Artificial Intelligence & Robotics Development Journal
Volume 5, Issue 3, pp 383-395, July 2025, https://doi.org/10.52098/airdj.20233343
ISSN: 2788-9696 Received: 14/4/2025 Revised: 30/4/2025 Accepted: 12/5/2025

Exploring the Impact of Artificial Intelligence on Student Academic Performance

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Abstract

This paper examines the impact of artificial intelligence on students' performance during their academic studies. With the widespread use of AI in education, teaching, and learning, students can acquire knowledge in their chosen fields. However, students may engage with AI technologies in ways that could slightly diminish their overall experience. The goal of this study is to assess how artificial intelligence influences students' academic performance. A group of 64 first-year students was selected and divided into two groups to compare different study methods and determine which one is more effective in improving knowledge and building experience. The first group followed traditional study methods, while the second group used AI technologies in their assessments throughout the semester. Afterward, interviews were conducted to evaluate the knowledge gained. The results showed that only a small number of students could answer questions about their AI-based assessments, with only 20% demonstrating significant knowledge retention. Various factors were identified as contributing to this outcome.

KEYWORDS: Artificial intelligence; student performance; teaching and learning; machine learning techniques; AI-based assessments.

1. Introduction

The field of information technology is constantly evolving, significantly contributing to the ease of business operations and education. As a result, many studies have emerged and continue to emerge, focusing on enhancing and improving work quality, including the use of artificial intelligence in academic settings. AI is being applied to tasks such as preparing reports on specific topics, solving exam questions, and even creating student projects (Yousif J. & Yousif M., 2025). While it is clear that AI can serve as a powerful tool to enhance business and academic development for university students, it often remains underutilized. Many students view it primarily to complete tasks, rather than as a valuable resource for deeper learning and skill development (Yousif J., 2025).

Students are the most vital members of both private and public educational institutions, as they represent the future of the nation. The effectiveness of these institutions plays a crucial role in shaping highly qualified and responsible graduates. To establish a strong reputation within the educational community, institutions strive to maintain the quality of the academic material they provide, ensuring it aligns with modern advancements (Yousif et al., 2021). However, it has been observed that many institutions prioritize their reputation over the actual quality of education (Norris, D et al., 2008). However, government agencies and accreditation bodies collaborate to ensure the sustainability of educational institutions by fostering a high-quality learning environment that promotes continuous education. While accreditation procedures are rigorous, they play a crucial role in compelling institutions to uphold their integrity by carefully developing and implementing plans and policies to maintain their standards. For example, the Oman Academic Accreditation Authority (OAAA) and the Accreditation Board for Engineering and Technology (ABET) work to ensure the long-term sustainability of educational institutions (Nettleman III , 2018).

In courses that rely entirely on activities, projects, and report writing rather than exams, lecturers now face challenges in distinguishing outstanding students from others. This is due to the increasing use of artificial intelligence in completing exam models, worksheets, student projects, report writing, and even model analysis, making it difficult to accurately assess individual performance. As a result, most lecturers are seeking alternative methods to nurture outstanding students while ensuring the continued quality of education while the performance of the students remain stable.

There are various methods for monitoring student performance, including predictive models designed for online learning (Umer et al., 2017; Yang et al., 2017). These models help to identify students at risk of dropping out by tracking their progress (Asogwa & Oladugba, 2015). Additionally, predictive models powered by machine learning algorithms have been implemented to forecast students' final results before the semester ends (Alabri et al., 2019; *Maghari AY, 2018;* Chen, H., 2018; Costa et al. 2017; Došilović et al., 2018).

Educational institutions utilize various technologies to gather data on students and the learning environment. Examples include learning management systems, intelligent teaching systems, and online learning platforms (Gašević et al., 2015). Different tools collect various types of data. Additionally, specific data can be analyzed to document student information, including behavior, performance in summative and formative assessments, interaction during online sessions, as well as administrative and demographic data (Tempelaar et al., 2018). To achieve certain goals like making the collected data useful and augmenting the decision making, the institution requires the teaching practice to be innovative and simple (Romanenko et al., 2019). Therefore, it becomes common to update complex materials with more understandable and easier to remember contents (Khan et al., 2019). As an example of that, eminent techniques in data mining course applied to extract eminent techniques. Furthermore, machine learning is considered as a supportive educational processing tool and an excellent forecasting precision of an event (Al-Abri et al., 2020; Hasoon et al., 2011).

Learning is inherently tied to its environment (Honebein et al., 1993; Visser J., 2001; Smith, G., 1992). The current models are effective only within their specific local context. Students in different educational environments may react differently (Caroet al., 2016; Manca & Delfino, 2021). In this paper, a group of 64 first-year diploma students was selected and divided into two study groups, each exposed to different technologies. To ensure fairness, both groups were equal in size, gender distribution, and study content. Each group consisted of 32 students, including 25 females and 7 males. The study focused on two courses: *Principles of Operating Systems* and *Web Development*, where the technology used influenced student behavior and the level of acquired experience. The research identifies the approach and ways that influences the performance of the students.

2. Literature Review

Artificial Intelligence (AI) aims to equip computers with sufficient intelligence to think and respond in a manner like humans (Kaplan J., 2016; Shabbir & Anwer, 2018; Korteling et al., 2021). Unlike computers, humans learn from situations and experience, allowing them to make/judge intelligent decisions based on the unique circumstances that they go through it. In contrast, computers must follow and apply predefined algorithms or approaches to complete the required tasks. Artificial Intelligence (AI) seeks to bridge this gap by developing innovative techniques that equip computers with intelligence similar to human brain, enabling them to mimic human thinking and behavior. The term AI is often associated with projects that replicate distinct human cognitive processes, such as reasoning, discovering meaning, and learning from past experiences. AI applications are rapidly expanding across various industries, including commerce, services, manufacturing, and agriculture, making the technology increasingly prominent (Rashid & Kausik, 2024). Future AI systems will be able to communicate with humans in their native languages and adapt to their movements and emotions (Zhang & Lu, 2021; Lu Yang, 2019).

Nowadays, predicting student performance has become a crucial topic in learning environments like universities and schools. Accurate predictions enable the development of effective strategies to improve academic outcomes and prevent setbacks. In the era of Education 4.0, Artificial Intelligence (AI) plays a vital role in identifying new factors influencing student performance, facilitating personalized learning, answering routine student inquiries, and utilizing learning analytics and predictive modeling. A key challenge in redefining Education 4.0 is recognizing and fostering creative and innovative intelligence among students while accurately assessing their academic outcomes. A Hybridized Deep Neural Network (HDNN) is employed by Zhongshan Chen (Chen et al., 2018) and his group to predict student performance in the Education 4.0 environment. The proposed HDNN method identified key factors influencing student outcomes, leveraging deep neural networks to monitor, predict, and assess performance effectively. The results indicated that the HDNN method outperforms other popular approaches, achieving higher prediction accuracy.

Alvarez-Cedillo (Alvarez-Cedillo et al., 2019) introduced a machine learning technique to analyze and identify educational behavior in the rapidly growing online learning environment, where course content is available in digital format. This approach enables data analysis and utilization to assess learning processes. Active and engaged student participation enhances learning outcomes, aligning with the goals of the Fourth Industrial Revolution in education. While machine learning methods have made significant progress in data processing and predictive analysis, they are still rarely used to measure learning levels (Alkishri et al., 2023). Gaol (Gaol et al., 2018) proposed an innovative approach to supporting AI in education, introducing the AI-assisted Higher Education Framework (AIHEF) equipped with intelligent sensors and wearable devices for self-regulated learning. Additionally, they examined the initial outcomes of Education 4.0's didactic approaches, integrating machine learning algorithms and learning analytics. This case study aims to predict students' final scores before they take the ultimate assessment.

Bagustari (Bagustari & Santoso, 2019) implemented Learning Management Systems (LMS) to enhance their functionality, emphasizing the critical role of the Adaptive User Interface (AUI) in keeping students engaged amid evolving technological advancements. Investigating AUI development in Education 4.0 is essential to understanding its impact at this level. This study examines AUI within learning models proposed and applied by other researchers. Using a qualitative approach, it analyzes the relationship between technology and pedagogical elements. Educational Data Mining (EDM) and Learning Analytics (LA) have emerged as crucial research fields, extracting valuable insights from educational datasets for various applications, including predicting student progress.

In modern educational settings, the ability to forecast a student's success can be instrumental in understanding learning behaviors (Buckley S., 2020). Existing approaches often focus on academic performance, family income, and assets, while factors such as family expenses and students' personal details are frequently overlooked. This study seeks to evaluate these overlooked factors by collecting data from scholarship recipients across multiple universities. Guo (Guo et al., 2020) developed FEEDAN, a federated learning-based framework for educational data analysis, enabling multiple institutions to collaborate without directly sharing student data. Each institution retains its data locally, ensuring student privacy and security. Their methodology was applied to two real educational datasets across distinct federated learning paradigms. Experimental results demonstrate that FEEDAN not only safeguards student privacy but also overcomes data silos, achieving a higher level of analysis. Table 1 presents the methods utilized by other researchers.

Table 1: Methods utilized by Researchers

Author	Approach	Results
Chen et al., 2018	Hybridized Deep Neural Network (HDNN)	The HDNN method identified key factors influencing student outcomes, leveraging deep neural networks to monitor, predict, and assess performance effectively
Alvarez-Cedillo et al., 2019	Machine Learning Technique (MLT)	The MLT analyzed and identified educational behavior in the rapidly growing online learning environment
Gaol et al., 2018	AI-assisted Higher Education Framework (AIHEF)	The AIHEF was able to predict students' final scores before they take the ultimate assessment.
Bagustari & Santoso, 2019	Learning Management Systems (LMS) with Adaptive User Interface (AUI)	This method examined AUI within learning models proposed and applied by other researchers. Additionally, it analyzed the relationship between technology and pedagogical elements
Buckley S., 2020	Educational Data Mining (EDM) and Learning Analytics (LA)	The approaches had emerged as crucial research fields, extracting valuable insights from educational datasets for various applications
Guo et al., 2020	FEEDAN, a federated learning-based framework for educational data analysis	The experimental results demonstrated that FEEDAN was not only safeguards student privacy but also overcomes data silos, achieving a higher level of analysis.

3. Participant Data

The number of participating students was 64 first-year students, divided into 48 female students and 16 male students from two sections studying the same subjects. In fact, there is no way to select the gender of participants, as the number of female students is greater than the number of male students enrolled in university studies. The courses selected are Web Development and Operating Systems.

The students participating in this study were carefully selected based on several factors:

- All participants were within a similar age range (19-20).
- All participants were studying the same subjects (all in level 1).
- One purely applied subject and one theoretical subject were chosen.
- Repeated students are not allowed to participate.

4. Research Methodology

In this study, two sections of first-year students were analyzed, with a total of 64 participants. Since these students follow the same schedule, studying the same number of course hours simultaneously, there was no need for additional grouping or redistribution. Each section consists of 32 students, but the instructional mechanisms used in each section differ entirely. Despite these differences, the study materials, timing, and assessments were conducted simultaneously for both sections. The assessments consist of two main types which are two tests and two reports in two different courses.

The first section followed a traditional learning approach, where students relied solely on conventional study methods to complete their assessments. This included using textbooks, PowerPoint slides, and notebooks, with no digital applications allowed. The primary focus was during lecture time, requiring students to take notes, summarize key points, and build their understanding through in-class discussions. This method has become somewhat outdated, as most students now prefer incorporating at least one digital study resource to enhance their knowledge and improve their GPA. As a result, this approach proved to be the most challenging, with students struggling to maintain engagement. The following figure illustrates the study methodologies for both sections.

On the other hand, the second group is allowed to use AI technologies in their study as a preparation for their quiz and to write a professional report in less effort. The challenge was significant for the students in this group, as they aimed to submit high-quality work within a short timeframe, striving to achieve top grades among their peers. However, the use of various types of artificial intelligence resulted in differences in quality and linguistic accuracy.

To ensure the success of this idea, raising awareness among the student volunteers and consistently reminding them of the importance of adhering to the conditions was crucial for achieving satisfactory results. To facilitate this, two WhatsApp groups were created, each assigned a mentor responsible for sending awareness and guidance messages. These messages focused on the work process, outlining what should be done and what should be avoided. Initially, student responses to the mentors were limited. However, over time, the students began asking questions themselves, and others in the groups started providing answers. This shift indicated that they had developed a sufficient level of awareness.

Once sufficient awareness was raised among the students in both groups, the courses and corresponding tasks were carefully selected. Two first-year courses were chosen: Web Development and Principles of Operating Systems, for the following reasons:

- The participating students were enrolled in both courses.
- The students were taking fall and spring courses during their first year.
- Additionally, Web Development is a practical course, while Principles of Operating Systems combines both theoretical and practical aspects.

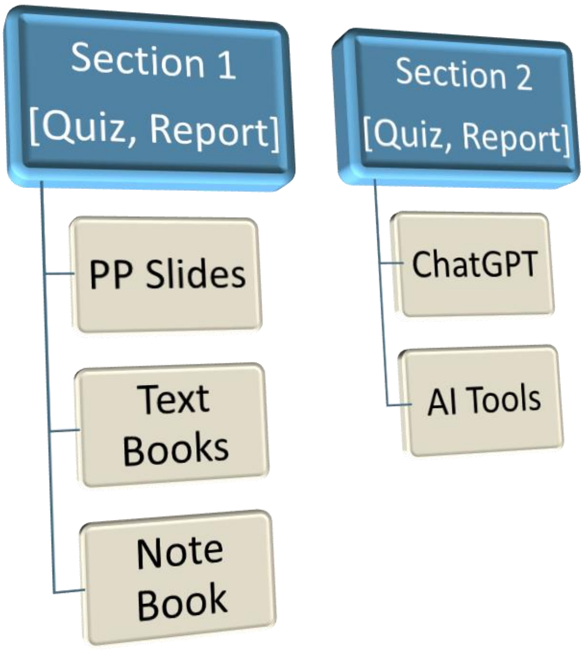

Figure 1: the study methodologies for both sections

Initially, the plan encompassed all assessments in both courses. However, due to concerns about the difficulty of completing them accurately stemming from the risk of students not fully complying and their fear of potential grade reductions two similar types of assessments were selected: the first exam and a course-related report.

After four weeks of study, the students underwent their first assessment a core quiz in both courses. The plan divided the students into two sections: the first section studied using traditional methods, such as notebooks and textbooks, while the second section was allowed to use artificial intelligence applications to summarize content and generate exam questions for the relevant material. Before the results were released, interviews were conducted with all students to gather their perspectives on the methods used and the challenges they faced. Subsequently, both sections were tasked with writing and submitting a course-related report, using the same tools assigned to them during the initial assessment. The following figure shows the flow of the applied method.

5. Results and Discussion

To understand the students' experiences in both sections after the assessments were administered but before the results were announced, interviews were conducted with each student in the first section. During these interviews, students emphasized the importance of taking notes during class, staying focused, studying in a timely manner, and asking questions when something is unclear. Additionally, they shared their emotional responses while taking the assessments.

Figure 1: The flow of the applied method

Table 2 summarizes the students' feedback on the experiment.

Table 2: Students' feedback

Category	Student Feedback
Classroom Strategies	- Taking notes during class was helpful- Staying focused improved understanding
Study Habits	- Studying on time reduced stress- Consistent review helped retain information
Asking Questions	- Asking questions when confused clarified key concepts
Emotional Responses	- Felt nervous before assessments- Gained confidence with preparation- Some anxiety remained
Overall Experience	- Found the process helpful- Liked the structured approach- Felt more responsible for learning

The same approach was applied to the second section to explore the insights gained from using AI tools. Interviews were conducted with each student in this section. During the interviews, students highlighted the importance of searching external resources for course-related information, using AI tools to generate exam questions, and improving their writing or creating reports. Additionally, they shared their emotional experiences while completing the assessments. Table 3 summarizes the students' feedback on the experiment.

Table 3: students' feedback 2

Category	Student Feedback
Use of External Resources	- Frequently searched for course-related information online- Found it helpful for deeper understanding
AI Tools for Studying	- Used AI to generate practice exam questions- Helped identify key topics and formats
Writing Support	- AI assisted in writing and enhancing reports- Improved structure and clarity of writing
Learning Benefits	- Felt more engaged with the material- Encouraged independent exploration of topics
Emotional Responses	- Initially unsure about using AI- Gained confidence over time- Mixed feelings about fairness
Overall Experience	- Found AI tools to be useful learning aids- Appreciated the guidance and support they provided

After the interviews were conducted with all participating students, the results of the assessments—both the quiz and the report—were announced for both sections. As expected, the second section showed a slight increase in performance, achieving an average score of 85.3%, while the first section experienced a small decrease, with an average score of 79%. The students were tested based on two assessments during the course, where the total is calculated by adding the quiz marks with the report marks. To protect student privacy, only one Course-Web Development-was selected for presentation. The results from the second course show similar trends, though some differences in student scores are present due to variations between the courses.

Figure 3 presents the frequency heatmap of student scores by quizzes and report marks of section-2. Darker areas are combinations with greater numbers of students. It is easier to identify which ranges of scores occur most frequently and where students cluster.

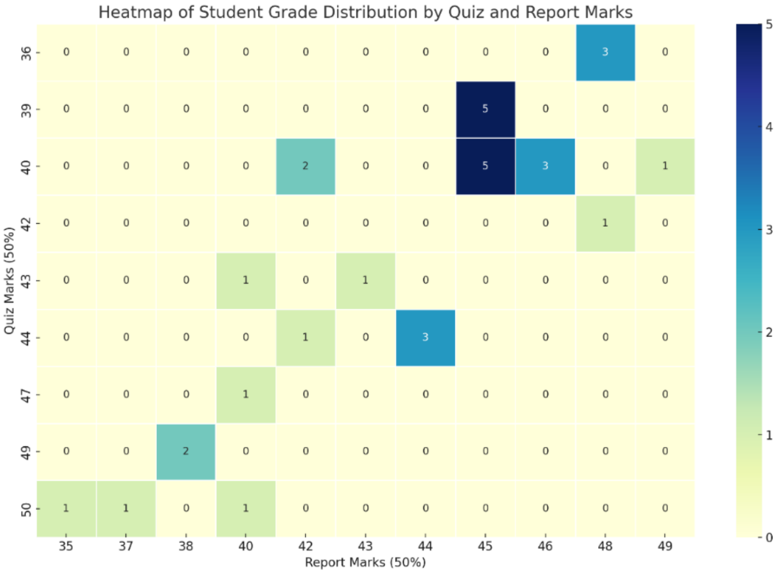

Figure 3: Assessment marks Section 2

Table 4 presents computational results for the quiz marks, report marks, and total scores (each out of 50%, 50%, and 100%, respectively). The overall scores clustered tightly between 82 and 90, indicating strong performance consistency across the group. The most common total scores are 85 (6 students), 84 (5 students), and 86 (5 students). The highest total score achieved is 90, by 2 students. The lowest total score is 82, achieved by 2 students.

Table 4 computational results for the quiz marks, report marks, and total scores of section-2

Metric	Quiz Marks (50%)	Report Marks (50%)	Total (100%)
Count	32	32	32
Mean	42.13	43.72	85.84
Std	4.18	3.59	2.07
Min	36.00	35.00	82.00
25%	39.00	42.00	84.00
50%	40.00	45.00	85.00
75%	44.00	45.00	87.00
Max	50.00	49.00	90.00

Figure 4 presents the assessment marks of Section 1, which determines the ranges of scores occur frequently and students' cluster.

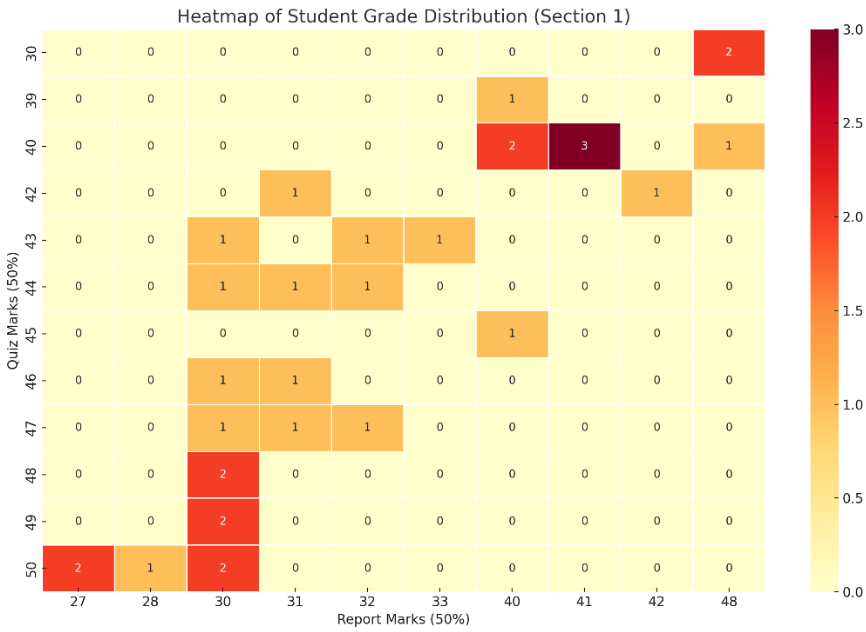

Figure 4: Assessment marks of Section 1

Table 5 presents computational results for the quiz marks, report marks, and total scores (each out of 50%, 50%, and 100%, respectively) of section 1. Average total score is approximately 78.6, with scores ranging from 73 to 85. The most common total score is 78, achieved by 6 students. Scores of 73, 74, 83, and 85 are each unique (achieved by only one student). Most students scored between 75 and 81, indicating a central cluster of performance.

Table 5 computational results for the quiz marks, report marks, and total scores of section-1

Metric	Quiz Marks (50%)	Report Marks (50%)	Total (100%)
Count	32	32	32
Mean	43.9375	34.5	78.625
Std	5.14899	6.420733	2.870877
Min	30	27	73
25%	40	30	77
50%	44	31	78
75%	48	40	80
Max	50	48	85

Figure 5 illustrates the actual performance of the students using AI tools, where their marks showed a slight increase in the performance of the reports rather than the quiz marks.

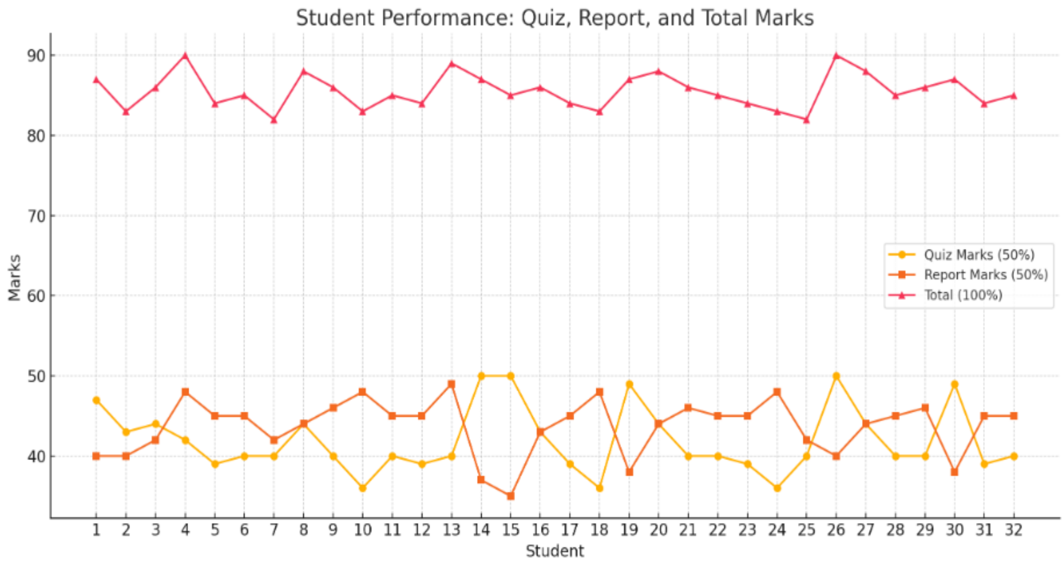

Figure 5: Student's performance of section 1

Figure 6 demonstrates the actual performance of students using traditional study methods, showing a slight increase in quiz scores compared to their report marks.

The experiment revealed the actual performance of all students, regardless of the study method used. Students who incorporated AI techniques showed a significant improvement in the quality and efficiency of their reports, completing them in less time compared to those who relied solely on traditional methods.

The letter group, which analyzed and constructed sentences manually, required more time but outperformed the AI-assisted group in the quiz. These findings suggest that AI, when used properly alongside traditional study methods, can enhance student performance. However, it should not replace reading and studying, as a solid understanding of course material still depends on active learning and knowledge acquisition through reading.

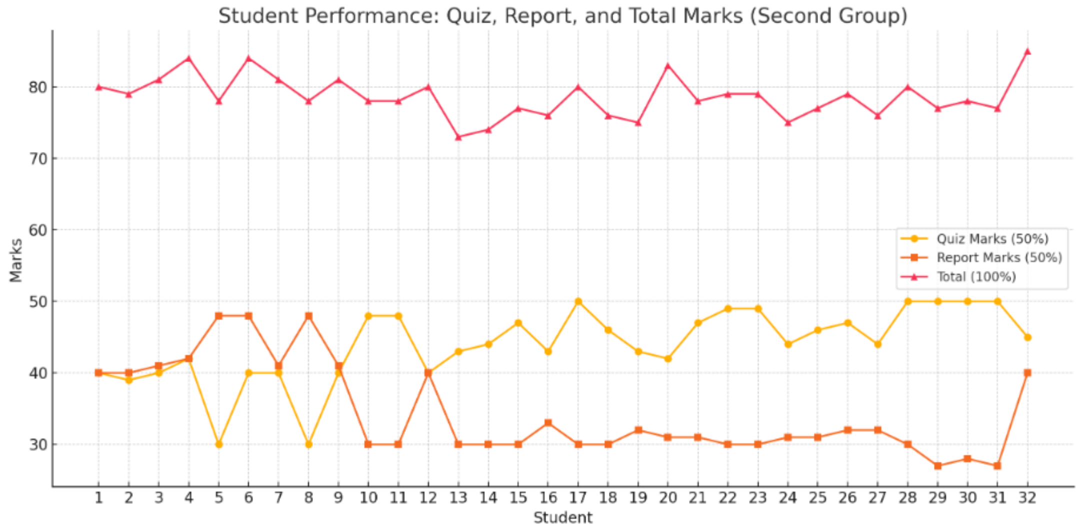

Figure 6: Student's performance of section 2

6. Conclusion

The findings of this study highlight both the potential benefits and limitations of using artificial intelligence in academic learning. While AI tools can streamline assessments and assist with tasks, they may not always promote deep understanding or long-term knowledge retention. The low percentage of students who retained meaningful knowledge from AI-assisted work suggests that passive engagement with technology is insufficient for effective learning. Therefore, while AI can be a valuable supplement to traditional study methods, it should not replace active learning practices. Educators and students alike should strive to use AI thoughtfully as a tool to enhance comprehension rather than as a shortcut around the learning process.

Acknowledgment

The research leading to these results would not be done without the participation of the students, who completely agreed to work, learn and study with the guidelines of the researchers.

Author contribution: All authors have contributed, read, and agreed to the published version of the manuscript results.

Conflict of interest: The authors declare no conflict of interest.

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