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Enhancing Learning in Data Analytics through AI Tutoring Systems: A Student-Centered Evaluation

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Abstract

This study explores the implementation and effectiveness of Artificial Intelligence (AI)-based tutoring tools in a higher education data analytics course. As AI becomes increasingly integrated into education, it is important to examine how students interact with such tools to ensure meaningful and ethical integration that supports learning. This research addresses the need to understand student perceptions, motivation, and concerns regarding AI tutors, particularly in technical subjects like data analytics. A structured quantitative methodology was employed, involving undergraduate students enrolled in a data analytics course at a Malaysian university named as Universiti Teknologi PETRONAS. Participants completed a 29-item survey instrument aligned with four research objectives. Results showed that students generally viewed AI tools positively describing them as helpful, user-friendly, and supportive of deeper learning. High agreement was recorded in areas such as usability, motivation, and content alignment, with many students reporting improved understanding and confidence in handling analytical tasks. Correlation heatmaps revealed consistent attitudes and experiences, while concerns such as overreliance and algorithmic transparency were more varied. Ethical issues including data privacy and equitable access were noted as ongoing challenges. Overall, this study contributes evidence that AI-based tutors can enhance student engagement and learning outcomes, provided their use is guided by ethical safeguards, student agency, and pedagogical alignment.

Keywords: Artificial Intelligence, AI-Based Tutoring, Effectiveness, Learning

Introduction

The integration of Artificial Intelligence (AI) into higher education has led to the development of AI-based tutoring tools that aim to provide personalized and adaptive learning experiences. In the context of data-intensive subjects such as data analytics, these tools offer promising potential to support learners through customized feedback, intelligent problem-solving guidance, and engagement-driven features. Students' perceptions of AI tools referred to as "expectancy" in educational research include their comfort, perceived usefulness, and competence in navigating such technologies (Butz et al., 2004; Gan et al., 2019). These perceptions significantly influence both engagement and academic success.

AI-powered tutoring systems have evolved rapidly, encompassing a variety of instructional strategies such as example-based, simulation-based, and feedback-driven methods. Tools like AI-Tutor, which provides personalized support based on cognitive diagnostic assessments, and agent-based intelligent tutors, which utilize semantic networks, have been effective in aligning instructional content with students' individual progress and goals (Gan et al., 2019; Keleş et al., 2009). (Kojima et al., 2020) and (Rızvı, 2023) emphasize that incorporating elements like knowledge graphs can further enhance the accuracy and relevance of AI-generated responses, ensuring learners receive contextually meaningful assistance throughout their learning journey.

Empirical studies support the effectiveness of AI tutoring systems in improving learning outcomes. For example, (Kularbphettong et al., 2015) observed that AI tools substantially reduced the time needed for students to master complex concepts, while (Afzal et al., 2019) found improvements in engagement and satisfaction. Furthermore, intelligent solving-based systems (SITS) have been recognized for their role in fostering critical thinking and increasing students' motivation (Hooshyar et al., 2018). In domains such as data analytics, where problem-solving and logical reasoning are central, these benefits are particularly relevant.

Student motivation and attitudes also play a crucial role in the adoption and success of AI tutoring systems. Studies show that interactive AI environments stimulate curiosity and help maintain learners' interest, thereby fostering active participation and deeper learning (Çakir, 2019). The ability of AI systems to adapt to learners' needs, provide immediate feedback, and support self-paced exploration further contributes to a positive learning experience.

However, despite their advantages, AI-based tutoring tools present challenges that merit careful consideration. Some users express concerns over the generic nature of AI responses (Merkle et al., 2024), and the potential for overreliance on technology raises issues related to academic integrity and critical thinking. Therefore, evaluating the effectiveness of these systems in actual classroom settings such as a data analytics course is critical to ensuring they deliver on their promise while addressing limitations.

This study aims to evaluate the use of AI-based tutoring tools in a data analytics course by examining students' perceptions, the effectiveness of these tools in enhancing learning and understanding, their attitudes and motivation toward AI-assisted learning, and the challenges or concerns related to their use in higher education. By understanding the factors that contribute to or hinder the success of AI tutoring systems in data-centric disciplines, the research seeks to inform the design and deployment of more effective and ethically responsible AI learning tools in higher education.

Related Work

Artificial Intelligence (AI) is reshaping the educational landscape, offering new possibilities for personalized, interactive, and scalable learning. The integration of AI technologies into teaching and learning processes has shown significant promise in supporting student engagement, critical thinking, and educational outcomes across disciplines. This review systematically examines recent advances in AI-supported educational systems, focusing on intelligent tutoring, conversational AI, strategic applications in higher education, and the associated ethical challenges.

Recent developments in AI-supported tutoring systems have demonstrated considerable potential in enhancing learning across a range of subject areas, including computer programming. Core to these systems are techniques such as solution analysis, model tracing, and rule-based reasoning, which enable tutors to identify student strategies, misconceptions, and errors. Examples include tools like LISP-Tutor, JITS, JavaBugs, and PROUST (Anderson et al., 1989; Suarez & Sison, 2008; Sykes, 2005). These methods enable systems to provide tailored feedback based on a student's underlying reasoning process. In domains like data analytics education—where students interact with datasets and construct workflows—such approaches are especially relevant. Furthermore, AI techniques that promote collaboration, such as modeling group interactions and deploying conversational agents, have been shown to foster peer learning and enhance engagement. Natural language processing (NLP)-powered dialogue systems also play a key role in guiding learners through complex topics by offering step-by-step reasoning, which improves accessibility to abstract concepts. When applied effectively, these AI mechanisms help build personalized and collaborative environments that develop students' critical thinking and data interpretation skills (Le et al., 2013).

Alongside traditional tutoring models, conversational AI has emerged as a key focus area in the development of Intelligent Tutoring Systems (ITS). Modern research increasingly emphasizes the need to combine machine learning techniques with explicit knowledge-based strategies to develop more adaptive, responsive, and effective learning tools. Neural models including deep learning and natural language understanding are particularly effective at interpreting student input and generating appropriate, context-aware responses (Gao et al., 2018). Tools like Dialogflow and Rasa Core enable conversational systems to track and manage dialogue context, thus improving the coherence and flow of educational interactions (Bocklisch et al., 2017; Boonstra, 2021; Harms et al., 2018). Hybrid models that merge explicit domain knowledge with implicit language understanding are being explored for their potential to enhance system responsiveness and personalize learning experiences (Harms et al., 2018; Olney et al., 2012). Knowledge representations such as concept maps and knowledge graphs are also used to assess student comprehension, generate questions, and support self-explanation and reflection. These developments illustrate a broader trend toward combining rule-based and data-driven techniques to enable more human-like, insightful, and pedagogically sound AI-driven instruction.

Beyond tutoring, AI is increasingly being applied at a strategic level in higher education to improve decision-making and institutional effectiveness. Even before the recent rise of generative AI models like ChatGPT, AI was recognized for its capacity to uncover meaningful educational insights. For instance, (Nguyen et al., 2020) emphasized AI's ability to reveal critical patterns and indicators that had previously gone unnoticed, thereby influencing educational strategies and student success. Further, (Zawacki-Richter et al., 2019) reviewed existing AI applications and highlighted the technology's role in creating adaptive learning systems, personalizing instruction, and supporting intelligent tutoring factors that contribute to more inclusive, learner-centered environments and increased engagement.

However, alongside these opportunities, significant ethical concerns must be addressed. Scholars such as (Essien et al., 2024) have cautioned against the risk of over-reliance on AI, which could undermine the development of students' critical thinking and problem-solving skills. Others have raised concerns about data privacy, algorithmic bias, and the unequal distribution of AI-enabled tools, which could inadvertently reinforce existing educational disparities if not properly managed (Holmes et al., 2022). The deployment of large language models in education introduces further ethical complexities. As (Nguyen et al., 2023) points out, these systems can introduce bias, breach privacy, and potentially amplify systemic inequities. These issues underscore the urgent need for responsible AI governance, transparency in design, and inclusive implementation practices that prioritize equity, accountability, and student empowerment.

In conclusion, the literature suggests a dual-perspective view of AI's role in education. On one side, AI has demonstrated the potential to revolutionize higher education by providing personalized, interactive, and engaging learning experiences. On the other, its effective and equitable integration requires addressing substantial ethical and practical challenges. To fully realize AI's transformative potential, educational institutions must embrace innovation responsibly balancing technological advancement with a commitment to transparency, inclusiveness, and sound pedagogical principles.

Methodology

To investigate students' experiences, perceptions, and concerns related to the use of AI-based tutoring tools in a data analytics course, this study employed a structured quantitative research design using a Google Forms-based survey. The participants were undergraduate students enrolled in a data analytics course at a Malaysian private university, Universiti Teknologi PETRONAS. Fig. 1 shows specific groups were chosen because they were actively using AI-powered tools in their coursework, providing relevant and timely insights into real-world classroom integration. A non-probability convenience sampling method was used, as participation was voluntary and limited to students who had direct exposure to AI tutoring tools. Students were informed that AI-based tutoring tools refer to computer-based systems powered by artificial intelligence (e.g., ChatGPT, DeepSeek, personalized learning assistants, automated feedback systems) that simulate human tutors by offering real-time support, answering questions, and assisting in problem-solving tasks. These tools were intended to supplement traditional instruction by providing accessible, on-demand learning assistance.

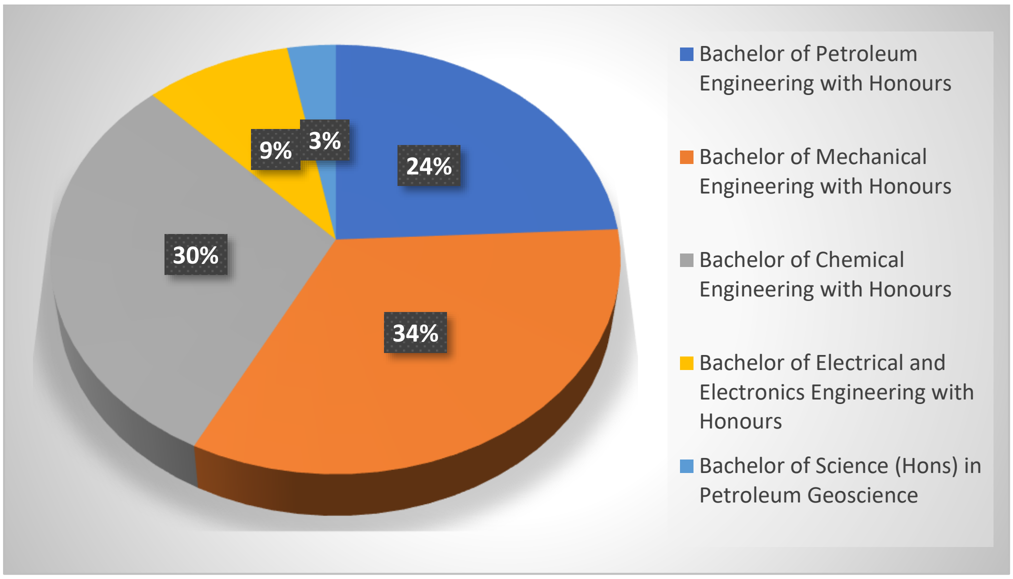

Figure 1: Academic programs of the respondents

The questionnaire comprised 29 items, grouped under four research objectives (ROs): perceptions of AI tools, effectiveness in learning, motivation and engagement, and challenges or concerns (Refer to Table 1). Each item used a 5-point Likert scale ("Strongly Disagree" to "Strongly Agree"). Data were analysed using Microsoft Excel, applying both descriptive and inferential statistics, including measures of central tendency, variability, and correlation analyses across dimensions.

Table 1
Survey Bases Questionnaire

Code	List of Questions
	RO# 1: Perception of Using AI Tools
Q1	I find AI-based tutoring tools helpful in supporting my learning in the Data Analytics course.
Q2	I feel confident using AI-based tutoring tools as part of my learning process in the Data Analytics course.
Q3	I prefer learning with the support of AI-based tutoring tools compared to traditional methods (e.g., lectures, textbooks).
Q4	Using AI tutoring tools in the course has been a positive learning experience for me.
Q5	I believe AI-based tutoring tools are a valuable addition to the Data Analytics course.
Q6	The AI tutor made learning more enjoyable and less intimidating.
Q7	I used the AI tutor regularly throughout the course.
	RO# 2: The Effectiveness of AI-Based Tutoring in Learning & Understanding Better
Q8	The AI-based tutoring tool helped me understand data analytics concepts better.
Q9	I found the AI tool easy to navigate and interact with.
Q10	The AI tutor provided explanations that matched the course material.
Q11	I was able to use the AI tutor to clarify doubts outside class hours.
Q12	The AI tutor supported my understanding of programming tools used in the course (e.g., Python, R, Excel).
Q13	The AI tutor helped me learn how to interpret data visualizations and results.
Q14	I was able to complete data analysis tasks more confidently with the AI tutor's help.

Q15	The AI tutor improved my understanding of statistical and computational methods used in the course.
Q16	I could apply course concepts more effectively after receiving support from the AI tutor.
RO#3: Attitude & Motivation Towards Learning Using AI Tools	
Q17	I was more motivated to study data analytics using the AI tutor.
Q18	I engaged more actively with course content when using AI tools.
Q19	I am motivated to put in extra effort when using AI-based tutoring tools in the Data Analytics course.
Q20	I feel encouraged to continue learning Data Analytics because of the AI-based tutoring tools.
Q21	I am eager to explore more advanced topics in Data Analytics with the help of AI-based tutoring tools.
Q22	I believe that AI-based tutoring tools help me stay focused and engaged in the course.
Q23	I am confident that using AI-based tutoring tools helps me achieve better results in the Data Analytics course.
Q24	I feel more motivated to complete assignments and projects in Data Analytics because of the AI-based tutoring tools.
RO# 4: Challenges and Concerns Related to the Use of AI Tools In Higher Education	
Q25	I am concerned about relying too heavily on AI tools for learning.
Q26	The AI tutor occasionally gave incorrect or misleading information.
Q27	I preferred consulting course instructors or peers over the AI tutor.
Q28	I was unsure about how to evaluate the correctness of AI tutor responses.
Q29	The AI tutor sometimes lacked context or failed to understand my questions.

Results

In this section, the findings are presented which are derived from the survey responses collected to address the four research objectives outlined earlier: students' perceptions, learning outcomes, motivation, and challenges associated with using AI-based tutoring tools in a data analytics course. The results are organised through descriptive statistics, visual representations of sentiment and agreement patterns, and correlation analyses that explore relationships among key variables. These findings provide a quantitative overview of students' experiences and lay the groundwork for evaluating the pedagogical implications of AI tutoring systems in higher education.

Descriptive Statistics

Descriptive statistics serve as a foundational step in data analysis, offering a summary of central tendencies, dispersion, and the overall distribution of responses. These statistics provide insights into how participants responded to each item by highlighting average scores (means), the extent of variability (standard deviation), and the shape of the distribution (skewness and kurtosis).

Table 2 provides a summary of participants' average responses and the variability within four key research objectives. The mean scores for most questions are above 4.0, suggesting that respondents generally agreed or strongly agreed with the statements. The highest means are Q1 (4.48) possibly indicating a strong agreement with a positively framed perception or experience. Q5 (4.39) and Q8 (4.32) are Likely tied to very favorable experiences or attitudes. The lowest means are Q26 (3.68) and Q27 (3.65), reflecting more mixed or neutral opinions, possibly related to challenges or concerns. Furthermore, the standard deviation values range from 0.62 to 1.08. Q1 (0.63) had the least variability, indicating high consensus whereas Q25 and Q27 (~1.08) had the highest variability, showing diverse responses—likely concern-based items where opinions were more spread out.

Table 2
Descriptive statistics for all Research Objectives

SN	**mean**	**std**	**min**	**max**	**skewness**	**kurtosis**
Q1	4.483871	0.625618	3	5	-0.8086	-0.252
Q2	4.193548	0.703295	3	5	-0.29098	-0.85823
Q3	3.774194	1.023383	2	5	-0.31114	-0.99158
Q4	4.225806	0.716923	2	5	-0.94788	1.770443
Q5	4.387097	0.667204	3	5	-0.63667	-0.548
Q6	4.193548	0.833441	2	5	-0.75857	-0.04925
Q7	4.16129	0.77875	3	5	-0.29677	-1.25714
Q8	4.322581	0.944708	2	5	-1.22353	0.473769
Q9	4.064516	0.853834	2	5	-0.47176	-0.59899
Q10	4.129032	0.718421	3	5	-0.19799	-0.95443
Q11	4.225806	0.668814	3	5	-0.2915	-0.67432
Q12	4.290323	0.739078	3	5	-0.53232	-0.93719
Q13	4.258065	0.773207	3	5	-0.49474	-1.1238
Q14	4.322581	0.791079	3	5	-0.66283	-1.05569
Q15	4.193548	0.749193	3	5	-0.33912	-1.09281
Q16	4.16129	0.77875	3	5	-0.29677	-1.25714
Q17	3.967742	0.948116	2	5	-0.43435	-0.83102
Q18	4	0.774597	3	5	0	-1.289
Q19	4	0.966092	2	5	-0.71131	-0.33327
Q20	4.032258	0.874981	2	5	-0.38424	-0.83864
Q21	3.967742	0.948116	2	5	-0.6852	-0.26529
Q22	3.935484	0.928636	2	5	-0.39976	-0.74957
Q23	4.225806	0.804557	2	5	-0.85605	0.395144
Q24	4.16129	0.860108	2	5	-0.66465	-0.41037
Q25	3.967742	1.079626	1	5	-0.95182	0.46489
Q26	3.677419	0.83215	2	5	-0.4239	-0.1109
Q27	3.645161	1.081616	2	5	-0.23242	-1.17455
Q28	3.806452	0.833441	2	5	-0.34931	-0.2126
Q29	3.806452	0.792437	2	5	-0.91918	0.989931

Most items have negative skewness, ranging from -0.20 to -1.22, which means that responses are skewed to the left, or more participants selected higher values (e.g., "Agree", "Strongly Agree"). Q8 has the highest negative skew (-1.22), indicating that most respondents selected the top end of the scale. Q18 has a skewness of 0, showing a perfectly symmetrical distribution of responses. Moreover, Kurtosis values mostly fall below 0, suggesting flatter distributions with less peakedness (platykurtic). The most platykurtic items include Q18 (-1.29) and Q27 (-1.17), showing wide variability and less concentration around the mean. Q4 (1.77) and Q29 (0.99) have positive kurtosis, indicating more peaked responses, or higher consistency near the average.

Overall questions like Q1, Q4, Q5, Q8, Q12, and Q14 stand out for their high means, low standard deviations, and strong negative skew, meaning participants responded positively and consistently. In contrast, items like Q25-Q29 likely addressing concerns or challenges have lower means, higher standard deviations, and less peaked or more variable distributions, indicating mixed perceptions or individual differences in user concerns. Generally, the statistical trends suggest that participants were mostly satisfied with their experiences and attitudes toward AI-based tutoring tools, though they held more diverse views on potential challenges or limitations.

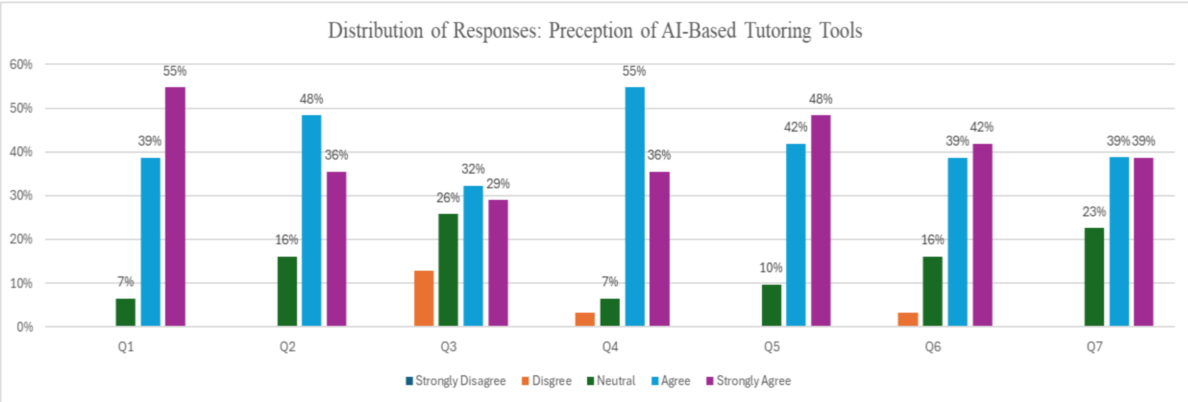

Figure 1: Distribution of Responses for Research Objective 1

~~The~~ Figure 1 displays responses to eight questions (Q1–Q7). The responses are categorized into five levels: *Strongly Disagree*, *Disagree*, *Neutral*, *Agree*, and *Strongly Agree*. Overall, the responses indicate a generally positive perception of AI-based tutoring tools among participants, with varying degrees of agreement. For instance, questions Q4 and Q5 showed particularly strong support, with 55% and 48% of respondents, respectively, strongly agreeing with the statements. This suggests that respondents believe in the usefulness or effectiveness of these tools. Similarly, Q6 and Q7 reflected a balanced but favorable perception, with both questions receiving around 39-42% in agreement or strong agreement.

In contrast, Q2 and Q3 showed more mixed perceptions. While Q2 had a substantial 48% agreement, the remaining responses were spread out, indicating some uncertainty. Q3 showed the most balanced distribution, with noticeable percentages in the neutral and disagree categories. This suggests that certain features or expectations of AI-based tutoring tools may still be unclear or under question among some users. Taken together, these results reflect an overall positive perception of AI tools among students, addressing the core concern of the first research objective.

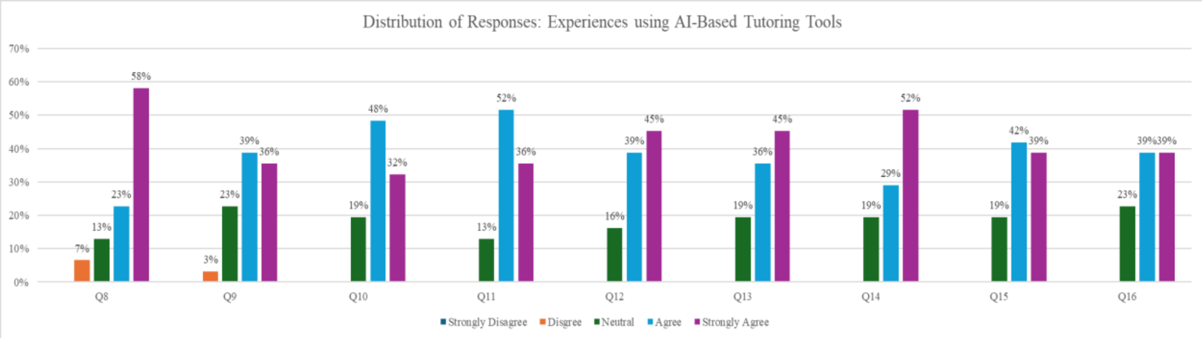

Figure 2: Response for Research Objective 2

~~The~~ Figure 2 refers to the objective 2, evaluates the actual experiences of users across questions Q8 to Q16. Most responses to questions Q8 through Q16 fall under the “Agree” and “Strongly Agree” categories, with Q8 and Q14 notably receiving 58% and 52% “Strongly Agree” responses, respectively. These figures suggest that users found the tools effective, user-friendly, and beneficial to their learning. Minimal disagreement across all questions indicates that negative experiences were rare.

While questions like Q15 and Q16 show a slightly more balanced distribution between “Agree” and “Strongly Agree,” the overall feedback remains favorable. The consistency of positive responses demonstrates high satisfaction and highlights the reliability and usefulness of AI-based tutoring tools in education. This reinforces the idea that such tools can significantly enhance learning experiences when implemented thoughtfully. These findings provide strong evidence that AI-based tutoring tools effectively support students’ understanding and learning outcomes, aligning closely with the aims of the second research objective.

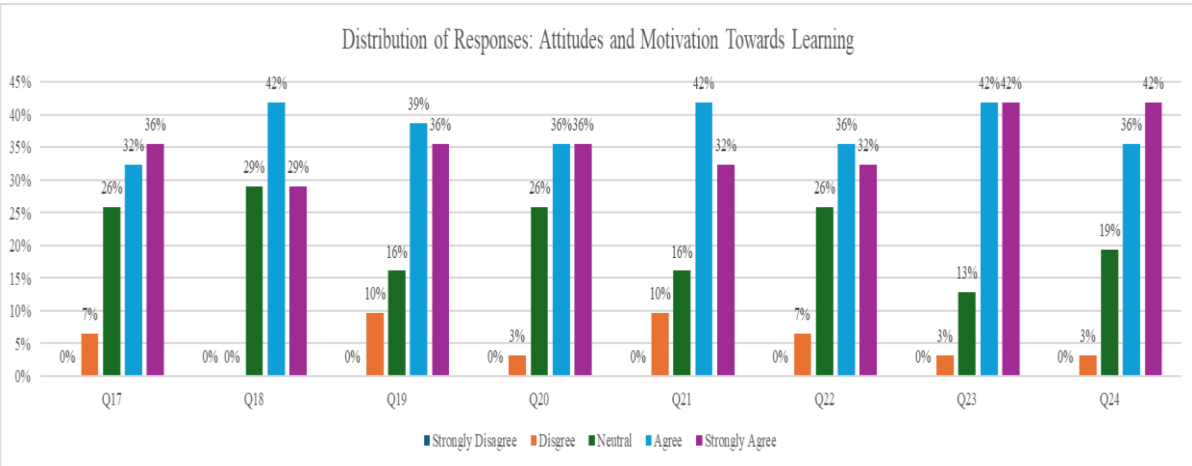

Figure 3: Response for Research Objective 3

Figure 3 presents data from questions Q17 to Q24, assessing how AI-based tools influence students’ learning attitudes and motivation. The responses show a predominantly positive trend, with a significant number of participants agreeing or strongly agreeing with the statements. For example, Q18 and Q21 both saw 42% of respondents agreeing, indicating that AI tools may enhance student engagement and learning behavior. Similarly, Q23 and Q24 reflected very strong approval, with both questions receiving 42% agreement and Q24 having an additional 36% who strongly agreed—demonstrating that most respondents felt motivated and positively influenced by AI integration in their educational experience. Neutral responses were moderate across questions, such as in Q17 (26%) and Q20 (28%), suggesting that while a portion of participants remained indifferent, the dominant sentiment leaned toward support. Notably, there were almost no “Strongly Disagree” responses in this section, reflecting the overwhelmingly optimistic attitude students have toward AI-enhanced learning environments. These findings indicate that AI tools have a positive impact on students’ attitudes and motivation, fulfilling the third research objective.

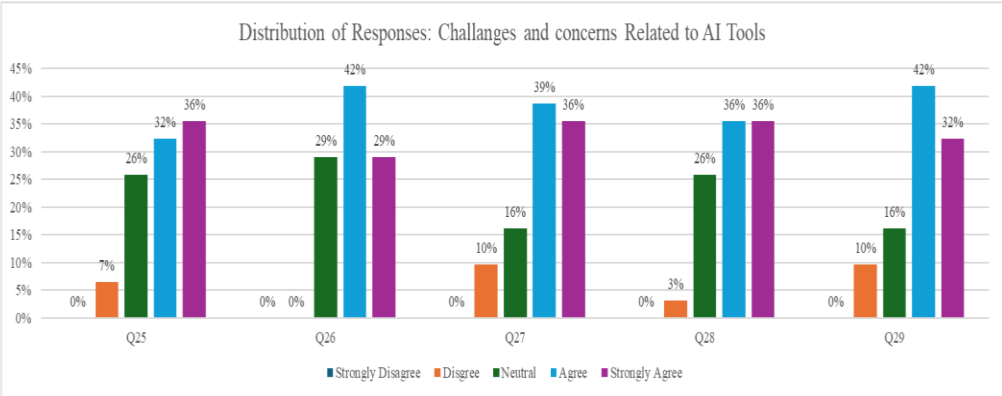

Figure 4: Response for Research Objective 4

The Figure 4 explores user concerns with questions Q25 through Q29. Although responses remained generally favorable, this section reveals a more mixed perspective, acknowledging the existence of practical or ethical issues with AI tools. For instance, Q26 showed the highest level of agreement at 42%, but also had a notable 29% neutral and 29% strong agreement, indicating that users recognize both the benefits and potential difficulties associated with AI use. Questions like Q25 and Q27 also displayed a relatively balanced distribution of responses, with Q27 receiving 39% agreement and 36% strong agreement, though 16% of respondents remained neutral and 10% disagreed highlighting that concerns such as data privacy, bias, or system limitations are still prevalent among users. Additionally, Q29 displayed a strong agreement rate of 42% and agreement rate of 32%, affirming that while challenges are acknowledged, the majority still support AI tools in education despite those concerns. These findings directly support forth research objective by revealing that while students are receptive to AI technologies, they also express legitimate concerns that must be addressed to ensure ethical and sustainable implementation in academic settings.

Collectively, the data from all four charts suggest that while initial perceptions of AI-based tutoring tools are generally positive, users’ actual experiences tend to be even more favorable once they engage with the tools. This shift indicates that any initial scepticism is often replaced with appreciation after hands-on use, emphasizing the importance of exposure in shaping attitudes toward AI in education. Students demonstrate strong motivation and a positive outlook regarding the integration of AI into their learning processes. However, they also express valid concerns, particularly regarding challenges and limitations associated with AI tools. These insights underscore the need for thoughtful and ethical implementation, proper user training, and continuous evaluation to ensure that the potential of AI in education is fully realized while minimizing risks. If addressed effectively, AI tutoring tools can play a transformative role in enhancing the quality and accessibility of modern education.

Correlation Matrix

Four correlation heatmaps are shown in figure 4, each of which represents a distinct research goal pertaining to AI-based teaching tools, including perceptions, experiences, attitudes and motivation, and challenges and concerns.

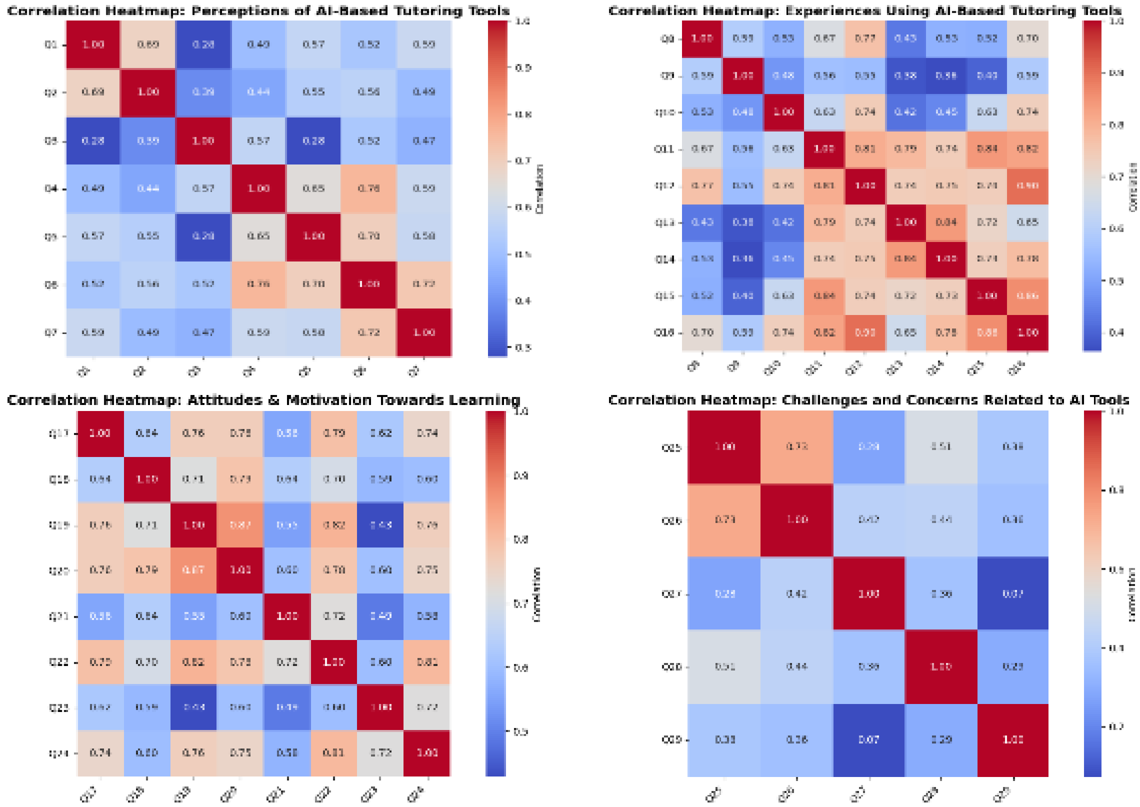

Figure 5: Correlation Heatmap for Research Objectives

In the Perceptions of AI-Based Tutoring Tools heatmap (top-left), the correlations among survey questions are generally moderate to strong, such as between Q4 and Q6 (0.76) and Q5 and Q6 (0.70), indicating that participants' views on the usefulness, reliability, and integration of AI tools are aligned. Similarly, the Experiences Using AI-Based Tutoring Tools heatmap (top-right) shows strong inter-item correlations (e.g., Q13 and Q14 = 0.84, Q15 and Q16 = 0.86), reflecting a coherent pattern in how respondents evaluate their direct interactions and satisfaction with these tools.

In contrast, the Attitudes & Motivation Towards Learning heatmap (bottom-left) exhibits some of the strongest correlations overall, especially between Q19 and Q20 (0.87) and Q20 and Q21 (0.86), suggesting a tightly connected set of beliefs and motivations related to learning with AI. This indicates that positive attitudes towards AI in education strongly align with students' motivational states. However, the Challenges and Concerns Related to AI Tools heatmap (bottom-right) reveals weaker and more scattered relationships (e.g., Q27-Q29 = 0.07), suggesting that concerns about AI vary more widely and are less consistently perceived among participants. Overall, the visualizations demonstrate strong internal consistency within most constructs, particularly attitudes and experiences, while concerns appear more individualized and less correlated.

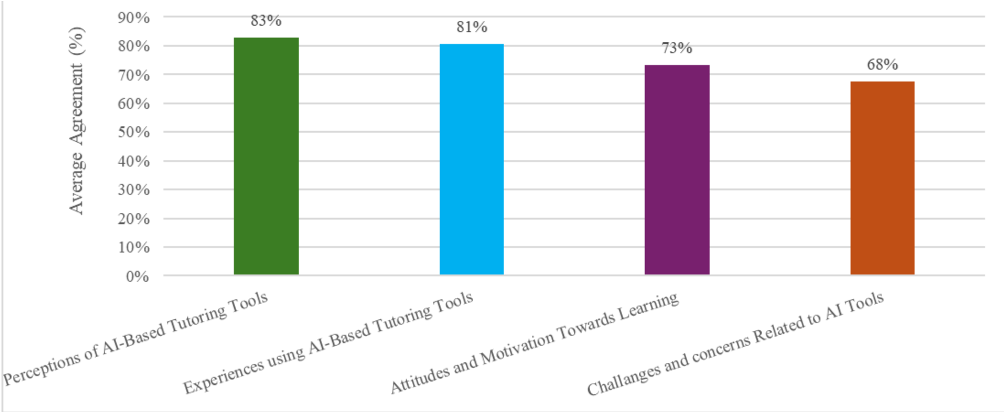

Figure 6: Comparison of Agreement across Research Objectives

The bar chart illustrates the level of agreement among participants across four research objectives related to AI-based tutoring tools. The highest agreement (83%) was observed in participants’ perceptions of these tools, followed closely by their actual experiences using them (81%), indicating a generally positive outlook and satisfaction. Attitudes and motivation towards learning also showed strong support at 73%, suggesting AI tools contribute positively to learners' engagement. However, agreement dropped to 68% regarding challenges and concerns, highlighting that while the overall response is favorable, some users do acknowledge potential issues or limitations with AI tools.

Conclusion

This study found that AI-based tutoring tools positively influence student learning in data analytics courses, with strong agreement on their usability, relevance, and support for deeper understanding. High mean scores across perception, learning effectiveness, and motivation indicate that students generally found the AI tutors helpful, engaging, and aligned with course objectives. Correlation analysis further confirmed consistent attitudes toward learning enhancement, particularly in motivation and conceptual clarity. However, challenges related to overreliance, occasional misinformation, and concerns about transparency and academic integrity were also acknowledged, showing that student concerns remain nuanced and valid. Based on these findings, educationalists should consider integrating AI tutoring systems as complementary tools that enhance engagement and understanding, especially in technical subjects. However, such integration must be accompanied by clear pedagogical frameworks that promote critical thinking and mitigate overdependence. Additionally, developers and institutions must prioritize transparency, data privacy, and ethical safeguards to ensure equitable and responsible use of AI in education. Future research should explore longitudinal impacts of AI tools and expand to diverse student populations to build on these insights.

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