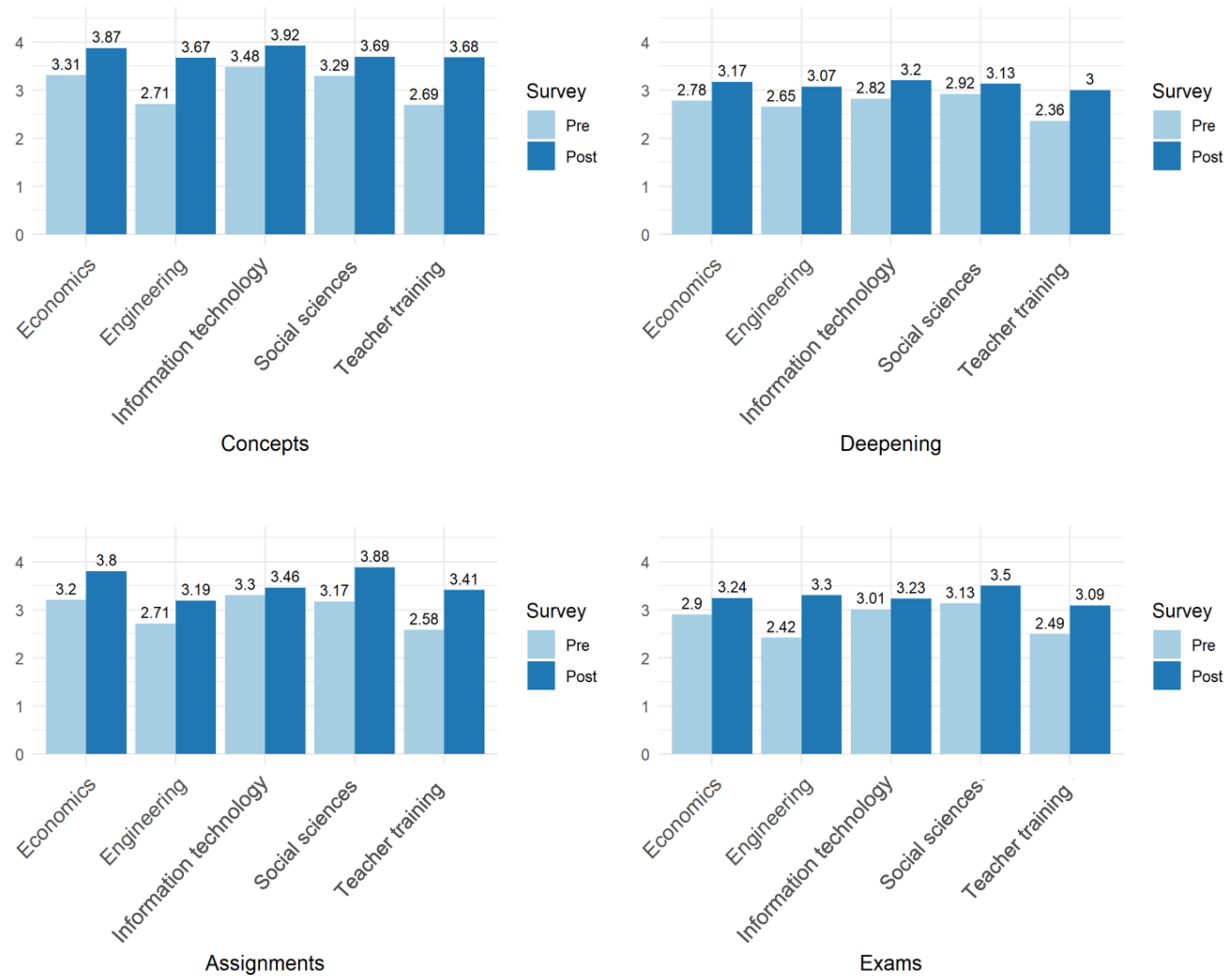

Figure 9. Perceived usefulness of AI tools across various types of tasks and fields of discipline.

When it comes to deepening what they have learnt, only the information technology and teacher training disciplines reported significantly increased usefulness of AI tools by the end of the semester. Information technology students led with an increase from 2.82 to 3.20, teacher training from 2.36 to 3.00. Economics students reported a rise from 2.78 to 3.17, and social sciences saw a similar trend from 2.92 to 3.13. Engineering students rated AI slightly lower in both pre-and post-semester assessments but still noted an increase from 2.65 to 3.07. Despite these increases, the ratings for deepening knowledge were generally lower compared to understanding concepts suggesting that while AI is helpful for initial comprehension; its effectiveness in aiding deeper learning might be more limited.

In the preparation of assignments, social sciences students rated AI the highest by the end of the semester with a jump from 3.17 to 3.88. Due to the relatively few students in this category, this jump is not statistically significant. Economics students followed with a significant rise from 3.20 to 3.80. Teacher training students also saw a significant increase from 2.58 to 3.41. Information technology students also rated AI positively but not with a statistically significant increase from 3.30 to 3.46. Engineering students, who started with the lowest pre-semester rating of 2.71, improved to 3.19. These results indicate that as the semester progressed, students across all disciplines increasingly relied on AI tools for completing assignments, highlighting AI's growing role as a practical resource for coursework.

For exam preparation, all disciplines showed an increase in the perceived usefulness of AI, with social sciences leading the way increasing from 3.13 to 3.50. Engineering students, who began with a low pre-semester rating of 2.42 saw an increase to 3.30. Economics students rated AI slightly higher post-semester, moving from 2.90 to 3.24. Information technology and teacher training students also reported increases, from 3.01 to 3.23 and 2.49 to 3.09, respectively. These findings suggest that AI tools became more integral to students' exam preparation strategies over time, though the ratings were generally lower compared to assignments and understanding concepts.

In a nutshell, across the different academic tasks, "understanding concepts" and "preparation of assignments" consistently received higher ratings post-semester across all disciplines, indicating that students found AI most useful in these areas. "Deepening" and "exam preparation" showed improvements but the ratings remained lower, suggesting that while AI is increasingly valued as a study tool, its effectiveness may vary depending on the specific academic task and discipline. The figures collectively suggest that while AI tools were perceived as increasingly useful as the semester progressed, the degree of perceived usefulness varied significantly across different fields of study and types of tasks.

6.4. Patterns of AI Tool Usage in Individual and Collaborative Learning

Figure 10 illustrates the evolving patterns of students' engagement with AI tools over the course of the semester, particularly highlighting their usage in both individual and collaborative learning contexts.

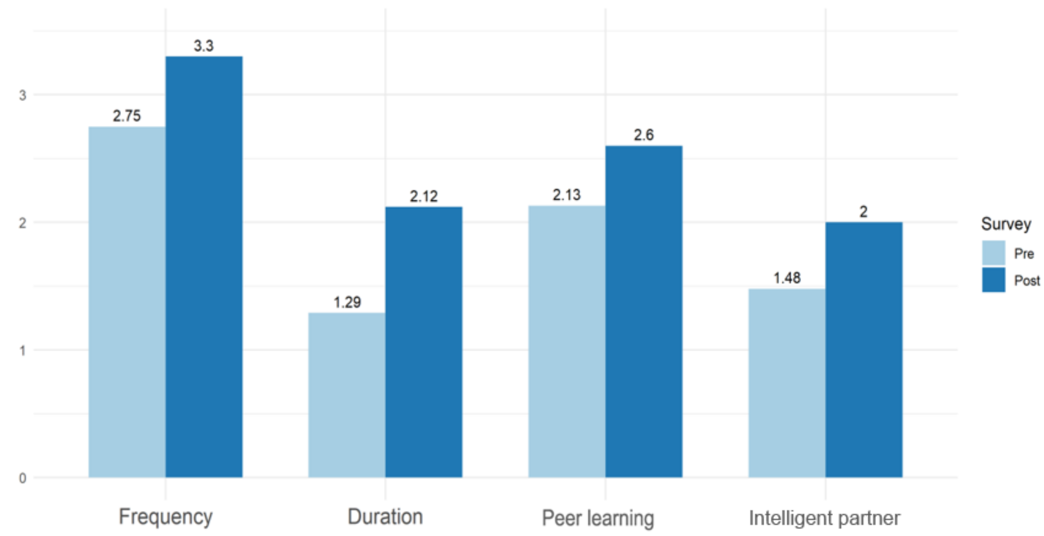

Figure 10. Patterns of students' engagement with AI tools.

Generally, there was a significant increase in the frequency and duration of AI tool usage as well as in their application for peer learning and as an intelligent partner; these activities remained moderate with all scores falling significantly short of the maximum score of 5.

Initially, students reported using AI tools only " sometimes " as reflected in a frequency score of 2.75. By the end of the semester, this increased to 3.30 indicating a shift towards more frequent usage, closer to " often" on the scale. Despite this rise, the usage still did not approach the highest possible engagement level. Similarly, the duration of AI usage showed an increase but from a very low starting point. Early in the semester, students spent less than 30 minutes per session with AI tools as indicated by a score of 1.29. This duration increased to 30 minutes and an hour by the semester's end with a score of 2.12, suggesting that while students were using AI tools for longer periods, their sessions remained relatively brief. In terms of collaborative learning, the use of AI tools for peer learning began at a modest level with a score of 2.13, reflecting occasional use. This increased to 2.60, suggesting more regular though still not extensive, use of AI in group learning contexts. The category that also saw a significant increase was the use of AI as an intelligent conversational partner. Initially, this was an infrequent practice, with a score of 1.48 (rarely). By the end of the semester, this usage had increased to 2.00, indicating that students were starting to " sometimes" use AI for interactive dialogues, although this remained the least utilized aspect of AI tools.

In summary, there was a clear trend towards increased use of AI tools in various aspects of learning, the engagement levels remained moderate, indicating that students became more accustomed to these tools, their integration into daily academic routines was still developing, with significant potential for further growth.

However, it could be interesting to explore how these tendencies are nuanced across different layers of students. In Figure 11, consider the frequency of use by age group and field of discipline.

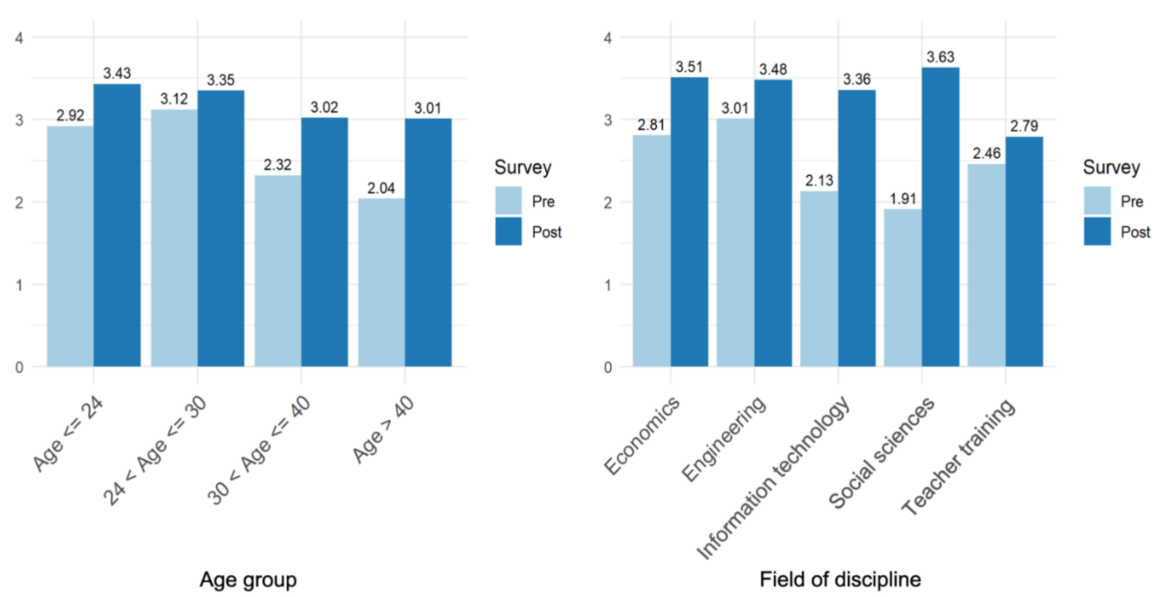

Figure 11. The frequency of AI tool usage across different age groups and fields of discipline.

In the first panel of the figure, the data reveals a general increase in the frequency of AI tool usage across all age groups, with the most significant growth observed among the oldest students. Initially, students aged 24-30 reported the highest frequency of AI tool usage, starting from a score of 3.12, which indicated usage " sometimes" to " often," and this increased to 3.35 post-semester, indicating a shift towards more consistent use (often). Notably, students aged 24 and under showed a substantial increase in frequency, moving from " sometimes" (2.92) to " often" (3.43) post-semester. The oldest group, those aged over 40, initially reported the lowest frequency of use, with scores suggesting they used AI tools "rarely" to "sometimes" (2.04). However, this group also experienced a significant increase rising to 3.01 post-semester indicating that their frequency of AI tool usage became more uniform with the other age groups by the end of the semester.

The second panel illustrates AI tool usage frequency across various academic disciplines. Initially, students in information technology reported the highest frequency of use with an average score of 3.01, indicating usage "sometimes." Economics students followed with a score of 2.81 also suggesting usage between "rarely" and " sometimes." By the end of the semester, students increased their usage frequency from "rarely" (1.91) to " sometimes" (2.79), showing a noticeable, though less dramatic, rise. Other fields, such as economics and engineering also experienced increases in usage frequency with economics rising to 3.51 and engineering to 3.48 indicating a shift towards more frequent use of AI tools across these disciplines.

It could be worth highlighting again whether the use of AI during a semester strengthens or weakens peer collaboration or, conversely, enhances individual work by using AI chat as an intelligent conversational partner, potentially making peer collaboration less necessary.

Based on the values in Figure 12, it appears that the use of AI tools during the semester did not substitute for peer collaboration but instead complemented it.

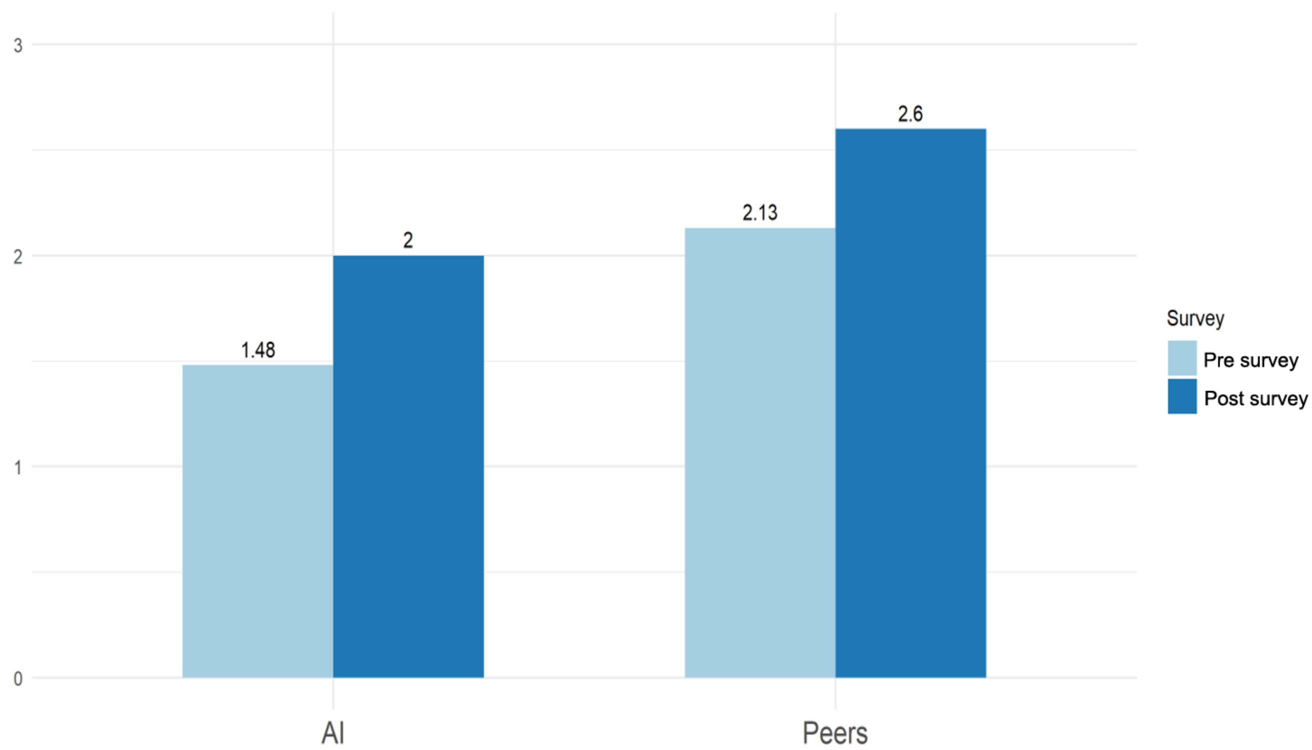

Figure 12. Peer collaboration and AI use as intelligent partners.

The data indicates that peer collaboration increased significantly from a score of 2.13 in the pre-survey to 2.60 in the post-survey, suggesting that students continued to engage with their peers and possibly even valued this interaction more as the semester progressed.

At the same time, the use of AI as an intelligent conversational partner also increased, rising from 1.48 in the pre-survey to 2.00 in the post-survey. This suggests that students increasingly relied on AI tools for individual work, this did not come at the expense of peer collaboration. Instead, both forms of engagement—peer interaction and AI use—grew over the course of the semester. This could imply that students saw value in balancing both approaches using AI tools to enhance their individual work while still recognizing the importance of peer collaboration in their learning process.

6.5. Key Motivations, Preferences, and Trust Levels in the Use of AI Chats

Figure 13 presents the motivations that students selected from four predefined categories: time saving, understanding difficult concepts, achieving better academic results, and diving deeper into the content. It's essential to clarify that motivation as understood in educational literature is a much more complex and nuanced concept. It often involves hidden or subconscious factors that students themselves may not fully recognize. A deeper exploration of these motivations, including their underlying complexities is addressed in a subsequent paper. In this analysis, we focus on the explicit choices that students made regarding their motivations for using AI-based chat tools.

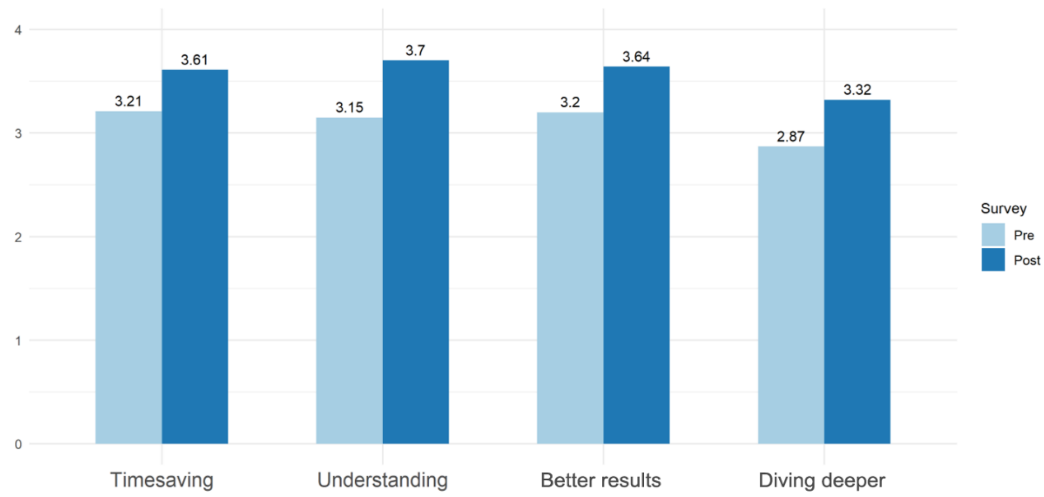

Figure 13. Students' choice from the motivational categories.

Overall, the levels of motivation across the different categories do not differ dramatically with scores ranging from 2.87 to 3.21 pre-semester and showing an increase to around 3.32 to 3.70 post-semester. This consistency indicates a uniform appreciation for AI tools in various aspects of learning. However, within each category, the pre-post differences are significant. Timesaving showed an increase from 3.21 pre-semester to 3.61 post-semester reflecting a stronger recognition of AI's efficiency benefits over time. Similarly, the motivation to use AI for understanding difficult concepts saw the most significant rise from 3.15 to 3.70 suggesting that students increasingly valued AI tools as a means to grasp complex material as the semester progressed.

The motivation to achieve better academic results also saw an increase from 3.20 to 3.64, indicating a growing belief in AI's positive impact on performance. Even the motivation to dive deeper into content which started at a lower level of 2.87 pre-semester increased to 3.32 post-semester showing that students began to see more value in using AI for a more thorough exploration of their study topics.

In a nutshell, the initial levels of motivation varied slightly across these categories, students' experiences over the semester generally led to a stronger appreciation for the benefits of AI-based chat tools, particularly in understanding difficult concepts and enhancing academic outcomes.

The analysis of students' preferences and trust in AI-based chat tools in Figures 14 and 15 offers valuable insights into their reliance on these technologies compared to more traditional resources like textbooks and websites. It is particularly insightful to examine how preferences and trust levels vary across different age groups and academic disciplines.

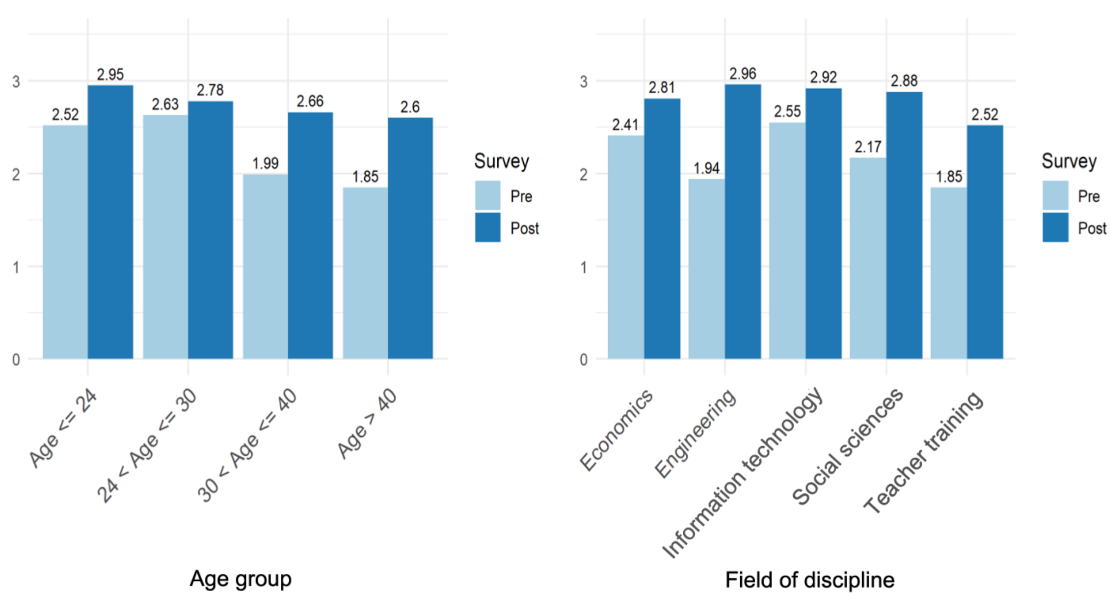

Figure 14. AI-based chats as the primary resource of information.

Figure 14 reveals that students aged 24-30 were the most frequent users of AI-based chats as their primary resource with a score of 2.63. Younger students aged 24 and under also showed a notable reliance on AI chats with a score of 2.52. In contrast, older students (age > 40) were less inclined to use AI chats as the first source, frequently with a lower score of 1.85.

In terms of academic disciplines, information technology students were the leading users with an initial score of 2.55 followed by students in social sciences and economics, who had scores of 2.17 and 2.41, respectively. Engineering and teacher training students were less frequent users in scores of 1.94 and 1.85, respectively.

There was an increase in the frequency of AI chat usage as a first choice across all age groups. Younger students, particularly those aged 24 and under, increased their usage from 2.52 to 2.95. Even among the older students, there was a significant rise with their scores moving from 1.85 to 2.60.

Across disciplines, information technology students continued to be near the top with a slight rise from 2.55 to 2.91. Students in fields like engineering and teacher training saw significant increases moving from 1.94 to 2.96 and from 1.85 to 2.52, respectively. This reflects a broader acceptance and integration of AI chats as a primary learning resource over the course of the semester.

Figure 15 illustrates students' direct trust in AI across different age groups and fields of discipline, providing insights that can be compared to the previous analysis of AI as the first source.

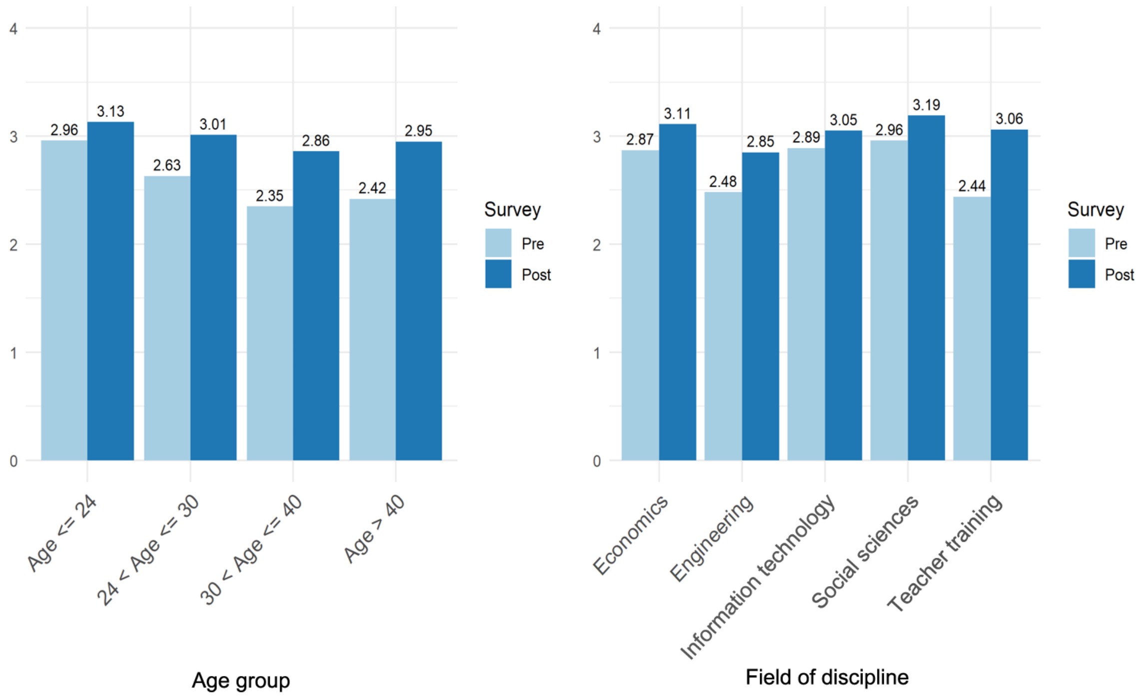

Figure 15. Trust in AI across age groups and fields of discipline.

In the age group analysis, younger students (age ≤ 24) consistently show the highest levels of trust in AI tools both before and after the semester with scores rising from 2.96 to 3.13. This increase mirrors their frequency of choosing AI as a first source where they also led in usage. The 24-30 age group follows a similar trend, with trust increasing from 2.63 to 3.01, closely aligning with their first usage patterns. Notably, students aged over 40 exhibited the lowest trust levels initially (2.42 but post-semester, they showed a significant rise to 2.95, nearly matching the other age groups. This suggests that even though older students were initially more cautious, their trust in AI grew substantially as they became more familiar with the technology.

Across different fields of discipline, students in social sciences showed the highest levels of trust in AI both before and after the semester with scores increasing from 2.96 to 3.19. This aligns with their relatively high frequency of AI usage as a first source. Students who also showed high AI usage frequency exhibited a similar increase in trust from 2.89 to 3.05. On the other hand, teacher training who had the lowest trust levels initially (2.44) showed a significant increase post-semester to 3.06. This rise is comparable to their increased usage of AI as a primary resource suggesting that as their reliance on AI grew, so did their trust in the tool. Economics and engineering students show a slight increase over the semester.

Overall, the patterns of trust generally align with the frequency of AI use as a first source; some variations indicate that trust is a nuanced factor influenced by both initial perceptions and the level of engagement with AI tools throughout the semester.

Figure 16 illustrates the levels of trust students place in different types of AI-based chat tools.

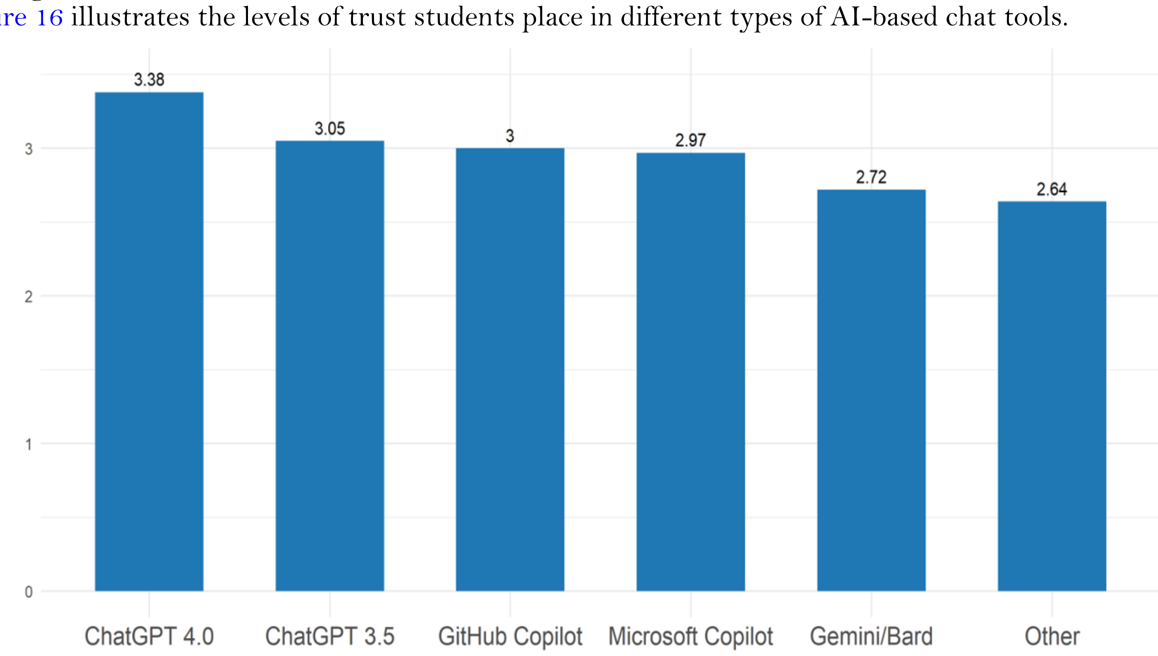

Figure 16. The levels of trust in different types of AI-based chat tools.

ChatGPT 4.0 received the highest level of trust, with a score of 3.38, indicating that students generally have more confidence in this version compared to others. ChatGPT 3.5 follows closely behind with a trust score of 3.05, suggesting that the free version also holds significant trust among users.

GitHub Copilot and Microsoft Copilot are similarly trusted with scores of 3.00 and 2.97, respectively, reflecting a moderate level of confidence in these tools, particularly in contexts related to programming and technical tasks. Gemini/Bard and other AI chat tools received lower trust scores, 2.72 and 2.64, respectively, indicating that students are somewhat less confident in these options compared to the more prominent AI tools like ChatGPT and Copilot. Overall, the figure suggests a clear preference and higher trust for the ChatGPT versions, particularly the paid 4.0 version, among the students.

7. Practical Implications for Teachers and Policymakers

This research provides actionable recommendations to optimize the employment of AI tools to aid the learning process. If teachers and policymakers engage them systematically at the semester's mid-point and incorporate age engagement trends, they can improve the quality and scope of AI learning environments.

AI technologies proved most useful in solving complex issues and understanding concepts in technical fields, such as mathematics, engineering, and programming. They assisted in summarization and discussion topic generation in the humanities and social sciences. Teachers need to customize AI applications within specific subject areas to optimize results. This could also be achieved by setting integration policy guidelines based on disciplines.

Students' enthusiasm for AI tools gradually decreased, specifically their receptiveness towards novel technologies. Wewaspace could employ gamification, adaptive learning or feedback sessions to keep motivation levels high. Even though older learners started off less engaged, by the end of the semester, their use of AI tools had dramatically increased. This means that older learners can adapt to AI-enriched environments provided there is sufficient guidance. Different age groups should be guided using different onboarding materials; older learners require basic while younger students need more sophisticated explanations.

The degree of expectation in premium tools such as ChatGPT 4.0 was profound when it came to trusting the tool. The trust can be built through more instructor-led sessions that showcase the strengths and weaknesses of the AI tools. Teaching students how to design prompts and evaluate them critically can boost confidence and enable responsible usage. Individual learning was enhanced while collaboration was not diminished by AI tools.

Teachers should allow students to work individually on AI personal projects and create activities that require discussion and collaboration. This makes sure that independent learning and interpersonal relations are nurtured. Students using paid AIs reported having higher trust and usefulness.

Support is required by teachers in the effective integration of AI tools. Schools need to spend money on training staff that offers the integration of AI with pedagogical outcomes and the use of the relevant tools in the courses.

All these suggestions provide a unified approach to using AI in education with reasonable limitations for the incorporation of diversity within learners' participation and engagement for the long- term.

8. Limitations of the Study and Directions for Future Research

Although this study offers insights into student participation in and attitudes toward AI-assisted learning, several areas remain insufficiently addressed. Though gamification and adaptive learning are suggested as means of maintaining engagement, there was no evaluation of their actual impact. These approaches could be tested in the future with intervention designs.

To make the research accessible, simple statistical methods (descriptive analysis, t-tests, and ANOVA) were employed. They may provide answers to some general questions but not to more intricate ones. Using such methods as Exploratory or Confirmatory Factor Analysis (EFA, CFA) or Structural Equation Modeling (SEM) would shed more light on the relationships between trust, engagement, and enthusiasm.

It should be noted that generalizability is limited. Although students from other fields were included, the sample does not represent all contexts of education. In addition, the study was based on a self-reporting survey which is prone to biases or misinterpretation. The data could be more triangulated and richer with the inclusion of classroom observations or interviews.

The conclusion of the study was informed by its focus on specific disciplines and courses which, it is important to note had already been changed to incorporate AI components into the curriculum. Other institutions that have not yet implemented such curricular changes or prepared students may not relate to these findings.

To expand on the scope of this work, further studies should consider a wider array of institutions from different cultural, geographic, or economic scopes. The use of longitudinal and experimental approaches in conjunction with qualitative methods would greatly enhance the understanding of the impacts of AI tools on learning processes over time, as well as aid in fine-tuning effectiveness integration models.

9. Conclusion

The analysis presented in this study offers important insights into how students interact with AI tools over the course of a semester—findings that are valuable for both educators and policymakers.

While students generally accepted the use of AI, their willingness to adopt new learning habits declined over time. This highlights the need for structured support to sustain engagement throughout the semester.

Initial attitudes toward AI varied by age and prior educational experience, but these differences diminished by the end of the term. Ongoing exposure appeared to foster broader acceptance, suggesting that time and consistent use can reduce resistance, particularly among older students.

AI was viewed as especially useful for understanding concepts and completing tasks in technical fields like programming. However, it was rated less helpful for deeper learning and exam preparation, indicating the need for more intentional integration to support higher-order thinking.

Contrary to concerns, AI use did not reduce peer collaboration. Both individual and collaborative use increased as the semester progressed suggesting that AI tools can enhance learning without disrupting traditional peer interactions.

For AI to be fully effective in education, it must be introduced in a sustained and supportive manner. Teachers should aim to integrate AI into individual and group learning activities and design interventions that promote surface-level understanding and deeper academic engagement.

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Appendix

Table A1. Pre-and post-semester questions.

Pre-semester	Post-semester
Q1. I look forward to learning new topics.	Q1. When using AI-based chat, I look forward to learning new topics.
Q2. I am open to trying new technologies or methods in my learning.	Q2. When using AI-based chat, I feel like the world opens up to me when learning.
Q3. I think technology can help me to connect better with the curriculum.	Q3. When using AI-based chat, I feel more connected to the learning material.
Q4. I am open to developing new learning habits.	Q4. Using AI-based chat to develop new learning habits.

Pre-semester	Post-semester
Q5. How often do you use AI-based chat in your studies? - Never (1) - Rarely (2) - Sometimes (3) - Often (4) - Very often (5)	Q5. How often did you use AI-based chat for your studies this semester? - Never (1) - Rarely (2) - Sometimes (3) - Often (4) - Very often (5)
Q6. If you use AI-based chat, how long do you use it on average in a row? - I don't use it (0) - Less than 30 minutes (1) - Between 30 minutes and 1 hour (2) - 1-2 hours (3) - 2-4 hours (4) - More than 4 hours (5)	Q6. On average, how long did you work on the AI-based chat in one go? - I don't use it (0) - Less than 30 minutes (1) - Between 30 minutes and 1 hour (2) - 1-2 hours (3) - 2-4 hours (4) - More than 4 hours (5)
Q7. For the following subjects, how useful do you find the help of AI-based chat? (Not at all useful → Extremely useful) - Mathematics - Programming - Other IT subjects - Technical, science subjects - Subjects in economics and humanities	Q7. For the following subjects, how useful do you find the help of AI-based chat? (Not at all useful → Extremely useful) - Mathematics - Programming - Other IT subjects - Technical, science subjects - Subjects in economics and humanities
Q8. For the following types of tasks, how useful would you consider AI-based chat to be? (Not at all useful → Extremely useful) - Understanding concepts - Deepening what you have learned - Preparation of assignments to be submitted - Preparing for the exam	Q8. For the following types of tasks, how useful would you consider AI-based chat to be? (Not at all useful → Extremely useful) - Understanding concepts - Deepening what you have learned - Preparation of assignments to be submitted - Preparing for the exam
Q9. How often do you use AI-based chat for peer learning? - Never (1) - Rarely (2) - Sometimes (3) - Often (4) - Very often (5)	Q9. How often have you used AI-based chat for peer learning? - Never (1) - Rarely (2) - Sometimes (3) - Often (4) - Very often (5)
Q10. Do you use AI-based chat as a smart chatting partner this semester? - Never (1) - Rarely (2) - Sometimes (3) - Often (4) - Always (5)	Q10. Have you used AI-based chat as a smart chatting partner this semester? - Never (1) - Rarely (2) - Sometimes (3) - Often (4) - Always (5)
Q11. What motivates you to use AI-based chat for learning? (Not at all motivated → Highly motivated) - To save time - Understanding difficult concepts - Achieving better academic results - Dive deeper into the content	Q11. What motivated you to use AI-based chat for learning? (Not at all motivated → Highly motivated) - To save time - Understanding difficult concepts - Achieving better academic results - Dive deeper into the content
Q12. How often do you choose AI-based chat as your first source compared to other options (such as textbooks or websites)? - I always use another method, I don't use AI-based chat (1) - I usually use other methods (2) - I prefer one or the other (3) - I usually prefer AI-based chat (4) - I always prefer AI-based chat (5)	Q12. How often did you choose AI-based chat as your first source compared to other options (such as textbooks or websites)? - I have always used other methods (1) - I usually used other methods (2) - I used AI-based chat and other resources in equal measure (3) - I usually used AI-based chat (4) - I have always used AI-based chat (5)
Q13. Do you trust the answers, information, and guidance provided by AI-based chat? - (1 Not at all - 5 I fully trust)	Q13. Do you trust the answers, information, and guidance provided by AI-based chat? - (1 Not at all - 5 I fully trust)
Q14. What is your gender? - Male - Female - I do not wish to answer	Not relevant in post-semester survey
Q15. What is your age?	Not relevant in post-semester survey
Q16. What discipline are you studying? - IT - Technical - Teacher training - Social Sciences - Economics	Not relevant in post-semester survey
Not relevant in pre-semester survey	Q17. Which AI-based chat do you use most often? - ChatGPT (OpenAI) Version 3.5 (Free version) - ChatGPT (OpenAI) Version 4.0 (Paid version) - Gemini/Bard (Google) - Microsoft Copilot - GitHub Copilot - Other
Not relevant in pre-semester survey	Q18. Do you think that the classes were sufficiently in-depth about the potential of Artificial Intelligence? - (1 Not at all - 5 Absolutely)
Not relevant in pre-semester survey	Q19. Do you think that the limitations of Artificial Intelligence were presented in sufficient depth in the class? - (1 Not at all - 5 Absolutely)

Table A2. Research questions and the corresponding survey questions.

Research question 1:
How does students' openness to new technologies and methods, along with their willingness to develop new learning habits, influence their engagement with AI-enhanced tools?
Pre-semester:
Q1. I look forward to learning new topics.
Q2. I am open to trying new technologies or methods in my learning.
Q4. I am open to developing new learning habits.
Post-semester:
Q1. When using AI-based chat, I look forward to learning new topics.
Q2. When using AI-based chat, I feel like the world opens up to me when learning.
Q4. Using AI-based chat to develop new learning habits.
Research question 2:
To what extent do AI tools help students better connect with the curriculum, and how do students perceive the usefulness of these tools across various subjects and specific academic tasks?
Pre-Semester:
Q3. I think technology can help me to connect better with the curriculum.
Q7. For the following subjects, how useful do you find the help of AI-based chat? (Mathematics, Programming, Other IT subjects, Technical, science subjects, Subjects in economics and humanities)
Q8. For the following types of tasks, how useful would you consider AI-based chat to be? (Understanding concepts, deepening what you have learned, Preparation of assignments to be submitted, Preparing for the exam)
Post-Semester:
Q3. When using AI-based chat, I feel more connected to the learning material.
Q7. For the following subjects, how useful do you find the help of AI-based chat? (Mathematics, Programming, Other IT subjects, Technical, science subjects, Subjects in economics and humanities)
Q8. For the following types of tasks, how useful would you consider AI-based chat to be? (Understanding concepts, deepening what you have learned, Preparation of assignments to be submitted, Preparing for the exam)
Research question 3:
What are the patterns of AI tool usage among students, including the frequency, duration, and application of these tools in both individual and peer learning contexts?
Pre-Semester:
Q5. How often do you use AI-based chat in your studies?
Q6. If you use AI-based chat, how long do you use it on average in a row?
Q9. How often do you use AI-based chat for peer learning?
Q10. Do you use AI-based chat as a smart chatting partner this semester?
Post-semester:
Q5. How often did you use AI-based chat for your studies this semester?
Q6. On average, how long did you work on the AI-based chat in one go?
Q9. How often have you used AI-based chat for peer learning?
Q10. Have you used AI-based chat as a smart chatting partner this semester?
Research question 4:
What are the key motivations driving students to use AI tools, and how do their preferences for AI as a primary resource and their level of trust in these tools affect their overall adoption and usage?
Pre-semester:
Q11. What motivates you to use AI-based chat for learning? (To save time, understanding difficult concepts, Achieving better academic results, Dive deeper into the content)
Q12. How often do you choose AI-based chat as your first source compared to other options (Such as textbooks or websites)?
Q13. Do you trust the answers, information, and guidance provided by AI-based chat?
Post-semester:
Q11. What motivated you to use AI-based chat for learning? (To save time, understanding difficult concepts, Achieving better academic results, Dive deeper into the content)
Q12. How often did you choose AI-based chat as your first source compared to other options (Such as textbooks or websites)?
Q13. Do you trust the answers, information, and guidance provided by AI-based chat?