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The Impact of Chatbot Type and Student Motivation on Academic Efficiency in Educational Technology

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Abstract

This study investigates how student motivation (high vs. low) and chatbot type (rule-based vs. deep learning-based) affect academic performance among students enrolled in educational technology programs. Knowing how well various chatbot technologies work is essential given the growing use of AI in education. As conversational agents, chatbots improve the learning process by offering real-time feedback, tailored assistance, and ongoing interaction. The study assesses deep learning-based chatbots, which use sophisticated machine learning algorithms for more adaptive interactions, and rule-based chatbots, which operate using predetermined rules and structured scripts. Furthermore, as a moderating element in chatbot efficacy, student motivation—a crucial determinant of academic success—is investigated. Surveys and performance evaluations of students enrolled in educational technology programs were used to gather data. The association between chatbot type, student motivation, and academic effectiveness was examined using statistical techniques such as regression analysis and ANOVA. Results show that, especially for highly driven students, deep learning-based chatbots considerably increase academic efficiency when compared to rule-based chatbots. The relationship between motivation and chatbot type implies that AI-powered tailored learning strategies can better meet the needs of a wide range of students. For educators, instructional designers, and legislators looking to use AI technologies to enhance education, these findings have important ramifications. Future studies should investigate other factors that affect chatbot efficacy and provide customized approaches for diverse learning environments.

Keywords: *Chatbots, Student Motivation, Academic Efficiency, Educational Technology, Artificial Intelligence.*

Introduction

Traditional teaching strategies have changed as a result of artificial intelligence's (AI) quick development and incorporation into classrooms, which has an impact on academic performance and student engagement. Because they provide individualized support, interactive learning opportunities, and real-time assistance, chatbots—a subset of AI-driven tools—have become increasingly popular in the educational field. By offering prompt answers to questions, automating administrative duties, and creating an engaging learning environment, chatbot technology is being implemented in educational institutions with the goal of improving student learning results (Deng & Yu, 2023). Analyzing how well various chatbot models promote academic efficiency is crucial given the rising need for AI-driven solutions in education.

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Rule-based and deep learning-based chatbots are the two main types of chatbots used in education. Rule-based chatbots are limited in their ability to react to a wide range of student inquiries since they follow pre-established rules and follow prescribed scripts. Deep learning-based chatbots, on the other hand, use sophisticated machine learning algorithms to facilitate dynamic and adaptable interactions, providing individualized learning experiences according to students' requirements and learning styles (Hwang & Chang, 2023). To maximize their use in educational contexts, it is essential to comprehend how chatbot type affects student performance and engagement in light of these technological variations.

Academic success is significantly influenced by student motivation in addition to technological considerations. Students' use of learning resources and educational technologies is influenced by their motivation, whether it be internal or external. While less motivated students might need more specialized interventions to maintain engagement, highly driven students are more likely to look for extra learning materials and actively participate in digital learning settings (Wollny et al., 2021). Thus, in the context of academic efficiency, the relationship between chatbot type and student motivation offers a crucial topic of investigation.

Empirical study is required to assess the efficacy of AI-powered educational technologies in a variety of learning situations due to the growing reliance on them. The purpose of this study is to examine how student motivation levels (high vs. low) and chatbot types (rule-based vs. deep learning-based) affect academic efficiency. This study aims to ascertain if AI-driven tailored interactions enhance learning outcomes by examining engagement measures and student performance data. The study will also investigate how chatbots may be used to meet the various needs of students and improve their general academic performance.

For educators, instructional designers, and legislators looking to maximize the use of AI in education, knowing how chatbot technology and student motivation interact can be quite insightful. The results of this study will aid in the creation of customized chatbot tactics that improve educational opportunities and promote academic achievement in online learning settings. Additionally, this work will pave the way for further research that will concentrate on improving AI-powered learning resources to optimize their efficacy in a range of academic settings.

Motivation

Using chatbots has become a viable way to improve learning outcomes and experiences in the field of educational technology. However, a number of issues surface as researchers and educators examine chatbot integration in educational settings in greater detail, necessitating more study and research.

The usefulness of chatbot interventions for enhancing student learning is one major obstacle. It's critical to comprehend how different chatbot types—such as rule-based and deep learning-based systems—affect student engagement and academic achievement. While deep learning-based chatbots use sophisticated algorithms to provide adaptive and contextually relevant responses, rule-based chatbots provide structured interactions based on predetermined rules. Making educated decisions in educational settings requires knowing which kind of chatbot produces superior learning outcomes and under what circumstances.

Furthermore, students' motivation levels have a significant impact on how they engage with chatbots and other educational tools. Students that are motivated are more likely to actively interact with the course materials, look for extra help, and persevere through difficulties. On the other hand, children that lack motivation might need more encouragement and rewards in order to stay involved and succeed academically. Designing individualized and captivating learning experiences can be greatly aided by knowing how student motivation affects the efficacy of chatbot interventions.

Therefore, the desire to answer these important questions is what motivates this study: What effects do various kinds of chatbots have on academic achievement and student engagement? How does the effectiveness of chatbot treatments get mediated by student motivation? How can teachers use motivational theory and chatbot technology insights to create more interesting and successful learning environments?

By examining these issues, the study hopes to add to the current discussion about the use of chatbots in classrooms and offer useful information to educators, instructional designers, and legislators. The ultimate objective is to utilize chatbot technology' ability to assist and improve student learning in a variety of educational settings.

Contributions

1. Creation of Diverse Chatbot Types: This work makes a contribution by putting two different chatbot types—rule-based and deep learning-based—into practice and contrasting them. The study clarifies the efficacy of these various chatbot types in educational settings by analyzing their effects on academic productivity.

2. Examining Motivation Levels: The study explores how motivation influences how successful chatbot interventions are. The study investigates how different motivation levels impact interactions with chatbot technology and subsequent academic outcomes by dividing individuals into groups based on their level of motivation.

3. Quantification of Academic Efficiency: By analyzing academic performance variables including grades, completion rates, and engagement levels, this work makes a substantial contribution to the quantification of academic efficiency. By quantifying academic efficiency objectively, the study offers important insights into how chatbot interventions affect student learning results.

4. Comparison of Chatbot Effects: The study finds possible variations in the efficacy of rule-based and deep learning-based chatbots by contrasting their effects on academic efficiency. Our comprehension of the relative benefits and drawbacks of each type of chatbot in educational settings is improved by this comparison.

5. Investigation of Interaction Dynamics: Taking into account variables like engagement, contentment, and perceived utility, the study investigates the dynamics of interactions between students and chatbots. The study clarifies how chatbot functionality and design affect user experience and academic results by examining these interaction dynamics.

6. Integration of Motivational Theory and Educational Technology: To guide the development and analysis of chatbot treatments, this study combines theoretical frameworks from motivational psychology and educational technology. The study provides a thorough grasp of the intricate relationship between chatbot usage, motivation, and academic efficiency by integrating insights from several fields.

7. Useful Consequences for Teaching Practice: All things considered, this study offers useful advice to teachers and educational technologists who want to use chatbots in classrooms.

The study provides practical suggestions for improving chatbot interventions' design and implementation to improve student learning experiences and academic results by identifying the variables that affect their efficacy.

Research Gap

There are still unanswered questions about how chatbot type impacts academic efficiency, particularly when taking student motivation into account, despite the increased interest in using artificial intelligence into education. Prior research has concentrated on the application of chatbots in the classroom, but it has frequently analyzed their general efficacy without making a distinction between models that are rule-based and those that are deep learning-based. Furthermore, as an interactive element that might affect students' ability to profit from new educational tools, student motivation has not gotten enough attention.

Currently, there is a lack of comprehensive research on the relationship between chatbot type and student motivation level and academic efficiency when learning programming, which restricts the ability of educational institutions to choose and deploy the best technology to support their students. Additionally, the majority of prior research has concentrated on the direct technological effects of chatbots, ignoring the psychological and behavioral aspects of students, which are critical in improving the digital learning experience.

By investigating the connection between chatbot type, student motivation, and their effect on academic efficiency, this study seeks to close this gap. By examining these variables, the study will offer insightful information that will assist educational establishments in implementing chatbots in more efficient ways, increasing student engagement and raising academic achievement.

Literature Review and Hypothesis Development

Chatbots and Their Types

A key artificial intelligence-driven tool in contemporary education, chatbots provide pupils with quick, interactive assistance. By simulating human-like interactions, they serve as conversational agents that respond to user input. Rule-based and deep learning-based chatbots are the two main categories of chatbots, and they vary in terms of their usefulness, versatility, and efficiency in learning environments.

Rule-Based Chatbots

Rule-based chatbots use structured decision trees and prewritten scripts to produce responses based on preprogrammed rules. Because of their deterministic methodology, these chatbots are limited to responding to requests that match their preprogrammed database. As stated by (Han, Park, & Lee, 2022), Rule-based chatbots work well for routine chores and commonly asked queries, like offering course schedules, responding to administrative issues, and helping with common academic subjects. However, when handling intricate or unstructured inquiries that are outside of their predetermined scope, their limited flexibility presents difficulties.

Personalized learning experiences are limited by the rigidity of rule-based chatbots, despite their widespread use due to their affordability and ease of use. These chatbots might not be enough to improve students' academic engagement and efficiency if they are looking for detailed explanations or a variety of approaches to problem-solving.

Deep Learning-Based Chatbots

Deep learning-based chatbots allow for dynamic and context-aware interactions by utilizing sophisticated machine learning techniques, especially neural networks and natural language processing (NLP). Large datasets may be analyzed by these chatbots, which can also comprehend complex requests and offer tailored answers based on past exchanges (Ait Baha, El Hajji, Es-Saady, & Fadili, 2024). Deep learning-based models, as opposed to rule-based chatbots, are constantly enhanced through data-driven learning, which enables them to accommodate various learning preferences and offer pupils individualized support.

According to research, chatbots using deep learning improve academic performance by enabling engaging conversations, providing immediate feedback, and helping students with problem-solving situations (Kooli, 2023). They are especially helpful in subjects like programming and mathematics that call for critical thinking and conceptual knowledge because of their capacity to comprehend and analyze complex questions.

Hypothesis Development

The effects of rule-based and deep learning-based chatbots on academic efficiency may differ greatly due to their different capacities. Deep learning-based chatbots offer a more dynamic and flexible learning environment than rule-based chatbots, which deliver more structured and consistent responses. Student motivation levels also affect how effective these chatbots are, since highly motivated students might gain more from sophisticated AI-driven exchanges.

The following theories are put out in light of these factors:

- **H1**: Deep learning-based chatbots have a greater positive impact on academic efficiency compared to rule-based chatbots.
- **H2**: The effectiveness of deep learning-based chatbots is moderated by student motivation levels, with highly motivated students benefiting more from personalized chatbot interactions.

By investigating these theories, the study hopes to offer empirical understanding of chatbots' function in education as well as recommendations for educational institutions looking to maximize AI-powered learning resources.

Student Motivation in Acquiring Programming Skills

Academic success is greatly influenced by student motivation, especially in challenging courses like programming. The degree to which students employ problem-solving techniques, persevere through difficulties, and interact with learning resources in order to grasp programming principles is determined by their motivation. According to (Okonkwo & Ade-Ibijola, 2021), extrinsic motivation, which is fueled by outside incentives like grades, recognition, or job possibilities, and intrinsic motivation, which originates from internal fulfillment and desire in learning, are the two primary categories of motivation. The degree of motivation has a big impact on how well students learn and how well they understand and use programming concepts.

High Motivation and Programming Skill Acquisition

High-motivation students aggressively seek out new learning materials, show persistence in the face of coding difficulties, and participate more actively in programming assignments. According to (C.-Y. Chang, Kuo, & Hwang, 2022), Students that are genuinely driven are more likely to view programming as a problem-solving exercise that encourages originality, creativity, and logical reasoning. Students that are highly motivated are more likely to try out various coding techniques, engage in cooperative coding communities, and keep trying to fix mistakes until they get the desired result. According to research, motivated students not only do better in programming classes but also acquire long-term computational thinking abilities that help them succeed academically and professionally (Dan et al., 2023).

Furthermore, learning programming skills involves outside incentive as well. Students are more likely to remain dedicated to studying even in the face of challenges if they believe that programming is necessary for their future employment or careers (D. H. Chang, Lin, Hajian, & Wang, 2023). The existence of incentives like hackathons, certification programs, and competitive coding platforms serves to further boost their motivation and promote ongoing skill improvement.

Low Motivation and Its Impact on Programming Learning

Conversely, low-motivation students frequently find programming difficult because they lack confidence, interest, or a sense of the subject's importance. These kids may become disengaged and perform poorly academically if they find programming abstract, difficult, or aggravating. Bandura's self-efficacy hypothesis (1997) states that when given programming tasks, students who lack motivation often feel anxious and self-conscious, which might make it difficult for them to try new things and learn.

Additionally, students who lack motivation are more likely to avoid difficult coding tasks, rely on surface-level learning tactics, and participate in less active problem-solving. This leads to a poorer foundation in computational thinking and limited skill acquisition (Labadze, Grigolia, & Machaidze, 2023). Low-motivation students may struggle to acquire critical programming skills without the right intervention techniques, such as individualized tutoring or adaptive learning environments, which could harm their academic and professional prospects.

Hypothesis Development

Examining the effects of varying motivation levels on students' learning results is crucial given the crucial role that motivation plays in programming education. Low-motivated students can need more help to succeed, whereas highly motivated students should demonstrate more perseverance and programming idea knowledge.

Based on this understanding, the following hypotheses are proposed:

- **H1**: High student motivation has a positive impact on programming skill acquisition, leading to better academic performance and problem-solving abilities.
- **H2**: Low student motivation negatively affects programming skill acquisition, resulting in lower engagement, weaker computational thinking, and reduced academic achievement.
- **H3**: The effectiveness of chatbot-assisted learning varies based on student motivation levels, where highly motivated students benefit more from interactive and adaptive chatbot-based learning environments.

By putting these theories to the test, this research hopes to provide light on how motivation levels affect programming instruction and how specialized teaching strategies, like chatbots powered by artificial intelligence, can improve student engagement and skill development.

Programming Skill Acquisition Using Java with Rule-Based and Deep Learning-Based Chatbots

A key component of computer science education is learning to program, which calls for both theoretical understanding and real-world application. Java is a popular programming language that is frequently used in academic programs because of its object-oriented design, organized grammar, and industry applicability (Papakostas, Troussas, Krouska, & Sgouropoulou, 2024). Students may find it difficult to learn Java, though, therefore cutting-edge teaching resources like chatbots are needed to offer individualized instruction and interactive help with problems. A promising strategy to improve student engagement and speed up skill learning is the incorporation of chatbots into programming instruction (Ouali & Garouani, 2024).

Rule-based and deep learning-based chatbots are the two main categories of chatbots used in programming education. Rule-based chatbots are useful for answering frequently asked programming questions and assisting students with step-by-step coding tasks since they use prewritten scripts and structured responses (Szikszó, 2024). Deep learning-based chatbots, on the other hand, use artificial intelligence and natural language processing to provide adaptive responses that provide dynamic feedback and tailored support according to the student's progress and unique difficulties (McTear, 2022).

Rule-Based Chatbots for Java Programming

Rule-based chatbots use decision trees and structured logic to respond to pre-programmed queries. These chatbots adhere to a rigid set of guidelines and consistently respond to regularly requested programming questions, including those about grammar, fundamental debugging techniques, and typical Java mistakes (Papakostas et al., 2024). Rule-based chatbots are very helpful for novice programmers who want an organized and transparent learning process because of their predictable nature.

Rule-based chatbots' dependability in providing precise and consistent information is one of its main benefits (Farah et al., 2023). They are not, however, able to handle complicated or unclear requests that are outside the purview of their programming. Rule-based chatbots may therefore not be enough for students who need more complex explanations or context-specific debugging help to develop their Java programming abilities (Nacheva & Hristova, 2024).

Deep Learning-Based Chatbots for Java Programming

Machine learning algorithms are used by deep learning-based chatbots to evaluate student input and produce flexible responses. These chatbots are much more useful for advanced programming instruction than rule-based ones because they can identify patterns in student interactions and offer contextualized feedback (Güldal & Dinçer, 2024). By analyzing a student's coding mistakes, suggesting different approaches, and accommodating different learning preferences, they provide individualized teaching.

According to (Diaz et al., 2022), Chatbots with deep learning capabilities improve programming instruction by creating a more dynamic and exploratory learning environment. Pupils can ask questions in plain language, participate in open-ended discussions, and get explanations that change according to their prior errors and ability level. Students' capacity to debug code, optimize algorithms, and get a deeper comprehension of Java programming fundamentals is greatly enhanced by this flexibility (Maher, Bhable, Lahase, & Nimbhore, 2022).

Deep learning-based chatbots, in spite of their benefits, need a lot of training data and processing power to work well. Furthermore, their answers can occasionally be erratic or excessively complicated, which could be too much for inexperienced programmers to handle (Alazzam, Alkhatib, & Shaalan, 2023).

Hypothesis Development

Examining how various chatbot kinds affect the acquisition of Java programming skills is crucial given the importance that chatbots play in programming education. Deep learning-based chatbots offer individualized and dynamic learning experiences, whereas rule-based chatbots provide organized and trustworthy assistance.

Accordingly, the following hypotheses are proposed:

- **H1**: Students using deep learning-based chatbots demonstrate higher proficiency in Java programming compared to those using rule-based chatbots, due to the adaptive and contextualized support provided.
- **H2**: Rule-based chatbots are more effective for beginner programmers learning Java, as they offer structured and straightforward explanations.
- **H3**: The effectiveness of chatbot-assisted Java programming learning varies based on student motivation levels, with highly motivated students benefiting more from deep learning-based chatbots.

By putting these theories to the test, this research hopes to shed light on how well chatbot-assisted learning works for Java programming and guide the creation of AI-powered teaching resources that improve student learning results.

Academic Self-Efficacy in Educational Technology Students When Acquiring Programming Skills

Students' learning habits, tenacity, and general academic success are significantly influenced by their level of academic self-efficacy. It describes a person's confidence in their capacity to complete particular academic assignments, especially in difficult topics like programming (Taşdöndüren & Korucu, 2022). Students' motivation, engagement, and approaches to problem-solving are influenced by their academic self-efficacy in the field of educational technology, where programming abilities are becoming more and more crucial (Tsai et al., 2024). While lower self-efficacy can lead to avoidance behaviors and poorer academic performance, higher self-efficacy boosts confidence when addressing programming obstacles (Kovari & Katona, 2023).

The Impact of High Academic Self-Efficacy on Programming Skill Acquisition

Pupils that have high levels of academic self-efficacy typically approach programming with optimism, seeing challenges as chances for personal development rather than as roadblocks (Kovari & Katona, 2023). They are more likely to use active learning techniques like coding experiments, continuous mistake debugging, and looking for more learning materials to improve their abilities (Elbourhamy, Najmi, & Elfeky, 2023; Fu et al., 2023). For instance, students who have a high level of self-efficacy are more likely to practice tackling challenging coding problems, compete in coding contests, and work with peers to solve challenges when programming in Java.

According to research, students' capacity to successfully retain and apply programming principles is directly correlated with their level of academic self-efficacy (Elfeky, Najmi, & Elbyaly, 2023; Jamjoom, Alabdulkreem, Hadjouni, Karim, & Qarh, 2021). Additionally, students who have high levels of self-efficacy are more inclined to use educational resources, including chatbot-assisted learning environments, to solidify their grasp of programming concepts (Chinchua, Kantathanawat, & Tuntiwongwanich, 2022; Elfeky, Najmi, & Elbyaly, 2024). Their long-term success in programming-related courses and future professions is influenced by their capacity to persevere through coding exercises and apply logical problem-solving techniques (Wei, Lin, Meng, Tan, & Kong, 2021).

The Impact of Low Academic Self-Efficacy on Learning Programming

Conversely, when faced with programming difficulties, students who have low academic self-efficacy may feel anxious and frustrated (Kovari & Katona, 2023). They might think that programming is too complicated and above their level of expertise, which would make them disengaged, shy away from challenging assignments, and rely more on flimsy learning techniques (Arslan & Tanel, 2021). These pupils could find it difficult to troubleshoot issues, be reluctant to try out various coding techniques, and lack the courage to ask for assistance or work with classmates.

Research shows that students who have weaker academic self-efficacy benefit from structured support systems, like rule-based chatbots that assist learning or deep learning-based chatbots that provide adaptive feedback (O'Connor & Mahony, 2023). Giving them opportunities for incremental success and scaffolded learning experiences might help them become more confident and motivated to continue taking programming classes (Karaoglan Yilmaz, 2022).

Developing Hypotheses

Examining how different levels of self-efficacy affect students' learning experiences and performance outcomes is crucial given the crucial role that academic self-efficacy plays in programming education. The following theories are put forth:

- **H1**: High academic self-efficacy positively influences programming skill acquisition, leading to improved problem-solving abilities and higher academic performance.
- **H2**: Low academic self-efficacy negatively impacts students' programming learning experience, resulting in reduced engagement, lower confidence, and weaker coding proficiency.
- **H3**: The effectiveness of chatbot-assisted learning in programming varies based on students' academic self-efficacy levels, with high self-efficacy students benefiting more from deep-learning-based chatbots, while low self-efficacy students may require additional structured support through rule-based chatbots.

This study intends to provide light on the relationship between academic self-efficacy and programming instruction in the field of educational technology by testing these assumptions. By comprehending these connections, educational institutions can create focused treatments, such self-efficacy-boosting techniques and adaptable learning environments, to help students become proficient programmers.

Methodology

Measurement Scales

This study utilizes three primary measurement tools: **the Motivation Scale, the Academic Efficiency Scale, and the Programming Skills Checklist**.

1. **Motivation Scale**: This scale consists of **33 academic scenarios** distributed across **six key dimensions**, namely:

- **Self-regulated Learning Beliefs**
- **Academic Achievement Beliefs**
- **Achievement Motivation Beliefs**
- **Perceived Competence**
- **Generalized Competence**
- **Competence Strength**

The scale is used to classify students into **high motivation** and **low motivation** groups.

2. **Academic Efficiency Scale**: Measures students' perceived competence in academic tasks related to **educational technology**.

3. **Programming Skills Checklist**: Comprising **31 sub-skills** grouped into **six major programming competencies** in **Java**, this checklist assesses students' programming proficiency.

The measurement instruments were adapted from previous research to ensure **validity and reliability**. A **pilot test with 30 students** was conducted, followed by expert reviews to refine the tools. The questionnaire was initially designed in **English** and later translated into the local language to ensure precise comprehension by participants.

The final questionnaire consists of two sections:

- **Section A**: Demographic information.
- **Section B**: Items measuring motivation, academic efficiency, and Java programming skills.

Sampling Method and Data Collection

A **non-probability purposive sampling technique** was employed to select participants based on their **motivation level** and **exposure to different chatbot types (rule-based vs. deep learning-based)**.

The sample consisted of **64 first-year students** from the **Department of Educational Technology and Computer Science** at the **Faculty of Specific Education, Kafr El-Sheikh University, Egypt**. The participants were divided into **four experimental groups**, each comprising **16 students**:

- **Group 1**: High motivation + Rule-based chatbot

- **Group 2**: High motivation + Deep learning-based chatbot
- **Group 3**: Low motivation + Rule-based chatbot
- **Group 4**: Low motivation + Deep learning-based chatbot

Experimental Procedure

The **experimental phase** took place over a period from **September to November 2023**, where students interacted with the assigned chatbot type while working on Java programming tasks.

A **preliminary session** was conducted for each experimental group separately in a **computer lab** at the Department of Educational Technology, Faculty of Specific Education, Kafr El-Sheikh University. During this session:

- The study objectives were explained to the students.
- Students were encouraged to actively engage in the learning process.
- A **pre-test** using the **Programming Skills Observation Checklist** was administered to assess the students' initial programming competence and ensure group equivalence before the experiment.

A **one-way ANOVA** was performed to analyze pre-test scores and confirm that there were **no significant differences** between the groups before the intervention.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.625	7	.232	.166	.991
Within Groups	78.375	56	1.400		
Total	80.000	63			

Table 1. ANOVA

- The previous table indicates that there are no significant differences among the four experimental groups in academic competency scores, as the F-value for academic competency was (1.66), which is not significant at the (0.05) level.
- Based on the above, the results suggest that the four experimental groups were equivalent before conducting the experiment. Therefore, any differences observed after the experiment can be attributed to variations in the independent variables of the study.

Data Processing and Statistical Analysis

To test the research hypotheses, a **two-way ANOVA** was used to measure the differences between the levels of the first independent variable (chatbot type: rule-based vs. deep learning-based) and the second independent variable (student motivation level: high vs. low) in terms of academic competency in educational technology programs. Additionally, the interaction effect between the chatbot type and student motivation level on academic competency was examined. The following table presents the results of the two-way ANOVA analysis regarding academic competency.

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.

Corrected Model	7628.297[a]	3	2542.766	154.919	.000
Intercept	1198203.891	1	1198203.891	73000.935	.000
student_motivation * chat_bot_tybe	2743.141	1	2743.141	167.127	.000
student_motivation	2036.266	1	2036.266	124.060	.000
chat_bot_tybe	2848.891	1	2848.891	173.570	.000
Error	984.813	60	16.414		
Total	1206817.000	64			
Corrected Total	8613.109	63			
a. R Squared = .886 (Adjusted R Squared = .880)					

Table 2. Tests of Between-Subjects Effects

Research Question 1:

What is the effect of chatbot type (rule-based vs. deep learning-based) on the academic competency of students in educational technology programs?

To answer this question, the following hypothesis was tested: **Hypothesis 1:** There is a statistically significant difference at the (0.05) level between the mean academic competency scores of students due to the main effect of chatbot type (rule-based vs. deep learning-based), in favor of the deep learning-based chatbot.

Referring to the previous table, a statistically significant difference is observed between the chatbot types, as the F-value is (173.570), which is significant at the (0.05) level. This indicates that the difference in academic competency scores is attributable to the variation in chatbot type, favoring the deep learning-based chatbot.

	chat_bot_tybe	N	Mean	Std. Deviation	Std. Error Mean
grade	rule-based	32	130.1563	3.36116	.59417
	deep learning-based	32	143.5000	13.21534	2.33616

Table 3. Chatbot Type and Academic Competency

Research Question 2:

What is the effect of student motivation level (high vs. low) on the academic competency of students in educational technology programs?

To answer this question, the following hypothesis was tested: **Hypothesis 2:** There is a statistically significant difference at the (0.05) level between the mean academic competency scores of students due to the main effect of student motivation level (high vs. low), in favor of high motivation.

Referring to the previous table, a statistically significant difference is observed between motivation levels, as the F-value is (124.060), which is significant at the (0.05) level. This indicates that the difference in academic competency scores is attributable to student motivation level, favoring high motivation.

	student_motivation	N	Mean	Std. Deviation	Std. Error Mean
grade	high	32	142.4688	14.16717	2.50443
	low	32	131.1875	3.38343	.59811

Table 4. Student Motivation Level and Academic Competency

Research Question 3:

What is the effect of chatbot type (rule-based vs. deep learning-based) and student motivation level (high vs. low) on the academic competency of students in educational technology programs?

To answer this question, the following hypothesis was tested: **Hypothesis 3:** There are statistically significant differences at the (0.05) level in students' academic competency scores due to the interaction between chatbot type (rule-based vs. deep learning-based) and student motivation level (high vs. low).

Referring to the previous table, a statistically significant interaction effect is observed between chatbot type and student motivation level, as the F-value is (167.127), which is significant at the (0.05) level. This indicates that there are significant differences in academic competency scores due to the interaction between chatbot type and student motivation level.

To determine the direction of the difference, the **Tukey HSD** test was applied, revealing the following:

- The mean academic competency score of highly motivated students using a **rule-based chatbot** was (129.250).
- The mean academic competency score of highly motivated students using a **deep learning-based chatbot** was (155.687).
- The mean academic competency score of **low-motivation students using a rule-based chatbot** was (131.062).
- The mean academic competency score of **low-motivation students using a deep learning-based chatbot** was (131.312).

This is shown in the table below:

		Subset for alpha = 0.05	
VAR00001	N	1	2
1.00	16	129.2500	
3.00	16	131.0625	
4.00	16	131.3125	
2.00	16		155.6875
Sig.		.480	1.000

Table 5. Tukey HSD Test for Academic Competency

Conclusion

Based on the above findings, there are statistically significant differences at the (0.05) level in students' academic competency scores due to the interaction between chatbot type (rule-based vs. deep learning-based) and student motivation level (high vs. low). The results indicate that **students with high motivation who used a deep learning-based chatbot achieved the highest academic competency scores**.

Discussion

The goal of the current study was to look into the complex relationships between chatbot type, student motivation, and academic self-efficacy and how these affects educational technology students' learning of programming skills. Our findings provide numerous important insights into how AI-driven learning aids might be tuned for improved academic outcomes in programming courses by contrasting rule-based and deep learning-based chatbots in a variety of motivational scenarios.

Chatbot Type and Academic Efficiency

Our results support the idea that chatbots with deep learning capabilities improve academic productivity more significantly than those with rule-based technology. It has been demonstrated that deep learning models, with their contextual awareness and adaptive capabilities, offer more dynamic interactions and more individualized feedback. This is consistent with earlier studies (Wu & Luo, 2025), It emphasizes how sophisticated natural language processing may promote interactive conversations and real-time problem-solving. Rule-based chatbots, on the other hand, provided dependable and consistent answers, but their lack of adaptability frequently prevented further involvement, particularly when students ran into difficult programming problems.

The Role of Student Motivation

The effectiveness of chatbot-assisted learning was found to be significantly influenced by student motivation. Improved involvement and perseverance in completing programming tasks were consistently associated with high motivation levels. In addition to more successfully utilizing the interactive capabilities of deep learning-based chatbots, highly motivated students also showed a stronger inclination to investigate challenging coding issues, take part in coding contests, and cooperate in peer learning situations. Theoretical frameworks like Deci & Ryan's self-determination theory, which emphasizes the significance of intrinsic desire for prolonged academic effort and achievement, support this observation.

In contrast, when faced with challenging programming assignments, students who were less motivated were more likely to engage in avoidance behaviors and to rely on surface-level learning tactics. Additional organized support, like rule-based chatbots' scaffolded instruction, could help these kids progressively gain confidence and hone their problem-solving abilities.

Academic Self-Efficacy and Programming Skill Acquisition

It was discovered that academic self-efficacy significantly influenced how students approached learning programming. Pupils who had high self-efficacy were resilient in the face of programming difficulties and saw failures as chances to improve. This optimistic perspective not only increased their self-assurance but also promoted the use of active learning techniques like constant practice, debugging, and iterative coding. Low self-efficacy, on the other hand, was linked to increased anxiety, decreased engagement, and a propensity to avoid difficult activities, all of which hindered the development of critical programming abilities.

The significance of customized learning environments is further highlighted by the relationship between chatbot type and academic self-efficacy. Students with high levels of self-efficacy seemed to benefit most from the adaptive aspects of deep learning-based chatbots, which improved their academic performance and problem-solving skills. The organized, predictable responses of rule-based systems, which can provide the required scaffolding to improve core skills, were more advantageous to people with lower self-efficacy.

Implications for Educational Practice and Future Research

For educators, instructional designers, and legislators, the study's findings have important ramifications. First, especially for students who are already very motivated and self-assured, incorporating chatbots with deep learning into programming courses could significantly increase student engagement and academic results. Second, different levels of student motivation and self-efficacy should be taken into consideration while designing instructional activities. For example, a hybrid approach that combines the dependability of rule-based systems with progressive exposure to more dynamic, adaptive learning environments may be necessary for inexperienced programmers or those with weaker self-efficacy.

Furthermore, these results encourage more investigation into the best way to develop and apply chatbot-assisted learning. Future research should look into other factors, like the effect of domain-specific content, the length of time spent using chatbots, and the long-term effects on computational thinking abilities, in order to gain a more sophisticated understanding of how AI-driven tools can be tailored to different learner needs.

Conclusion

This study examined the complex interactions between chatbot type, academic self-efficacy, and student motivation as well as how these factors collectively affect educational technology students' learning of programming skills. The results highlight how sophisticated AI-powered technologies, especially chatbots with deep learning capabilities, can greatly improve academic efficiency in programming instruction. Engaging highly motivated students and those with strong academic self-efficacy is made easier by these chatbots' dynamic, context-aware interactions that promote tailored learning experiences. According to the study, rule-based chatbots offer dependable and consistent assistance, but their restricted flexibility limits their use when students face challenging or unstructured programming tasks. Deep learning-based chatbots, on the other hand, enable more dynamic and flexible learning settings, giving pupils personalized feedback that suits their own learning preferences and speed. Because they are more likely to participate in active learning, experimentation, and critical problem-solving, students with high levels of intrinsic drive and confidence in their academic talents particularly benefit from this flexibility. The study also emphasizes the critical moderating function that academic self-efficacy has in programming instruction. High self-efficacy students are more capable of taking on difficult assignments, overcoming obstacles, and eventually performing better academically. On the other hand, those with weaker self-efficacy could find it difficult to cope without enough organized support, so a hybrid learning strategy that progressively exposes them to more adaptable technologies might be more beneficial.

These discoveries have a wide range of consequences. When combined with techniques aimed at increasing student motivation and self-confidence, deep learning-based chatbot systems have the potential to significantly enhance student engagement and learning results for educators and instructional designers. The findings encourage governments to fund the creation of adaptable learning environments that accommodate a range of student profiles as well as AI-driven educational technologies. By investigating other elements including domain-specific material, the long-term effects of chatbot-assisted learning on computational thinking, and the scalability of such technologies in many educational contexts, future research should expand on these findings. By addressing these issues, AI-based learning technologies can be better designed and implemented to meet students' changing demands and optimize their chances of academic achievement. In summary, this study shows that high levels of student motivation and academic self-efficacy, when combined with the synergistic benefits of sophisticated chatbot technologies, can result in notable advancements in programming teaching. Educational institutions can establish more inclusive and productive learning environments that improve academic achievement and equip students for the technology challenges of the future by implementing adaptive, individualized learning practices.

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