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The Effectiveness of (SWOM) Strategy Based on ChatGPT Technique on Academic Achievement in Science Subject for Eighth-Grade Students

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Key Words

School-Wide Optimum Model (SWOM),
ChatGPT,
Academic Achievement,
Active Learning.

Abstract

The study explored the integration of an AI language model such as ChatGPT into (SWOM) Strategy to enhance the science academic achievement of eighth graders. In many traditional classroom settings, higher-order thinking skills and meaningful student engagement are not developed, both of which are crucial for deep and long-lasting learning. AI tools such as ChatGPT may help bridge gaps in education by offering immediate feedback, promoting interactive learning, and tailoring instruction to individual student needs. This study was conducted in a private school and involved a sample of (40) students divided into two groups: an experimental group, which was treated with the SWOM strategy enhanced by ChatGPT, and a control group, which was taught via regular teacher-led teaching methods. Academic achievement was measured using a 30-item multiple-choice test to assess the outcome. To ensure the reliability of the test, two methods were employed. First, Kuder-Richardson Formula 20 (KR-20) was used. to evaluate the internal consistency of the test, which yielded a reliability coefficient of 0.891, indicating high reliability. Second, split-half reliability was used, resulting in a coefficient of 0.886. Drawing on Cognitive Learning Theory, Constructivism, and Mayer's Cognitive Theory of Multimedia Learning (CTML), the study posits that meaningful learning can occur more readily when students construct knowledge actively through verbal communication and digital interaction. There was a statistically significant increase in the academic performance of the experimental group, highlighting the advantages of using AI techniques in combination with novel teaching methods. These results will support educators, curriculum developers, and efforts to modernize science education.

1. Introduction

With the rapid advancement of science and technology, and increasing specialization in various fields, education must continuously adapt to keep up. This progress highlights the growing need for more effective methods that better prepare students for the future. Traditional teaching methods, which are often based on lecture-based instruction and rote memorization, have been failing to engage students actively and foster deep learning (Freeman et al., 2014). On the other hand, active learning strategies, such as inquiry-based learning (IBL) and problem-based learning (PBL), have been shown to enhance students' engagement and understanding (Hmelo-Silver, 2004). More recently, the emergence of artificial intelligence (AI) in education—particularly the use of AI chatbots such as ChatGPT—has opened new avenues for critical thinking and interactive learning (Holmes et al., 2021; Brown, 2021). Various studies provide evidence that technology can be successfully integrated into various forms of educational contexts (e.g., Mayer, 2008; Clark and Mayer, 2016). However, the effect of combining AI tools like ChatGPT with teaching strategies like SWOM on students' achievements remains relatively unexplored. The study would investigate the effectiveness of ChatGPT integrated into SWOM in producing a better learning outcome for eighth graders. By analyzing the impact of this approach, the research seeks to provide valuable insights into the role of AI in education and its potential benefits in students' outcomes.

1.1. The Problem Statement

Although AI-based educational tools are becoming more prevalent, many students find it difficult to acquire higher-order thinking skills, develop, and achieve academic success in the science subject (Luckin et al., 2016; Selwyn, 2019). Because the use of traditional teaching methods is more frequent in the classroom, which relies on a teacher-centered approach and passive learning, it cannot fully meet the diverse learning styles (Prince, 2004; Bonwell and Eison, 1991), limiting opportunities for students to actively engage with scientific concepts (Felder and Brent, 2016). This lack of interactive learning experiences can hinder students' ability to develop a deeper understanding of the subject matter (Jones, 2019; Bergmann and Sams, 2012).

The core issue addressed in this study is whether the SWOM strategy enhanced by ChatGPT would lead to a significant improvement in academic achievement among eighth-grade students, in terms of establishing how much this method is greater than the traditional ones and whether AI learning would make sense in gaining a better understanding and motivation in science learning (Zawacki-Richter et al., 2019; Hwang et al., 2020).

1.2. Research Questions:

We can state the problem of the research to answer the main question:

- What is the impact of using a School-Wide Optimum Model (SWOM) strategy integrated with the ChatGPT technique on academic achievement in the subject of science for eighth-grade students? The following branched out from this question.

1.3. Significance of the Study

The significance of this research is stepping towards the field of educational technology, as it contributes to the growing body of research on integrating artificial intelligence, AI-assisted learning, and science education, especially in understanding the effectiveness of the School-Wide Optimum Model (SWOM) Strategy when linked with ChatGPT (Luckin, 2018; Zhai et al., 2021). This study plays a crucial role in exploring the potential benefits of this technology in improving students' outcomes, including academic achievement, and modernizing teaching methodology by incorporating AI.

The significance of this study could be summarized in the following:

- Examine whether integrating ChatGPT into the SWOM strategy improves scientific academic achievement (Kasneci et al., 2023; Marzano, 2017).

- Adds to AI education research through an exploration of the effect of ChatGPT within structured teaching methods (Dai et al., 2023; NRC, 2012).
- Explores whether ChatGPT integration with SWOM can help increase students' performance in science across diverse backgrounds.
- Redefine teacher roles in AI Classroom by evaluating how ChatGPT changes teacher's roles from just giving lectures to guiding students as they lean with AI (Molenaar, 2022; Selwyn, 2019).

1.4. Research Objectives

The School-Wide Optimum Model (SWOM) strategy is meant to enhance students' thinking skills and promote critical thinking among them. By incorporating the powerful AI language model ChatGPT into this strategy, this research aims to:

1. Evaluate the effectiveness of ChatGPT integrated into the SWOM strategy on 8th-grade students' academic achievement in science.
2. Compare the academic achievements of 8th-grade students taught with the SWOM strategy based on ChatGPT and a traditional method.

1.5. Research Hypothesis

There is NO significant difference at the level of significance ($\alpha = 0.05$) between the mean marks of the experimental group and the control group on the achievement test.

1.6. Field and Limitations of the Study

- **Limited Location:** The study geographically is limited to one educational setting, a single private school in one district.
- **Sample Size:** The sample size is 40 students in 8th grade.
- **The Study Subject Matter:** The strategy is implemented in four specific chapters of the 8th-grade biological science curriculum.
- **Time Limitation:** The academic year is 2024-2025; the data collection and implementation of the research were confined to the months of November and December.
- **Content of the Study:** The content of the subject matter is the Grade 8 science book.

1.7. Definition of Key Terms

- **School-Wide Optimum Model (SWOM) Strategy:** is related to a specific method to engage students to focus on the educational process effectively and efficiently by making them the center of the process through diverse methods that help them develop their teamwork and communication skills which engage students in exercising decision-making and information mastery through a variety of pedagogical tools.
- **ChatGPT** is a smart or intelligent program that was developed by OpenAI also known as a language model used to understand and generate human-like text based on the input it receives. ChatGPT can perform tasks such as answering questions, providing information, conversing with the user, and carrying out tasks, including working on assignments, brainstorming ideas, and more.
- **Academic Achievement** refers to the knowledge and skills obtained by students via educational experiences that are aimed at achieving their learning goals. Students' outcomes, attention, and problem-solving cognitive processes influence academic achievement through many other factors such as learning strategies and motivation. The evaluation of academic achievement is measured through standardized tests, classroom participation, assignments, and presentations.

2. Literature Review

2.1. Theoretical Background of the SWOM Strategy

The theatrical foundation in education provides a structured framework to understand how students learn and the mechanisms that affect their learning outcomes. This section frames the theoretical framework that is used to guide research on the effectiveness of the School-Wide Optimum Model (SWOM) based on ChatGPT in enhancing academic achievement and developing scientific curiosity among eighth-grade students. This model fosters multimedia learning, active learning, discovery learning, and collaborative learning, and it fits very well with several key educational theories. The subsequent sections explain the theoretical frameworks that inform this study: Cognitive Learning Theory and Constructivism Theory. These learning theories provide a comprehensive understanding of how this innovative educational model can potentially enhance student learning. Additionally, types of learning that can be related back to each theory are discussed, followed by an explanation of how these theories connect to the research strategy and approach.

2.2. Cognitive Learning Theory:

Cognitive Learning Theory (CLT) is a psychological framework that explains learning as an active process that pursues a clear understanding of learning, with a primary focus on the internal mental processes that are fundamental to how individuals acquire knowledge, process it, and retain it (Schunk, 2020).

2.3. Cognitive Theory of Multimedia Learning

Richard Mayer's Cognitive Theory of Multimedia Learning (CTML) can give us another understanding of how a learner processes information presented through different modalities such as text, sound, pictures, images, and so on (Mayer, 2009). The theory builds its ideas around three main principles (Sorden, 2015), which are assumed:

1. Dual-channel assumption – Humans use auditory and visual channels in processing information (Mayer, 2005).

2. Limited capacity assumption – Each channel has a limited capacity for processing information at any given time (Sorden, 2015).

3. Active processing assumption – States that meaningful learning occrurs when learners actively select, organize, and integrate a specific piece of information (Mayer, 2014).

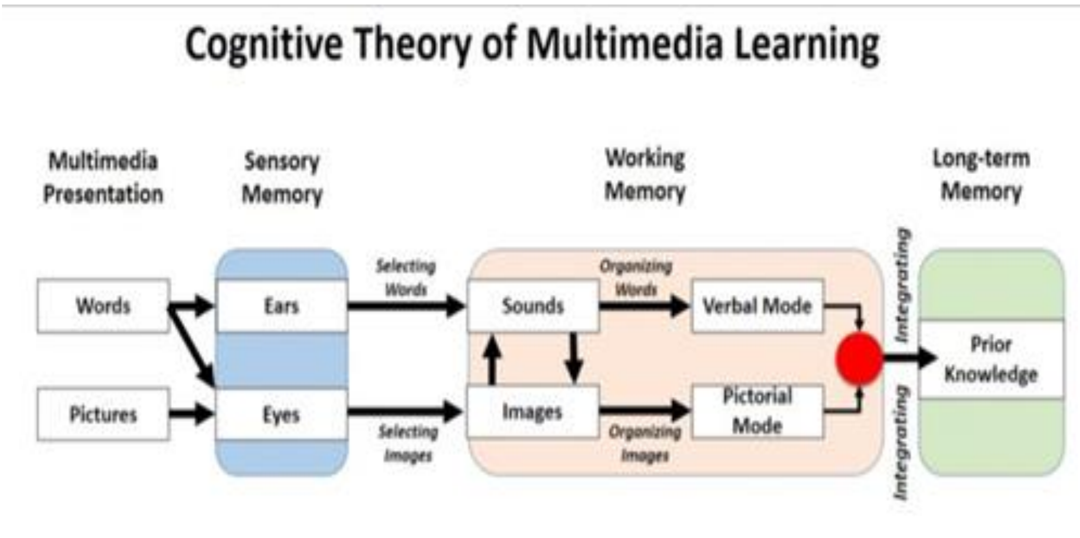

Figure 2.1: Cognition in Multimedia Learning Reference: (Mayer andMoreno, 2023, p.4)

2.4. Constructivism Theory and Vygotsky's Sociocultural Theory

It is an educational theory as proposed by Piaget and Vygotsky that grounds the idea that students bring valuable prior knowledge to their classes through interaction with their environment, and teachers can help learners build up that knowledge through personally meaningful learning activities rather than passively received information (Candy, 2019, p. 112; Piaget,2013, p. 24; Vygotsky, 2012, pp. 86, 57-91). Lev Vygotsky highlights the importance of social interaction and cultural tools in developing cognitive ability (Brooks and Brooks, 2020, pp. 45-60). He believes that learning occurs in society through interaction with others, peers or teachers, for example, or other instruments like ChatGPT technology. According to Vygotsky, knowledge is constructed collectively through these social interactions rather than learners developing in isolation from social situations and cultural tools (Wertsch, 2018).

2.5. Alignment of Learning Theories with the SWOM Strategy and ChatGPT

The integration of the SWOM strategy and ChatGPT aligns well with several foundational learning theories. Cognitive Learning Theory emphasizes internal mental processes such as memory, attention, and self-regulation, which are supported by ChatGPT's personalized feedback and SWOM's focus on learner autonomy (Schunk, 2020; Belay, 2022). Mayer's Cognitive Theory of Multimedia Learning (CTML) explains how learners process visual and auditory information through dual channels, limited capacity, and active processing. ChatGPT's use of multimedia responses and structured outputs aligns with key CTML principles: modality, personalization, segmenting, and signaling that enhance comprehension and retention (Mayer, 2009; Sorden, 2015). From a constructivist perspective, learners build knowledge through exploration and reflection. SWOM encourages this by engaging students in meaningful interactions with ChatGPT, allowing them to connect new information with prior knowledge (Çibukçiu, 2025; Ertmer and Newby, 1993). Furthermore, Vygotsky's Sociocultural Theory highlights the role of social interaction and cultural tools in learning, with ChatGPT acting as a digital More Knowledgeable Other (MKO) that guides students within their Zone of Proximal Development (ZPD) through questioning, feedback, and scaffolded support (Johnson et al., 2024; Bull and Hillier, 2023). Together, these theories demonstrate that SWOM and ChatGPT foster active, personalized, and socially supported learning.

2.6. School-Wide Optimum Model (SWOM) Strategy

The SWOM strategy is an innovative educational framework designed for improving learning as well as the development of thinking skills (Ahmed, n.d.). It stands for School-Wide Optimum Model. It was developed by Omer Ahmed, Director of the Idrak Center for Learning, Thinking, and Talent Development in the United Arab Emirates. SWOM was also developed through collaboration with the US National Center, which indicated a foundation built on established best-practice concepts in education. Hence, understanding the history behind SWOM gives quite an interesting perspective into the thinking that underlies it as a belief that developed thinking is the most important factor in learning and the all-round development of the student. SWOM comprises a student-centered strategy that integrates thinking skills into the curriculum. "It is defined as a series of planned sequences and learning activities dependent on the following thinking skills such as questioning, comparing, generating possibilities, production, solving problems, and making Discussion," (Al-Edwan and Daoud, 2018; Jasim, 2020; Raji, 2016).

2.7. The Procedure and Steps of SWOM Based on Thinking Skills

The implementation of SWOM is basically a series of properly sequenced processes and stages designed to develop specific thinking skills.

• **Questioning Phase:** The first phase is questioning where students consider questions before, during, and after the learning process as a way to understand the material in a better and more integrated way with what they already know. It also encourages students to come up with questions of their own, which involves them actively with intellectual curiosity (Hussein and Mater, 2020, p. 26).

• **Comparison Phase:** In this phase, students learn to recognize similarities and differences between various pieces of information, whether given or researched. This ensures the systematic organization and effective storage of new knowledge, as students learn to categorize and relate different concepts (Al Ali, Wardat and Al-Qahtani, 2023, p. 6).

• **Generate Possibilities:** The third stage fulfills the requirement of generating probabilities as it motivates students to think of newer possibilities by reframing given information and to come up with new solutions through the constructive use of previous knowledge. This stage is important for developing creative thinking and for approaching a problem with a fresh perspective (Naji, Ali and Qasim, 2021, p. 11125).

• **Prediction Phase:** This is the phase that induces students to think about the possible consequences of engaging activities or reading materials and generate solutions to problems. In fact, it is like imagining future scenarios and possible solutions; thus, it develops students' ability to think ahead and anticipate consequences (Elmalhy, 2022, p. 15).

• **Problem Solving:** The fifth one is problem solving, in which previous knowledge and experience are used to clarify challenging situations by performing a series of specific steps. This phase aims at developing students' mental capacities and ability to recognize and implement appropriate solutions to various problems (Hussein and Mater, 2020, p. 30).

• **Decision-Making:** This phase means that students consciously select from a range of available alternatives in a given situation based on carefully considered criteria in order to meet desired objectives. This final stage requires a critical application of judgment for informed decision-making. These six phases provide an organized framework for educators to integrate thinking skills into their teaching practices (Al Ali, Wardat and Al-Qahtani, 2023, p.7).

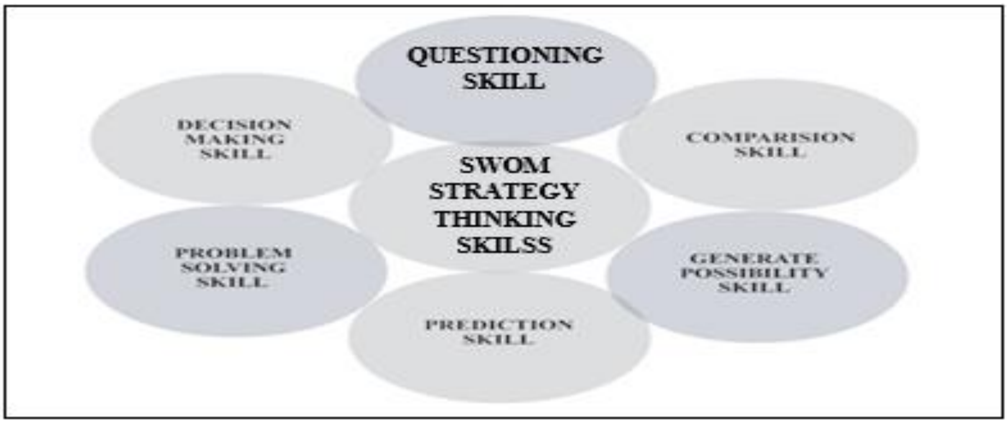

Figure 2.2: SWOM Strategy Six Thinking Skill (Created by Author).

2.8. The Role of Artificial Intelligence and ChatGPT in Education:

Artificial Intelligence (AI) is transforming education by offering personalized learning, tutoring, and automating educational processes for students. At one level, adaptive learning platforms such as Khan Academy with Khanmigo AI and Duolingo use AI to individualize students' needs and provide educational materials (Tech and Learning, 2023). Educationally, ChatGPT is one of the most promising applications in individual tutoring. AI-supported tutoring systems, which now increasingly incorporate LLMs, provide a personalized education adjusted to the unique learning pace and needs of each student (Teachflow, 2023).

AI and ChatGPT have taken center stage in reshaping education, making it more personalized, effective, and accessible. As AI continues to grow, its role in teaching and learning will expand, transforming education at different levels.

2.9. Previous Studies

Understanding the effectiveness of instructional strategies is crucial to improving both academic achievement and cognitive engagement, especially in science education. Recent research emphasizes the role of motivational frameworks, digital tools, and innovative approaches such as the SWOM strategy in enhancing student outcomes. The following four studies provide insight into how these elements influence learning and form a foundation for the current research, which investigates the effect of the SWOM strategy supported by ChatGPT on eighth-grade students' achievement and scientific curiosity.

The first research was conducted by Hayder Qays Naji, Asst. Prof. Dr. Ali Hussein Ali, and Asst. Prof. Dr. Ebtighaa Mohammed Qasim (2021) at the University of Babylon, Iraq. This study explored the impact of the SWOM (School-Wide Optimism Model) strategy on personal struggle and combined offensive skill learning among fourth-year university students. Thirty students were divided into experimental and control groups. Using a Personal Struggle Scale and Offensive Skills Test, the results revealed a significant increase in motivation and performance among those taught using the SWOM strategy. This supports the strategy's ability to foster resilience and learning effectiveness.

The second research was carried out by Sahar Abdulkareem Jameel (2019) in Tikrit, Iraq, and focused directly on the impact of the SWOM strategy on academic achievement and mathematical power among fourth-grade preparatory male students. With 64 participants (32 in each group), the study employed an achievement test and mathematical strength test. Findings showed that the experimental group significantly outperformed the control group, highlighting the SWOM strategy's effectiveness in boosting cognitive abilities and academic performance in mathematics.

The third research, conducted by Daniel Idowu Oludipe, Isaac Ayodele Ojediran, and Oluwaseyi Adeniran Odueke (2013) in Nigeria, examined the effectiveness of cooperative learning strategies on academic achievement in basic science among 150 junior secondary students. Using a quasi-experimental pre-test/post-test design and the Basic Science Attitudes Scale (BSAS), the researchers found that cooperative learning significantly improved students' academic performance. This study reinforces the value of active, student-centered approaches in enhancing learning outcomes.

The fourth research was conducted by Zare, Sarikhani, Salari, and Mansouri (2016) in Iran. Their study investigated the influence of e-learning on academic achievement and creativity among university students studying chemistry. Forty students (20 experimental and 20 control) participated, and pre- and post-tests were used to assess both academic performance and creativity. Results indicated that e-learning significantly enhanced both content understanding and creative thinking, compared to traditional methods. This demonstrates the potential of digital learning environments to support higher-order thinking and knowledge retention.

Together, these studies demonstrate the value of motivational strategies, collaborative learning, and digital tools in improving students' academic achievement and engagement. However, none of them investigated the integration of the SWOM strategy with AI technologies such as ChatGPT. This research addresses that gap by examining how combining SWOM with ChatGPT can enhance both academic achievement and scientific curiosity among eighth-grade students.

2.10. The Benefits of the Previous Studies to the Current Research

The researcher gained the following benefits from previous studies that helped shape the current research design and analysis:

- **Design Validation:**
  Previous studies used a quasi-experimental design, supporting the researcher's choice of a similar approach suitable for educational settings without random assignment.
- **Group Formation:**
  Experimental and control groups were commonly used, guiding the researcher to form comparable groups for effective comparison.
- **Equivalence Checking:**
  The use of tests like Chi-square to ensure group similarity before intervention inspired the researcher to check parents' education for equivalence.
- **Statistical Testing:**
  Pre-and post-tests analyzed with paired and independent t-tests were standard, influencing the researcher's choice of these tests to measure learning gains.

3. Research Methodology and Procedure

This describes the research methodology and procedures followed by the researcher in choosing the research design, defining the research community and selecting the sample, conducting the equivalence process and instructional procedure between the experimental and control groups, data collection instruments, and data analysis techniques. The methodology ensures the validity and reliability of the study, providing a comprehensive framework for examining how ChatGPT integration as a teaching tool impacts students' learning outcomes compared to traditional direct instruction methods. A quasi-experimental design will be employed to assess the effects of the SWOM strategy in a controlled educational setting.

3.1. Research Design

Choosing an experimental design represents the first step a researcher takes when conducting an experiment. Experimental design is the researchers' plan to obtain the answer to the research question and helps to control variables by representing a set of instructions on how to collect data and analyze in a specific way. The research design compares two groups one experimental group exposed to the independent variable (SWOM strategy based on GPT Technique), and the other (i.e., the control group) was taught in the usual way (direct instruction), as shown in Figure 3.1.

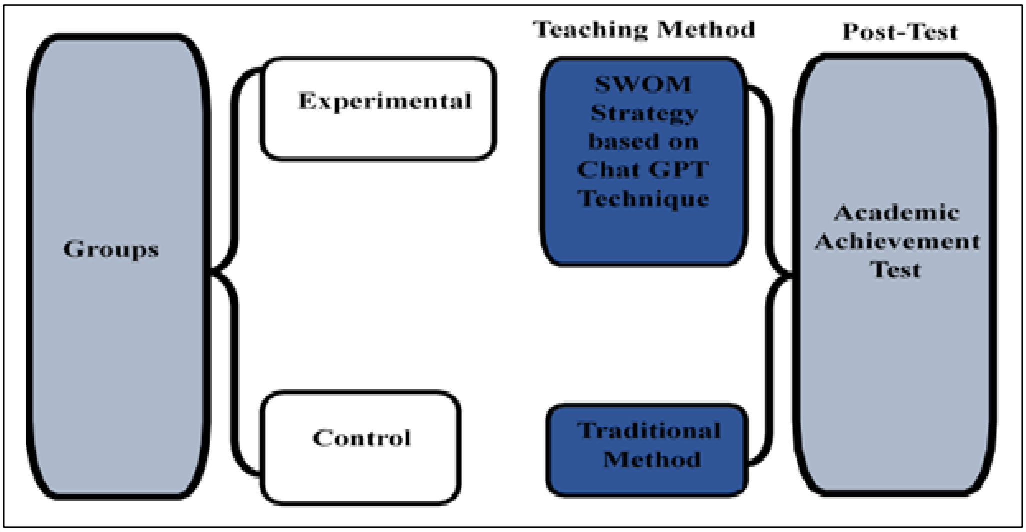

Diagram 3.1: Quasi-experimental Design (Created by the Authors)

3.2. Participants

For the 2024-2025 academic year, the research school had two Grade 8 classes. Therefore, the study sample consists of around 40 Grade 8 students between the ages of 13 and 15 within Yad Private School. Notably, the school has a co-educational system, involving both male and female students attending the same classes. In this two-class study, one class was chosen randomly as an experimental group, and the other was chosen as a control group. At the outset, there were 40 students, 20 in each class (see Table 3.1).

Table 3.1: The final sample of the study comprised a total of 40 students

Groups	Eighth Grades	Number of Students Before Exclusion	Number of Failing Students	Number of Students After Exclusion	Total
Experimental	A	20	0	20	40
Control	B	20	0	20	

3.3. Equivalence Between the Two Groups

This study followed a systematic way of achieving equivalence between the two groups in key demographic and academic variables before the intervention. The equivalence process included matching the two groups based on factors such as academic performance (i.e., their final science grade from the previous school year), age by month, IQ (measured by Raven SPM), degree of general science (based on the students' latest report card grades), and parents' educational levels (both father and mother). Before conducting a statistical comparison between the experimental and control groups, normality was previously established for demographic and academic variables. Following the normality test, a group equivalency test was conducted to determine whether there were statistically significant differences between the two groups regarding key variables before the implementation of the SWOM strategy. The results are summarized in the table below:

Table 3.2: Equivalence Between Two Groups of Students Based on Their (Age, IQ, Academic Score, and Degree of General Science)

Categories	Normality test	Test	Group	df	Mean	Std. Deviation	Test Value	P-Value	Significant
Age by month	Not Normal	Mann-Whitney U Test	Experimental	20	164.20	9.785	203.0	0.935U	No significant Difference
	Normal	Mann-Whitney U Test	Controlled	20	163.30	8.820			
IQ	Not Normal	Mann-Whitney U Test	Experimental	20	3.20	1.240	256.5	0.112U	No significant Difference
	Not Normal	Mann-Whitney U Test	Controlled	20	3.80	1.322			
Science Academic Score	Normal	Independent Sample T. Test	Experimental	20	66.55	18.257	-0.405	0.688t	No significant Difference
	Normal	Independent Sample T. Test	Controlled	20	68.90	18.450			
Degree of general Science	Normal	Independent Sample T. Test	Experimental	20	894.70	105.015	-0.219	0.827t	No significant Difference
	Normal	Independent Sample T. Test	Controlled	20	902.75	126.036			

3.4. Equivalence of Fathers' and Mothers' Academic Achievement Between Groups

To prevent parental education from acting as an intervening variable in this study, the academic achievement levels of the fathers and mothers in the experimental and control groups were compared by using the Chi-Square Fisher-Freeman-Halton Exact test to determine if a significant difference existed between the two groups. The result is summarized in the table below:

Table 3.3. The Significance was Determined by the p-value

		Experimental Group	Controlled Group	Total	P_Value	Significant
Father Academic Achievement	Primary	7	5	12	0.426	No significant Difference
	Secondary	4	7	11		
	High school	4	3	7		
	Diploma	0	3	3		
	Bachelor	3	1	4		
	No degree	2	1	3		
Total		20	20	40		
Mother Academic Achievement	Primary	7	6	13	0.555	No significant Difference
	Secondary	5	4	9		
	High school	0	3	3		
	Diploma	1	1	2		
	Bachelor	0	1	1		
	No degree	7	5	12		
Total		2o	20	40		

3.5. Research Requirements

To conduct the current study, a clearly defined set of preparatory steps was established to ensure its accuracy and reliability. These requirements included preparing the academic achievement test, identifying scientific materials, developing behavioral objectives for learners, preparing the academic achievement test, and detailed teaching plans for both groups of learners: experimental and control.

To fulfill the goal of the study and test its hypotheses, both groups studied the same content from Chapters 3, 4, 5, and 6 of the Grade 8 Science textbooks for the first semester of the academic year (2024-2025). Sixty-three behavioral objectives were developed to cover the scientific material comprehensively. These objectives were formulated based on Bloom's Taxonomy, a widely used framework that classifies educational goals into cognitive levels, including Knowledge, Comprehension, Application, and Analysis to ensure a structured progression from basic recall to higher-order thinking skills.

The experiment lasted for nine weeks, starting from Sunday (27/10/2024) to Wednesday (25/12/2024), during which five science lessons were delivered every week. Thus, each group attended a total of 42 lessons. The final test, however, was conducted on Wednesday (25/12/2024) to determine students' level of academic achievement. The procedure for the preparation of academic achievement is summarized in the diagram below:

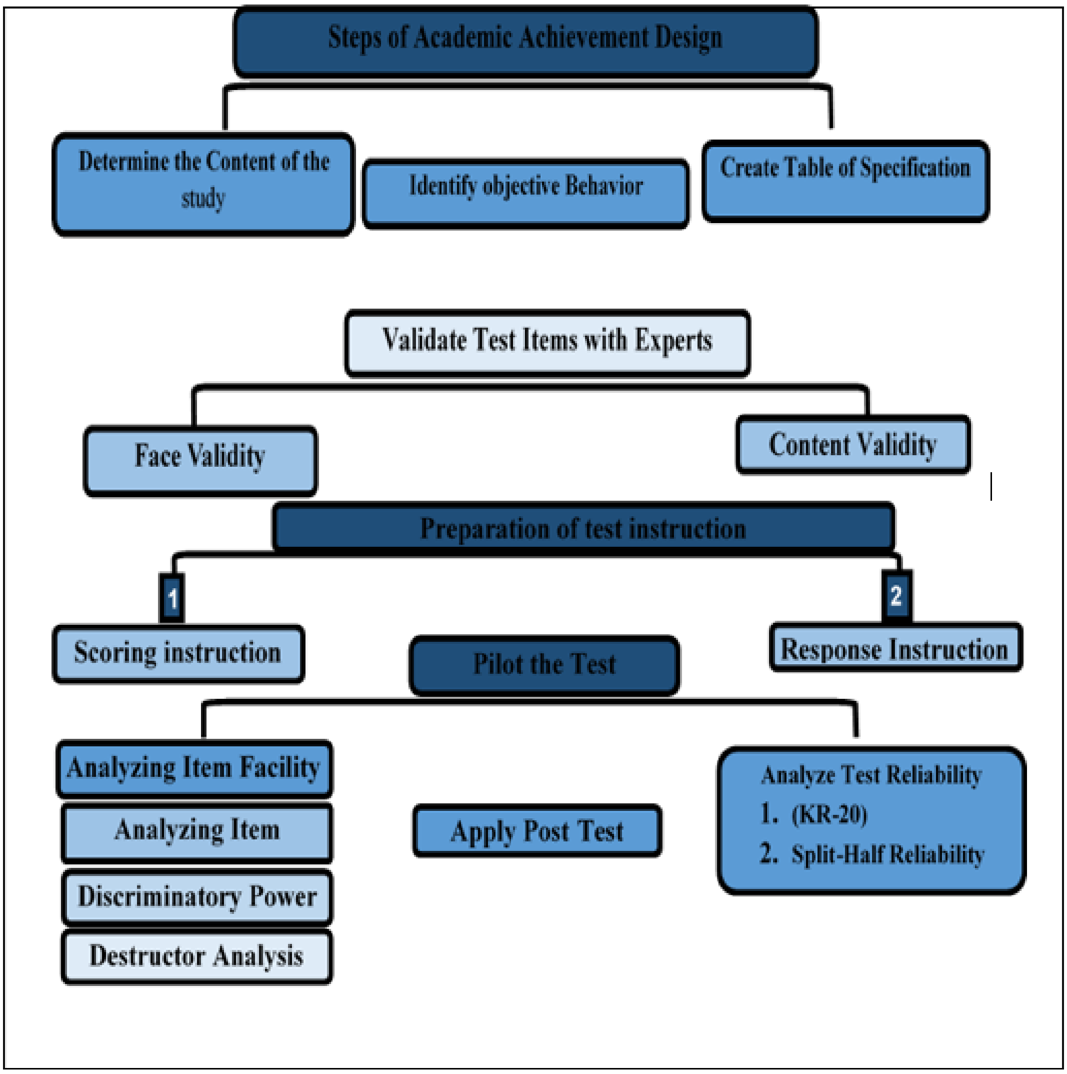

Diagram 3.2: Academic Achievement Test Implementation

3.6. Table of Specification (Test Map)

The exam blueprint at this point was developed by integrating the concept percentages and the weight ratios of the cognitive objectives. The purpose was to determine the appropriate number of questions to be selected from each chapter and each level of Bloom's Taxonomy. The researcher selected 30 questions that were part of the total 63 items and were directly aligned with the behavioral objectives. Each question was carefully analyzed and classified according to the appropriate cognitive level, as shown in the table below:

Table 3.4: Exam Specification (Making 30 Questions from 63 Questions of Scientific Concepts)

Content	chapters	subject	Page numbers	Percentage of concepts	Knowledge	Comprehension	Application	Analyzing	Total Questions
					49%	24%	17%	10%	
Unit one	Chapter 3	Plant Process	11	21%	3	2	1	1	7
Unit two	Chapter 4	Animals	14	27%	4	2	1	1	8
Unit two	Chapter 5	Fish, Amphibians and Reptiles	18	35%	5	3	1	1	10
Unit two	Chapter 6	Birds and Mammals	9	17%	2	1	1	1	5
	Total		52	100%	14	8	4	4	30

3.7. Test Validity

1. **Face Validity:** Face validity refers to how appropriate and clear the test items appear to experts at first glance. In this study, test items were reviewed by experts for clarity and relevance. Cooper's agreement formula, with an acceptance level of 86% and above, was utilized.
2. **Content Validity:** Content validity ensures that test items comprehensively represent the intended subject matter. The researcher prepared a total of 63 questions, which were aligned with the behavioral objectives and the test specification table. This was followed by having them reviewed by a panel of subject matter experts to establish their agreement and provide recommendations based on their feedback.

3.8. Pilot Study for the Academic Achievement Test

A pilot study was conducted prior to administering the final test to the research sample to ensure the reliability, clarity, and appropriateness of the test items. Before administering the test to the research sample, the first pilot test was conducted under the supervision of the researcher, who cooperated with the school̓s administration and subject teacher. The pilot test sample consisted of 100 Grade 8 students from four different private schools. The testing time was determined by recording the time taken by the first five students and the last five students to finish their examinations. The first five completed the test in 45 minutes, while the last five completed it in 55 minutes. Adding these two times and dividing by two gave an average of 50 minutes for the completion of the test.

3.9. Statistical Analyses

To ensure the academic achievement test's reliability and validity, a thorough statistical analysis was done to examine relevant parameters concerning test item quality and test structure.

3.9.1. Test Reliability: According to Cohen, Manion, and Morrison (2018), reliability refers to the consistency, stability, and dependability over time while being used under different conditions. Reliability measurement of the Scientific Concepts Acquisition Test was determined by two methods:

3.9.1.1. Kuder-Richardson-20 Formula: A pilot study with 100 students produced a KR-20 coefficient of 0.891, which indicates a high level of internal consistency, as shown in Table (3.5).

Table (3.5)- Reliability of Academic Achievement Test out of 100 students

Reliability Statistics		
Kuder-Richardson	Kuder-Richardson Based on Standardized Items	N of Items
.891	.891	30

3.9.1.2. Split-half reliability: To assess the internal consistency of the academic achievement test, the split-half method was employed, followed by the application of Spearman̓s rho prophecy formula. The correlation between the two halves of the test was 0.795 and to estimate full test reliability the Spearman-Brown formula was applied and the reliability coefficient result was 0.886 which indicates high internal consistency. See Table (3.6).

Table (3.6): Split-Half Correlation and Estimated Full-Test Reliability Using the Spearman–Brown Formula

Correlation Between Halves (Spearman's rho)	Estimated Full-Test Reliability(r_sb)	Interpretation
0.795	0.886	High Internal Consistency

3.9.2. Facility and Difficulty Index The facility index, or item difficulty index, indicates the percentage of students who answered the item correctly. Contrary to the use of the term 'difficulty,' a higher P-value indicates a much easier item, whereas a lower P-value would define the item as more difficult (Brown, 2020; Popham, 2020). The acceptable range is between (0.20 - 0.80); most test items in this study lie within the ideal difficulty range between 0.20 and 0.80 (Haladyna et al., 2013). (See Table 3.7).

Table (3.7): Facility Index, Difficulty Index, for Academic Achievement Test Items

Items	Correct Answer	Number of Correct answer in Both Group		Facility Index (P_value)	Difficulty index (P_Value)	Items	Correct Answer	Number of Correct answer in Both Group		Facility Index (P_value	Difficulty index (P_Value
		Upper Group	Lower Group					Upper Group	Lower Group		
Q1	A	14	1	0.28	0.72	Q16	A	25	14	0.72	0.28
Q2	C	21	11	0.59	0.41	Q17	B	26	8	0.63	0.37
Q3	B	20	6	0.48	0.52	Q18	D	26	16	0.78	0.22
Q4	B	23	10	0.61	0.39	Q19	B	25	4	0.54	0.46
Q5	D	27	8	0.65	0.35	Q20	B	26	13	0.72	0.28
Q6	A	25	5	0.56	0.44	Q21	A	27	4	0.57	0.43
Q7	A	15	2	0.31	0.69	Q22	C	22	10	0.59	0.41
Q8	C	22	6	0.52	0.48	Q23	B	27	6	0.61	0.39
Q9	B	23	10	0.61	0.39	Q24	A	27	3	0.56	0.44
Q10	D	23	7	0.56	0.44	Q25	B	26	5	0.57	0.43
Q11	B	21	8	0.54	0.46	Q26	A	21	10	0.57	0.43
Q12	A	16	2	0.33	0.67	Q27	B	25	15	0.74	0.26
Q13	B	23	3	0.48	0.52	Q28	C	23	11	0.63	0.37
Q14	A	23	4	0.50	0.50	Q29	B	26	13	0.72	0.28

3.9.3. Discrimination Index:

Items were assessed based on their ability to distinguish high- and low-performing students. D-value states that items whose discrimination index is 0.40 or above are considered excellent; items between 0.30 and 0.39 are considered good; items with values between 0.20 and 0.29 discriminate acceptably but should be improved upon; and items with D-values below 0.20 are considered weak in discrimination and are recommended for deletion. The analysis thus showed an acceptable index of discrimination for all items above 0.30, indicating that each item could differentiate performance levels. (See Table 3.8).

Table (3.8) - Discrimination Index for Academic Achievement Test

Items	Correct Answer	Number of Correct answer in Both Group		Discrimination Index	Items	Correct Answer	Number of Correct answer in Both Group		Discrimination Index
		Upper Group	Lower Group				Upper Group	Lower Group	
Q1	A	14	1	0.48	Q16	A	25	14	0.41
Q2	C	21	11	0.37	Q17	B	26	8	0.67
Q3	B	20	6	0.52	Q18	D	26	16	0.37
Q4	B	23	10	0.48	Q19	B	25	4	0.78
Q5	D	27	8	0.70	Q20	B	26	13	0.48
Q6	A	25	5	0.74	Q21	A	27	4	0.85
Q7	A	15	2	0.48	Q22	C	22	10	0.44
Q8	C	22	6	0.59	Q23	B	27	6	0.78
Q9	B	23	10	0.48	Q24	A	27	3	0.89
Q10	D	23	7	0.59	Q25	B	26	5	0.78
Q11	B	21	8	0.48	Q26	A	21	10	0.41
Q12	A	16	2	0.52	Q27	B	25	15	0.37
Q13	B	23	3	0.74	Q28	C	23	11	0.44
Q14	A	23	4	0.70	Q29	B	26	13	0.48
Q15	C	25	11	0.52	Q30	C	24	7	0.63

3.9.4 Effectiveness of Distractors

To evaluate Distractor Effectiveness (DE), the test response patterns of upper and lower groups were analyzed. In general, the researcher concluded that most distractors within the test items are effective and well-chosen, as indicated in (Table-3.7). Thus, all of the distractors were functioning distractors because they showed appropriate selection patterns favoring the lower-performing group, contributing to the overall quality of the test itself.

Table (3.9) - Distractor Effectiveness (DE) for Academic Achievement Test Items Choice

Items	Correct answer of the upper group				Correct answer of the lower group							
	A	B	C	D	A	B	C	D	A	B	C	D
1	14	5	4	4	1	10	9	7	✓	-0.19	-0.19	-0.11
2	1	1	24	1	6	6	11	4	-0.19	-0.19	✓	-0.11
3	3	20	2	2	7	6	7	7	-0.15	✓	-0.19	-0.19
4	1	23	2	1	7	10	7	3	-0.22	✓	-0.19	-0.07
5	0	0	0	27	6	6	7	8	-0.22	-0.22	-0.26	✓
6	24	2	1	0	5	8	8	6	✓	-0.22	-0.26	-0.22
7	15	6	4	2	2	7	9	9	✓	-0.04	-0.19	-0.26
8	2	2	22	1	8	7	6	6	-0.22	-0.19	✓	-0.19
9	2	23	1	1	7	10	5	5	-0.19	✓	-0.15	-0.15
10	1	1	2	23	7	4	9	7	-0.22	-0.11	-.0.26	✓
11	2	21	2	2	8	8	6	5	-0.22	✓	-0.15	-0.11
12	16	4	4	3	2	6	9	10	✓	-0.07	-0.19	-0.26
13	2	23	1	1	11	3	8	5	-0.33	✓	-0.26	-0.15
14	23	1	2	1	4	7	11	5	✓	-0.22	-0.33	-0.15
15	1	1	25	0	7	4	11	5	-0.22	-0.11	✓	-0.19
16	25	1	1	0	14	5	4	4	✓	-0.15	-0.11	-0.15
17	1	26	0	0	6	8	9	4	-0.19	✓	-0.33	-0.15
18	0	1	0	26	5	3	3	16	-0.19	-0.07	-0.11	✓
19	2	25	0	0	8	4	8	7	-0.22	✓	-0.30	-0.26
20	1	26	0	0	5	13	7	2	-0.15	✓	-0.25	-0.07
21	27	0	0	0	4	7	9	7	✓	-0.26	-0.33	-0.26
22	2	2	22	1	7	6	10	4	-0.19	-0.15	✓	-0.11
23	0	27	0	0	8	6	8	5	-0.30	✓	-0.30	-0.19
24	27	0	0	0	3	10	8	6	✓	-0.37	-0.30	-0.22
25	0	26	0	1	8	5	9	5	-0.30	✓	-0.33	-0.15
26	21	1	3	2	10	6	6	5	✓	-0.19	-0.11	-0.11
27	1	25	0	1	3	15	5	4	-0.07	✓	-0.19	-0.11
28	1	1	23	2	5	5	11	6	-0.15	-0.15	✓	-0.15
29	1	26	0	0	6	13	6	2	-0.19	✓	-0.22	-0.07
30	1	1	24	1	7	7	7	6	-0.22	-0.22	✓	-0.19

3.10. Experiment Implementation

An orderly structured approach was followed in conducting the experimental phase as it entailed preparation, pre-testing, intervention, and post-testing. Preparation was undertaken adequately, with all necessary materials timely provided: laptops and internet connectivity were given to students free by the school and the researcher. Fairness and reliability in testing procedures were assured through the administration of a pre-test under parallel conditions: Raven's Standard Progressive Matrices Test on 21/10/2024.

The intervention, from 27/10/2024 until 26/12/2024, consisted of the application of lesson plans under the SWOM strategy and GPT technology to the experimental group. Students were grouped into clusters that rotated their assigned roles (Researcher, Recorder, Group Leader, Presenter, Analyzer) to ensure active participation and cooperative learning. The post-tests for both groups were given after the intervention: the Academic Achievement Test on 25/12/2024. The Academic Achievement Test was designed to be administered only post-intervention so as to assess academic performance.

4. Presentation of Research Results and Conclusion

This section presents and discusses the results of the study and data analysis to be able to test the effect of using the School-Wide Optimum Model (SWOM) strategy in conjunction with ChatGPT on academic achievement among eighth graders in science.

4.1. The Hypothesis

Eighth-grade students exposed to the ChatGPT-integrated SWOM strategy will demonstrate significantly the same levels of academic achievement in science compared to those who receive instruction using the traditional method. The test of normality for post-tests of academic achievement shows that the Academic Achievement scores for the experimental and control groups are drawn from a normal distribution. A Shapiro-Wilk test was performed. The post-test p-values in both groups are greater than 0.05 (in the experimental group, p= 0.350 and in the control group, p=0.340). It means the null hypothesis was not rejected. Thus, the data are normally distributed.

Table 4.1- Academic Achievement Normality Test Using the Shapiro-Wilk Test

Tests of Normality					
		Shapiro-Wilk			
	Group	Statistic	df	Sig.	Decision
Total Score	Experimental	.949	20	.350	Normally Distributed
	Control	.948	20	.340	Normally Distributed

Since the p-values were greater than 0.05, the assumption of normality was satisfied. Therefore, an Independent Samples t-test was applied to determine the difference between Academic Achievement post-test scores of the experimental and control groups. The table below represents the achievement results for both groups.

Table 4.2- Comparison between Control and Experimental Groups' Academic Achievement Test Using Independent Samples t-Test

Group Statistics								
Test	Group	df	Mean	Std. Deviation	T-Value	P-Value	Decision	Effect Size
Independent Sample T.Test	Experimental Group	20	21.8500	4.28308	3.361	0.002	We reject the Null Hypothesis	1.063
Independent Sample T.Test	Controlled Group	20	15.8500	6.73776				Large Effect

4.2 Result and Interpretation of the Hypothesis

This hypothesis proposed that there would be no significant difference in academic achievement between the experimental and control groups. However, this hypothesis was rejected, because there was a statistically significant difference between the academic achievement of the experimental and control groups. The mean post-test score for students in the experimental group was 21.85, compared to the control group which was 15.85. An independent samples t-test confirmed a highly significant outcome ($p = 0.002$), with a very large effect size (Cohen's $d = 1.063$). These findings suggest that the SWOM strategy, combined with ChatGPT, not only develops scientific curiosity but also supports better academic achievement.

One of the key factors contributing to this success is the effectiveness of ChatGPT in offering immediate feedback. Students benefited from, personalized clarification, and multiple pathways for understanding concepts—features that supported deeper learning and greater confidence. The full academic test scores used in this analysis can be found in the appendix data (Table 22). The data shows this clearly: students in the experimental group achieved consistently high marks (e.g., 28, 27, 26), whereas the control group had several low scores (e.g., 4, 7, 8). This achievement gap can highlight the benefits of a dynamic, student-centered learning environment—one that encourages exploration and supports individual needs. In comparison, the control group, which followed traditional teacher-led instruction, lacked this flexibility. The approach was less adaptive and offered fewer opportunities for students to actively engage with the content, which likely contributed to their lower achievement. Overall, these results strongly support the idea that AI-assisted strategies like SWOM with ChatGPT can significantly enhance academic success in science education. This is visually represented in Figure 4.1.

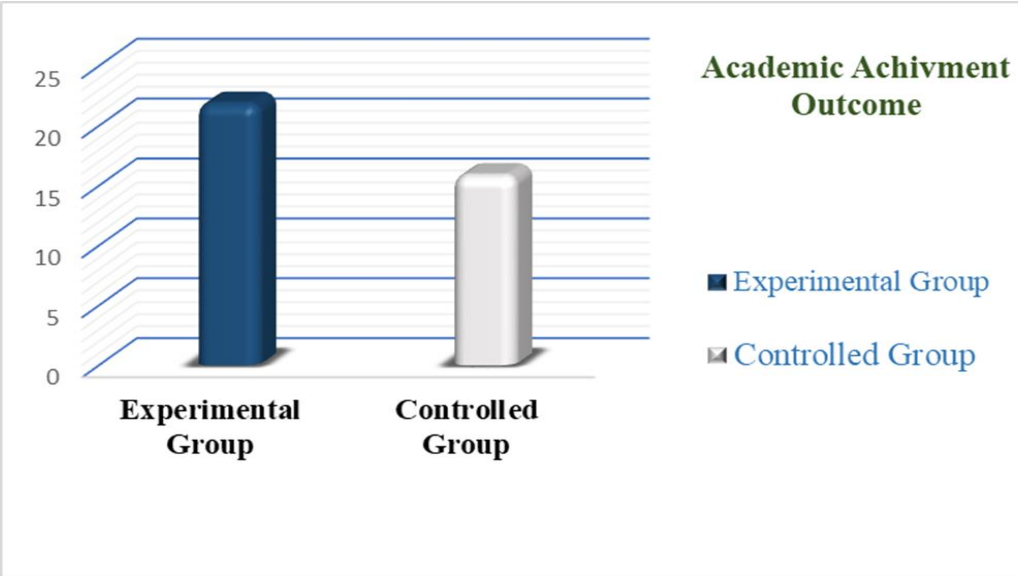

Figure 4.1 - Comparison between the control and experimental groups' academic achievement test using a Bar chart.

5. Conclusion

The result of this study indicates that the (SWOM)Strategy based on ChatGPT is highly effective in enhancing academic achievement among eighth-grade students compared to the traditional teaching method. The experimental group, which was exposed to a student-centered learning environment using ChatGPT, showed significantly higher performance and engagement compared to the control group that received direct instruction. This finding indicates that integrating AI-powered educational tools like ChatGPT, when combined with a structured and student-centered framework like (SWOM), can provide meaningful improvements and foster better engagement, deeper understanding, and heightened motivation in science learning. Furthermore, the equivalence in pre-test scores and IQ levels between the two groups confirms that the improved outcomes are directly, due to the teaching method rather than prior ability or external variables.

In light of the study's results, it is recommended that educators, educational institutions, curriculum designers, and school administrators integrate AI technologies such as ChatGPT into their science teaching practices through innovative strategies like SWOM to enhance science education. Teacher preparation programs should also include training modules on how to effectively integrate AI tools to enhance classroom instruction. Schools are encouraged to provide the necessary technological infrastructure and support to ensure smooth implementation.

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Appendix (1): Validity Evaluation for Scientific Concepts Acquisition

Order	Name	Specialty	Scientific Title	Work place
1	Dr. Farhad Ali Musafa	Teaching Method	Professor	Salahading university-Erbil
2	Dr. Fatimah E.H.Al Bajalani	Teaching methods	Professor	SUE, College of Languages
3	Dr: Mohammad ismail sulaiman	Teaching Method	Assistant Professor	University of Zakho \ College of Education
4	T. Ara Jalal Hamad Ameen	Teaching Method	Assistant Lecturer	Faculty of Education, Soran University
5	Dr. Talb Muhhamad Sharef	Teaching Method	Lecturer/ Head of Mergasor Technical Institute	Mergasor Technical Institute
6	Dr. Hussein Side Ebrahim	Teaching Method	Professor	Salahadin University-Erbil
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کاریگەریی ستراتیژی (SWOM) لەسەر بنەمای تەکنیکی ChatGPT لەسەر دەستکەوتی ئەکادیمی لە بابەتی زانست بۆ قوتابیانی پۆلی هەشتەم

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پوختە

ئەم توێژینەوەیە لێکۆڵینەوە دەکات لە تێکەڵکردنی مۆدێلێکی زمانیی ژیری دەستکرد وەک ChatGPT لەناو ستراتیژی (SWOM) بە ئامانجی بەرزکردنەوەی دەستکەوتی زانستیی قوتابیانی پۆلی هەشتەم. لە زۆربەی ژینگە تەقلیدییەکانی پۆلدا، کارامەییەکانی بیرکردنەوەی ئاستی باڵا و بەشداریکردنی مانادارانەی قوتابیان پەرەیان پێنادرێت،کە هەردووکیان بۆ فێربوونی قووڵ و درێژخایەن زۆر گرنگن. ئامرازەکانی ژیری دەستکرد (AI) هاوشێوەی ChatGPT وەک چارەسەرێک بۆ پڕکردنەوەی کەلێنەکانی سیستەمی پەروەردە دەردەکەون، لە ڕێگەی پەرەپێدانی فێربوونی تاکەکەسی لەگەڵ دابینکردنی میکانیزمەکانی فیدباکی دەست بەجێ. ئەم توێژینەوەیە لە قوتابخانەیەکی تایبەت ئەنجامدرا و ٤٠ قوتابی بەشدارییان تێدا کرد کە دابەشکرابوون بۆ دوو گرووپ: گرووپی تاقیکاری کە ستراتیژی SWOM ی بەهێزکراو بە ChatGPT یان بەکارهێنا و گرووپی کۆنترۆل کە بە ڕێگەی وانەوتنەوەی ئاسایی لەلایەن مامۆستاوە فێردەکران. دەستکەوتی ئەکادیمی لە ڕێگەی تاقیکردنەوەی فرەهەڵبژاردنی ٣٠ برگەیی پێوانەکرا. بۆ دڵنیابوون لە متمانەپێکراویی تاقیکردنەوەکە، دوو شێواز بەکارهێنران: یەکەم، یاسای ٢٠ی کودەر-ڕیچاردسۆن (KR-20) بۆ هەڵسەنگاندنی یەکدەنگیی ناوخۆیی تاقیکردنەوەکە، کە هاوکۆڵکەی متمانەپێکراوی ٠.٨٩١ ی بەدەستهێنا، کە ئاماژەیە بۆ متمانەپێکراوییەکی بەرز. دووەم، متمانەپێکراویی نیوەی دابەشکراو() بەکارهێنرا کە ئەنجامەکەی ٠.٨٨٦ بوو. بە پشتنەستن بە تیۆری فێربوونی مەعریفی، بونیادگەرایی، و تیۆری مەعریفی فێربوونی مالتیمیدیا مایر (CTML) دانراوە، ئەم توێژینەوەیە وای دادەنێت کە فێربوونی مانادار بەباشی ڕوودەدات کە قوتابیان بە شێوەیەکی چالاک زانیاری بونیات بنێن لە ڕێگەی پەیوەندی زارەکی و کارلێکی دیجیتاڵییەوە. ئەنجامەکان زیادبوونێکی بەرچاویان لە ڕووی ئامارییەوە لە ئەدای ئەکادیمیی گروپی تاقیکاریدا نیشاندا کە سوودەکانی بەکارهێنانی تەکنیکەکانی ژیری دەستکرد لەگەڵ شێوازە نوێیەکانی وانەوتنەوە دەردەخات. ئەم ئەنجامانە هاوکار دەبن بۆ پەروەردەکاران، گەشەپێدەرانی پرۆگرامی خوێندن و هەوڵەکانی پەروەردەی زانست.

وشە سەرەکییەکان: مۆدێلی باشترین شێوازی فێربوون (SWOM)، ChatGPT، دەستکەوتی ئەکادیمی، فێربوونی چالاک.

فعالية استراتيجية (SWOM) المستندة إلى أسلوب ChatGPT في التحصيل الدراسي في مادة العلوم لدى طلبة الصف الثامن الأساسي.

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الملخص

درست هذه الدراسة دمج نموذج الذكاء الاصطناعي اللغوي مثل ChatGPT في استراتيجية (SWOM) بهدف رفع المستوى التحصيل الأكاديمي في مادة العلوم لدى طلاب الصف الثامن. ففي العديد من بيئات الصفوف التقليدية، لا يتم تطوير مهارات التفكير العليا ولا يتم تحقيق تفاعل فعّال من قبل الطلاب، وكلاهما عنصران أساسيان للتعلم العميق والمستدام. تُعد أدوات الذكاء الاصطناعي بديلًا فعالًا لمعالجة النقاط الضعيفة في النظام التعليمي من خلال تعزيز التفاعل والتعلم الفردي، بالإضافة إلى توفير آليات تغذية راجعة فورية. أُجريت هذه الدراسة في مدرسة خاصة ويتكون عينة من (٤٠) طالباً تم تقسيمهم إلى مجموعتين: مجموعة تجريبية خضعت لاستراتيجية SWOM مدعومة باستخدامChatGPT ، ومجموعة ضابطة تم تعليمها بالطرق التقليدية المعتمدة على المعلم. تم قياس التحصيل الأكاديمي من خلال اختبار مكون من ٣٠ سؤالًا من نوع الاختيار من متعدد لتقييم النتائج. ولضمان موثوقية الاختبار، تم استخدام طريقتين: أولاً، معادلة كودر–ريتشاردسون ٢٠ (KR–20) لتقييم الاتساق الداخلي للاختبار، حيث بلغت قيمة معامل الثبات ٠.٨٩١، مما يشير إلى موثوقية عالية. ثانيًا، تم استخدام طريقة التجزئة النصفية(Split–half reliability) ، وكانت قيمة معامل الثبات ٠.٨٨٦. واستنادًا إلى نظرية التعلم المعرفي، والبنائية، ونظرية ماير للتعلم المتعدد الوسائط(CTML) ، تفترض الدراسة أن التعلم ذو المعنى يمكن أن يحدث بشكل أفضل عندما يبني الطلاب المعرفة بنشاط من خلال التواصل اللفظي والتفاعل الرقمي. وقد أظهرت النتائج وجود فرق ذي دلالة إحصائية في الأداء الأكاديمي لصالح المجموعة مما يؤكد جدوى دمج تقنيات الذكاء الاصطناعي مع استراتيجيات التعليم لمعاصرة. وتدعم هذه النتائج المعلمين ومطوري المناهج التعليمية والمهتمين بمجال التعليم.

الكلمات المفتاحية: إستراتيجية (SWOM)، (ChatGPT)، التحصيل الدراسي، التعلم النشط.