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Integration of ChatGPT to Enhance Active Learning at the Undergraduate Level

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ABSTRACT This study was aimed to investigate how ChatGPT can enhance active learning in a higher education classroom. Undergraduate students pursuing a Bachelor of Science in Computer Science (BSCS) degree were specifically selected as the targeted sample. Using a sample size of 60, an experimental approach was employed to evaluate the effect of using ChatGPT. Means were computed for the questionnaire. Likewise, t-test and Mann-Whitney U test were used to compare the pre-test and post-test data. Findings of the quantitative part confirmed that utilisation of ChatGPT during active learning had a favourable impact on the students. The post-test means scores of the experimental and control groups show a clear difference in terms of learning. In the experimental group, the mean scores were 29.88 and 37.92 while the mean scores of the control group were 24.29 and 33.46, respectively. Therefore, this study concludes that teachers should use ChatGPT as a learning tool in their everyday classroom practices.

INTRODUCTION

Artificial intelligence is now an emerging discipline within the field of educational technology. Recent advancements in artificial intelligence (AI) have led to the development of AI generative models (Baidoo-Anu and Ansah 2023; Lee 2024). These models make the educational process more interactive and creative by fostering critical thinking and problem-solving abilities (Upadhyaya and Rimzim 2025).

Biswas et al. (2023) claimed that the desire of learners to learn can be increased by using ChatGPT to give them a better interactive learning experience. Self-directed learners can improve their performance and develop their self-learning skills with the help of ChatGPT's individualized guidance and feedback, which will eventually make them more self-reliant (Biswas et al. 2023; Biswas 2023). This research specifically examined the utilisation of ChatGPT, an OpenAI-designed and developed chatbot that launched for the general public in November 2022. Its basis was Generative Pre-trained Transformer version 3.5, or GPT-3.5. ChatGPT can provide interactive learning environments where students interact with online teachers who can effectively address their queries and explain a range of ideas (Lo 2023; Rawas 2024). Nurtayeva and Muhammed Al-Kassab (2022) supported ChatGPT's ability to evaluate students' writing and responses, offer personalised feedback, and suggest solutions to meet their individual requirements. Han et al. (2024) acknowledged ChatGPT for its expert assistance that students can access at any time and from anywhere. Ahn (2024) also demonstrated the significant advantages of using large language models (LLMs) like ChatGPT into educational activities, which promote dynamic learning environments and increase student engagement. These positive consequences reflect a transforming potential that has the capacity to profoundly alter the context of education. Bruneau et al. (2023) also concluded that ChatGPT has the ability to offer detailed instructions to assist students in resolving complex physics problems, encouraging self-directed learning and improving problem-solving skills.

Although ChatGPT proved to be promising as a tool for teachers (creating lesson plans, mak-

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ing recommendations, etc.) and as a virtual instructor for students (responding to queries promoting teamwork, etc.), however, issues with its use had appeared, including the production of false or misleading information and avoiding plagiarism detection software. It was suggested that immediate action be taken to modify institutional policies and assessment practices in educational settings (Adeshola and Adepoju 2023; Sallam 2023). Additionally, it was determined that in order to control the consequences of ChatGPT on the educational landscape, teacher training and student education are essential. Biswas et al. (2023) identified ChatGPT as a powerful computer programming tool that could be used for the following programming-related tasks, including completing and correcting code, anticipating and demonstrating code snippets, automatically fixing syntax errors, optimising and refactoring code, generating documents, developing chatbots, generating missing code, generating text-to-code, and offering technical assistance.

In addition to answering questions, this virtual assistant facilitates tasks like writing essays, creating software code, and creating emails (Baidoo-Anu and Ansah 2023). As active learning is a constructivist approach, ChatGPT facilitates students in their constructive self-learning by providing a more personalised and engaging experience. Therefore, the current study was aimed to investigate how ChatGPT can enhance active learning in a higher education classroom through an experimental design.

Conceptual Framework

The current study was based on Kirkpatrick's model and constructivism's learning theory. According to constructivism, through their experiences and interactions with their surroundings, people actively develop their own knowledge and understanding of the world (Piaget 1973). In other words, people's experiences and how they interpret them shape their own conception of the universe (Hung et al. 2024).

Kirkpatrick's model is a commonly used framework for evaluating courses. Basically, it is a framework for determining the kinds of queries that ought to be asked during evaluation and the standards that would be appropriate for assessment. Reaction, learning, behaviour and results are the four levels upon which this framework is based (Hung et al. 2024; Kirkpatrick and Kirkpatrick 2006). Kirkpatrick's model's Level 1 evaluates the participants' feelings or level of satisfaction with the training program. At this stage, the assessors are able to assess how well the training was received by the participants by analysing their responses, contributions, and degree of engagement. Using measurable indicators, Level 2 of Kirkpatrick's approach focuses on assessing the participants' values, knowledge, and abilities gained during the training. At this level, it is determined whether the training has enhanced the participants' knowledge and/or skills. This level also evaluates participants' motivation to portray the modified behaviour that the training was designed to target, as well as their confidence in their ability to accomplish accordingly. The third level of Kirkpatrick's approach assesses how the training has affected the participants' behaviour at work. Measurement of behavioural changes that occur weeks or months after the participants' training is part of this level. Kirkpatrick's model's last level, Level 4, assesses the institutional outcomes that the training program is accountable for and shows a profitable return on investment (Bergamo et al. 2022). Previous research had provided a framework for determining the parameters that might be used to test each level, as this study was restricted to assessing Kirkpatrick's model's first two levels (Ruiz and Snoeck 2018). Based on the revised Bloom's taxonomy, this level assesses how well students have learned the material as a result of receiving instruction (Krathwohl 2002). It measures how much and what kind of learning took place during the course.

Research Objectives

The main purpose of this work is to explore the major outcome of ChatGPT on students' reaction, learning, and applying level of the revised Bloom's taxonomy. To achieve this goal, the following objectives were set.

1. To examine the reaction of participants about utilisation of ChatGPT at the undergraduate level.
2. To evaluate the learning of students using ChatGPT in an active learning environment. This objective was particularly designed to apply three levels of Revised

Bloom's Taxonomy to assess the difference in students' learning in pre-test, post-test.

RESEARCH METHODOLOGY

To assess the impact of undergraduate students' use of ChatGPT on active learning, the current study employed quasi-experimental design with equivalent control groups and an experimental group for measuring the research variable. Table 1 illustrates the formation of groups for the current study.

Research Design

This study's research design was categorised into three levels. Level one employed a pretest-posttest quasi-experimental design with two equivalent control groups and an experimental group for measuring the research variable, learning. Whereas, levels two and three were descriptive. In the second level, a questionnaire was used to assess the other variable, reaction. Level three's last stage involved examining ChatGPT conversation history in order to verify the findings of the previous two levels, address the primary research question, and draw conclusions on adopting ChatGPT for active learning.

Research Context and Participants

The study was delimited to only undergraduate students enrolled in Islamabad's public colleges. Undergraduate students pursuing a Bachelor of Science in Computer Science (BSCS) degree were specifically selected as the target demographic for the experimental study on active learning, since the degree program included technical courses that were most suited for active learning. Purposive sampling was the sampling strategy used in this study, and the participants were the students of Islamabad Model College for Boys H-9, Islamabad' enrolled in the three-plus-one (3+1) credit first semester BSCS course on introductory programming, Problem-Solving and Programming. The selected sample size was 60 (Table 1). In addition, this study was carried during semesters for the academic years 2023-2025.

Lesson Plans

For the experimental study, weekly lessons were prepared for plans for an active learning environment in the computer science classroom. These included the active learning concepts proposed by Fink (2003) and Felder and Brent (2009) as well as the teaching model developed by Hazzan et al. (2020), which consists of stages for discussion, activity, trigger, and summary. Following the Backward Design Template (Bowen 2017) and in accordance with the course's credit requirements, each week included six hours of active learning and lab work. Students were split up into sub-groups of three and provided educational ChatGPT accounts. Group discussions and activities carried out in a computer lab equipped with PCs, multimedia projectors, whiteboards, and internet connection.

Instruments

To assess participants' level 1 and level 2 for the affective reaction and their utility judgments about using ChatGPT to evaluate students' learning at both the understanding and applying levels of Revised Bloom's taxonomy, a questionnaire perceived learning usefulness by Ruiz and Snoeck (2018) was created and modified. Moreover, two tests, that is, one with multiple-choice questions to gauge students' understanding and an-

Table 1: Groups formation (Total Participants = 60)

Category	*Range of scores*	*Categories of students based on previous experience of studying computer science*	*Number of participants*
Above average	13-29	Studied computer science at HSSC level	22
		Did not study computer science at HSSC level	02
Average	11-12	Studied computer science at HSSC level	02
		Did not study computer science at HSSC level	00
Below average	5-10	Studied computer science at HSSC level	08
		Did not study computer science at HSSC level	26

other with coding exercises to measure students' learning at the applying level, were also used.

To assure the validity of the research instruments, an extensive procedure of expert validation involving online as well as in-person discussions with experienced subject-experts was conducted. Additionally, pilot testing was carried out in order to make sure the instrument was reliable, and IBM SPSS Statistics version 26 was further used to analyse the results. The questionnaire's overall Cronbach Alpha values were 0.837, but its three main dimensions, namely, Affective Reaction, Utility Judgment (applying level), and Utility Judgment (understanding level), had Cronbach Alpha values of 0.749, 0.761 and 0.805' respectively. As a result, it can be stated that the questionnaire was very reliable for this study.

Data Collection and Analysis

The process of data collection involved multiple stages. IBM SPSS Statistics version 26 was employed for data analysis, integrating both content analysis and descriptive statistics. To evaluate the hypotheses and achieve the goals of the study, descriptive statistics were used, including frequency, mean calculation, and tests such t-tests and Mann-Whitney U tests, all of which were performed at a 5 percent level of significance. In particular, data from the closed-ended questionnaire was collected and examined for objective 1a in order to evaluate students' affective responses and utility judgments of the instruction and ChatGPT usage.

RESULTS

Reaction of Experimental Group about Instruction and the Usage of ChatGPT

The reaction of the participants was measured in terms of their affective reaction and utility judgment basis. Table 2 shows the participants' responses by estimating the overall mean of each category.

Affective Reaction

Table 2 represents the detailed assessment of 04 items related to Affective Reaction. When participants were asked whether they would use

Table 2: Reaction of the participants (category-wise, frequency details (N=30 and calculated mean

Variable	*Item*	*Strongly disagree*	*Disagree*	*Slightly disagree*	*Neutral*	*Slightly agree*	*Agree*	*Strongly agree*	*Mean total*
Affective Reaction	AR1	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	15 (50.0%)	15 (50.0%)	6.50
	AR2	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	11 (36.7%)	19 (63.3%)	6.63
	AR3	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (3.3%)	8 (26.7%)	17 (56.7%)	4 (13.3%)	5.80
	AR4	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	15 (50.0%)	15 (50.0%)	6.50
	Mean of means	6.36							
Utility Judgment (Understanding Level)	UK1	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	3 (10.0%)	17 (56.7%)	10 (33.3%)	6.23
	UK2	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	4 (13.3%)	20 (66.7%)	6 (20.0%)	6.07
	UK3	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	3 (10.0%)	22 (73.3%)	5 (16.7%)	6.07
	UK4	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	2 (6.7%)	14 (46.7%)	14 (46.7%)	6.40
	UK5	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	6 (20.0%)	13 (43.3%)	11 (36.7%)	6.17
	Mean of means	6.19							
Utility Judgment (Applying Level)	UA1	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	11 (36.7%)	19 (63.3%)	6.63
	UA2	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	13 (43.3%)	17 (56.7%)	6.57
	UA3	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	16 (53.3%)	14 (46.7%)	6.47
	UA4	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	13 (43.3%)	17 (56.7%)	5.57
	Mean of means	6.31							

ChatGPT to learn more about programming if they get a chance in future (AR1). Interestingly, almost all had shown their intentions for it. Similarly, 63 percent strongly agreed to using ChatGPT in the classroom in the future (AR2). However, on inquiring whether they were enthusiastic about using ChatGPT in their learning (AR3), 3 percent remained neutral. Likewise, 50 percent of the participants strongly agreed that using ChatGPT to learn programming was a positive experience (AR4). The participants' mean affective reaction score, as shown in Table 2, is 6.36, falling inside the cut-off range of 6.17 to 7.0. It may be deduced that the students generally believe that using ChatGPT had a positive influence on the affective reaction of students. Therefore, the null hypothesis that there is no statistically significant impact of ChatGPT on undergraduate students' affective reactions, is rejected.

Utility Judgment (Understanding and Applying)

Table 2 also represents the detailed assessment of 04 items related to Utility Judgment at understanding level. On inquiring whether using ChatGPT improved understanding of the topics covered in this course (UK1), remarkably, 33 percent had shown their strong intentions for it. Besides, 10 percent lie in the range of somewhat agree. Similarly, 33 percent agreed that using ChatGPT helped in understanding the topics much faster (UK2). The response for the question, whether using ChatGPT helped in learning programming concepts more easily (UK3), shows 27 percent agreement. Surprisingly, on enquiring whether students used ChatGPT to explain concepts that they were feeling difficulty to comprehend (UK4), responses of students ranged from slightly agree to strongly agree out of which 6.7 percent lies in the range of slightly agree and 46.7 percent in strongly agree. Likewise, when they were asked about ChatGPT based generated examples to understand the concepts, 20 percent lie in the range of slightly agree and 37 percent strongly agree. Upon further evaluation it was observed that the means for items UK2 and UK3 falls within 5.31 to 6.16' which indicates that students agree with each of these items while means for the item UK1, UK4, and UK5 fall within the range of 6.17 to 7.0' which indicates that students strongly agreed with these items.

Utility Judgment (Applying Level)

Utility Judgment at the Applying Level was assessed by inquiring whether using ChatGPT students were able to develop programs with less difficulty (UA1). Interestingly, almost all had shown their intentions for it. On enquiring whether students used ChatGPT to explain code to them that they were finding difficult to understand (UA2), 43 percent lie in the range of agreement and 57 percent in strong agreement. Likewise, whether students used ChatGPT to identify and correct errors that they made in programming (UA3) and whether students used ChatGPT to generate equivalent and more optimised code (UA4), 43 percent were observed to be in the range of agree and 56 percent in strongly agree. Similarly, Table 2 shows that the participants' mean utility judgment score is between 6.19 and 6.31, falling within the cut-off range of 6.17 to 7.0. According to this quantitative study, the majority of students agreed that using ChatGPT to learn at both the understanding and application levels of the revised Bloom's taxonomy became beneficial.

Pre-test Analysis

For the quantitative data analysis, the dataset was split into two sections according to the students' competencies (below-average and above-average performing students), as demonstrated by results of their pre-test and the previously described grouping strategy. After ensuring that all the assumptions were met, the researchers used an independent sample t-test to compare the experimental group and control group's mean scores on the test for understanding the level of updated Bloom's taxonomy before and after the six-week intervention. The pretest data analysis details are listed below, followed by the post-test data analysis details.

Independent Samples t-test of Results based on Understating Level

The researchers employed an independent sample t-test to compare the control group and the experimental group groups in order to assess the variation in the students' learning levels before the experiment was conducted for this study.

The researchers further used IBM SPSS Statistics version 26 to assess the pre-test results of both groups' understanding levels of Revised Bloom's taxonomy using an independent sample t-test. The results that followed are described in Table 3. The pre-test mean scores of the experimental and control groups are nearly equal in the two tables above, wherein the average and above-average performing students in the experimental and control groups had mean scores of M=18.69 and 18.92 respectively, while the below-average performing students in the two groups had mean scores of M=7.0 and 7.18. Additionally, with p-values of 0.76 and 0.9, or $p>0.05$, it is clear that there was no significant difference between the experimental and control groups prior to the experiment's conduct in terms of students' learning in terms of their understanding of revised Bloom's Taxonomy.

Post-test Analysis

After a six-week intervention, the researchers compared the experimental group and control group's mean scores on the test for knowledge level of revised Bloom's taxonomy using an independent samples t-test. The post-test data analysis details are listed below.

Independent Samples t-test of Results based on Understating Level

The researchers compared the two groups after teaching the control group using active learning methodology without ChatGPT and the experimental group using active learning methodology with ChatGPT integration in order to assess students' learning of the revised Bloom's taxonomy understanding level. Using IBM SPSS Statistics version 26, the researchers used the independent samples t-test to examine the post-test results for both groups. The results that followed are described in Table 4. There is an apparent distinction between the experimental and control groups' post-test mean scores in the tables above. In the experimental group, the mean scores of the students who performed below average on the pretest and those who performed average and above average in the control group were M=29.88 and 37.92 respectively, while the mean scores of the students who performed below average on the pretest and those who performed average and above average in the control group were M=24.29 and 33.46, respectively. Additionally, the researchers assert that there is no statistically significant difference between the experimental and control groups' learning on the post-test at the Understanding Level of Revised Bloom's taxonomy, with a p-value of.001 or $p < 0.05$.

Applying Level

Rubrics created especially for this purpose were used to evaluate students' test results in an efficient manner thus minimising biases. To compare the mean scores of the test for the applying level of updated Bloom's taxonomy between the experimental group and the control group after a six-week intervention, the researchers intended to use an independent sample t-test. Although

Table 3: t-test results (pretest for the selected groups

Category	*Variable*	*N*	*Mean*	*df*	*t-value*	*P*
Students learning at understanding level: Below average	Control group	17	7.0	32	-0.31	0.76
	Experimental group	17	7.18			
Students learning at understanding level: Average and above average	Control group	13	18.69	24	-0.12	0.9
	Experimental group	13	18.92			

Table 4: Posttest results for the selected groups

Category	*Variable*	*N*	*Mean*	*df*	*t-value*	*P*
Students learning at understanding level: Below average	Control group	17	24.29	32	-5.09	0.001
	Experimental group	17	29.88			
Students learning at understanding level: Average and above average	Control group	13	33.46	24	-4.52	0.001
	Experimental group	13	37.92			

the assumption of a normal distribution of the data could not be verified, the researchers tested the assumptions required to perform the independent samples t-test. The statistical analysis t-test for this dataset was substituted with the Mann-Whitney U test because it does not assume normality and is appropriate for comparing two independent groups.

Mann-Whitney U Test of Results based on Applying Level

In Table 5 post-test mean score and their total shows an apparent distinction between the control and experimental groups. In contrast to the experimental group, which exhibited a higher mean rank and sum of ranks of 33.43 and 1208 respectively, the control group demonstrated a mean rank of 28.6 and a sum of ranks equal to 622. Additionally, there is strong evidence against the null hypothesis, indicating a statistically significant difference between the groups, as indicated by the U value of 157, Z statistic of -4.381, and p-value of.001 (below the significance level of 0.05).

Content Analysis: ChatGPT Accounts Conversation History

In order to address the main research question, to offer a more thorough comprehension of the data presented in the preceding sections, and offer further insights, students' conversation histories in the specified ChatGPT accounts during the study period were subjected to content analysis. The experimental group consisted of 30 students in total, who were divided into 10 subgroups, each of which had three randomly chosen students. Following that, the students were given ChatGPT accounts, which they utilised while studying in an interactive setting that covered both theory and lab work in accordance with HEC course requirements.

The four main phases of the active learning approach were trigger, activity, discussion, and summary. In addition, there were extra lab exercises to strengthen concept acquisition and provide coding practice. Using C++ as the foundational programming language, the teaching-learning phase ensured that students understood the fundamentals of programming. Variables, primitive data types, operators, input/output statements, conditional structures, iterative structures, and modular programming utilising functions were among the subjects that were discussed during the study period. The three main categories of lab work tasks were constructing programs based on problem statements, analysing code, and making comments in code, which involved identifying and fixing mistakes in a sample of code, as well as running a code to determine its output.

The participants' first chats and any follow-up questions they asked during those conversations are analysed. The researchers has established three categories of Conceptual Understanding, Coding, and Exploration, that encompass the major themes found in the content analysis. As the name suggests, the interaction of students who fit into the conceptual understanding category aided in their learning at the new Bloom's taxonomy understanding level. In the second group settings, students' interactions with ChatGPT assisted in their programming education. In other words, it enhanced students' learning within the domain using the revised Bloom's taxonomy. The third category that was identified also included students' progressive questions pertaining to subjects beyond the course's basic level. Students' questions in this category also included inquiries that appeared to have come about as a result of brainstorming and critical analysis of the subjects they were studying. For instance, they inquired as to why a particular code operated in a particular way or why the various data kinds used varying sizes of memory.

The findings showed that students received adequate responses to their questions, with the exception of just a few erroneous answers from ChatGPT that created program codes. Furthermore, it was noted that the appropriate codes were

Table 5: Mann-Whitney U test results of students learning at the Applying Level

Variable	*N*	*Mean rank*	*Sum of ranks*	*Mann-Whitney U*	*Z statistic*	*P*
Control group	30	28.6	622.00	157.00	-4.38	.001
Experimental group	30	33.43	1208.00			

subsequently created upon additional clarification of the participant's initial statement or inquiry throughout the next conversation.

Besides this, it was noted that:

- In certain instances, since the user's settings were not configured to create C++ code, or because the user did not specifically mention C++ during his inquiry, code in other programming languages was generated.
- ChatGPT was able to comprehend user communications with grammatical and spelling errors.
- When instructions were typed in Urdu using an English keyboard, it was able to understand them properly and generate the right answers.

The content analysis makes it clear that the participants used ChatGPT for both theoretical and lab-based learning, as evidenced by their conversation history, which relates to both conceptual understanding and proficiency in coding. Table 2 summarises the students' responses regarding their use of ChatGPT at both the understanding and application levels of the revised Bloom's taxonomy. Even though the students in each group studied exactly the same subjects, their use of ChatGPT provided them a personalised learning atmosphere because each group's queries were different from those of other groups.

DISCUSSION

Reaction of Participants About Utilisation of ChatGPT

This study's primary objective was to evaluate how ChatGPT affected students' active learning. Based on this primary objective, the first goal was to understand how students engaged when they employed ChatGPT for their learning. According to the study's findings, students who utilised ChatGPT for their studying had positive affective and utility judgment reactions. Students' responses to questions about their decision to use ChatGPT to learn more in the future, their thoughts on using ChatGPT in the classroom, their excitement for utilising ChatGPT in the classroom, and their experiences with it were utilised for measuring their affective reaction. Their utility judgment was separated into two categories of utility judgment at understanding level and utility judgment at applying level, because the research focused on the understanding and application levels of the revised Bloom's taxonomy. The utility judgment evaluated students' responses at two levels of the understanding level, which primarily focused on the course's theoretical content, and the focus of the applying level on the lab work. The study's findings regarding affective response are consistent with those of other researchers (Amin et al. 2025; Bitzenbauer 2023; Chan and Hu 2023; Fu et al. 2025; Lozano and Blanco Fontao et al. 2023). Findings of these research studies revealed that students have a positive attitude regarding the incorporation of ChatGPT into the classroom. Lozano and Blanco Fontao (2023) also demonstrated that students feel positively about ChatGPT's incorporation into the classroom. Additionally, the findings of this study concerning the utility judgment of ChatGPT are consistent with the findings of Singh et al.'s (2023) study, which showed that students believe ChatGPT can be used to help them understand concepts they did not fully grasp in class and to help them code by producing code. Similarly, the conclusions align with the research of Shoufan (2023), who focused on students in a computer engineering program and found that students viewed ChatGPT as a useful and efficient learning tool that offered well-organised answers and a satisfactory explanation of their questions.

Evaluation of Students' Learning in an Active Learning Environment

An additional objective of this study was to evaluate the learning of students using ChatGPT in an active learning environment. The findings showed that ChatGPT enhances students' learning in terms of their understanding and application of the updated Bloom's taxonomy. Regarding the application of AI like ChatGPT to enhance learning outcomes, the findings are consistent with other earlier studies (Bahroun et al. 2023). Findings showed that the usage of generative AI, such as ChatGPT is helpful to explain programming concepts and revolutionise creative programming education, indicating that AI may improve comprehension of complex programming concepts. In addition, researchers also suggested that integrating advanced chatbots and text generation models may enhance problem-solving and active learning. The researchers suggest using the approach he employed in his experimental study to address the main question of this study, which is how ChatGPT can be used to improve active learning at the undergraduate level, that is, grouping students and designing active learning lessons around the four essential stages of trigger, activity, discussion, and summary, along with prearranged lab activities.

Overarching Question

According to the study's qualitative analysis, students utilised ChatGPT as an alternative in an active learning setting. This result is consistent with research by Mohamed et al. (2024), which also argued that ChatGPT should be viewed as a helpful addition to conventional teaching techniques that enhances and supports the learning process. According to this research, the students utilised ChatGPT because it offered them a personalised learning experience that enhanced their comprehension and application of the revised Bloom's taxonomy. The aforementioned study results are consistent with the findings of Kooli (2023), which highlighted the importance of making adjustments to the AI-driven environment by incorporating ChatGPT and other AI technologies into educational settings.

In accordance with Kooli's viewpoint, this study emphasises ChatGPT's importance as a tool to improve learning experiences since it gives students access to a variety of information and personalised learning experience. Furthermore, this study's findings support Kooli's research, which found that although ChatGPT is a useful educational aid, human knowledge, autonomy and creativity ought to remain acknowledged. Based on the quantitative and qualitative findings, it is evident that ChatGPT facilitates students with a personalised learning experience through conversation in a discovery-based active learning framework. Jeon and Lee (2023) also highlighted ChatGPT's function as an evaluator by offering immediate feedback and assessment and as an interactive interlocutor by facilitating meaningful dialogue, which encourages students to learn more about topics they are interested in and fosters curiosity and self-learning skills.

The findings of the qualitative study further made it clear that ChatGPT's responses were accurate in that they gave students satisfactory answers that aided in their learning at both the understanding and application levels of the revised Bloom's taxonomy. This result is consistent with the findings of other researchers (Jeon and Lee 2023; Ouh et al. 2023). These researchers observed that ChatGPT may be employed as a content provider for gathering an extensive quantity of information. Therefore, these researchers highlighted how ChatGPT might help students in programming classes investigate different approaches to solving code-related problems and also emphasise ChatGPT's importance as an essential resource for students facing programming difficulties.

CONCLUSION

This study has examined the impact of ChatGPT on students' affective responses and utility judgment in an active learning environment. Furthermore, ChatGPT's effect on students' learning at the comprehension and application levels was evaluated. The study's findings demonstrated that ChatGPT improves students' responses and learning in an undergraduate programming course that uses active learning. Teachers should use ChatGPT as a learning tool when developing courses for a discovery-based collaborative active learning method in order to give students personalised support in their everyday practice.

RECOMMENDATIONS

The current study yielded the following recommendations based on its findings:

1. In an active learning classroom, teachers may give students the chance to utilise ChatGPT as a learning tool to help them understand code, debug code, learn programming constructs, and generate code to solve problems.
2. Educational institution administrators may support students' usage of smart devices in the classroom so they can access ChatGPT and other AI tools while they are learning.

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