Use of Motives and Utilization of Artificial Intelligence as Predictors of Information Retention in Science

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ABSTRACT

The ongoing issue of poor information retention continues to hinder students' mastery of scientific concepts. This study examined the predictive power of the Use of Motives and Utilization of Artificial Intelligence on Information Retention in Science, as measured by students' subjective assessment of their ability to recall and apply scientific concepts. The study was conducted among 266 Grade 12 STEM students in Davao City. Adopting a predictive research design, data were selected through total enumeration and rigorously analyzed using descriptive statistics, Pearson Product-moment correlation, and multiple linear regression analysis.

Descriptive results revealed that Use of Motives, Utilization of AI, and Information Retention all achieved "High" descriptive levels, suggesting that students possess strong internal drives and frequently engage with AI tools. Correlation analysis further indicated significant, moderately high positive relationships between both Use of Motives ($r=0.674$, $p<0.05$) and Utilization of AI ($r=0.677$, $p<0.05$) with the criterion variable. The multiple regression results demonstrated a significant combined predictive relationship, with the model ($F=143.1$, $p<0.001$) accounting for 52.1% of the total variance in perceived retention levels.

These findings partially confirm the Technology Acceptance Model (TAM), suggesting that students' cognitive success is significantly associated with the interplay between perceived usefulness and strategic digital engagement. The results are significant for school leaders and administrators in formulating technology-integrated policies to mitigate retention gaps. Furthermore, this study offers a foundational framework for future research to explore the remaining 47.9% of unexplained variance through qualitative factors or additional predictive variables.

Keywords: Motives and utilization of artificial intelligence, predictors of information retention, science

INTRODUCTION

The Problem and its Scope

There has been a noticeable decline in students' ability to retain information learned in Science (Karam et al., 2022). Many learners tend to forget lessons shortly after they are discussed, making it difficult to recall important details during assessments or discussions.

In the international context, educators have observed a widespread decline in learners' ability to retain academic information over time. According to Willingham (2020), high school students commonly experience significant information loss just days after instruction. Similarly, Akgun and Toker (2024) noted that students' recall decreases over time despite teachers' continued efforts to provide adequate instruction.

In the national context, declining information retention has become a growing concern among Senior High School learners. Bravo (2023) noted that even after comprehensive instruction, students tend to forget important details when tested later on. Additionally, observations in the educational setting indicate that students increasingly struggle with memory recall over time; this trend suggests deficits in both short-term and long-term retention (Doyaoen et al., 2023). Similarly, Cabrera et al. (2025) found that low information retention in Science is true in Davao Oriental State University.

Low information retention among students poses a challenge to the quality of education, as it hinders their ability to fully grasp and apply scientific concepts essential for academic and professional growth (Abucayon, 2025). The growing concern about students' struggles to retain and recall knowledge threatens future competencies and overall productivity in science. Despite these findings, limited research has examined how students' motivations for using AI and their utilization of it predict their ability to retain scientific information.

Significance of the Study

This research holds profound significance as it addresses the optimization of student learning outcomes, a critical component of Sustainable Development Goal 4 (Quality Education), by identifying how the synergy of motivation and technology sustains high-quality, inclusive academic achievement. Within the Philippine educational landscape, these findings directly support the mandate of the Department of Education to produce globally competitive STEM learners by providing data-driven insights into how AI-integrated curricula can help mitigate information retention gaps. At the institutional level, the results provide Holy Cross of Davao College with a strategic framework to enhance faculty digital literacy and refine classroom interventions. By aligning technological adoption with the college's commitment to excellence and holistic formation, this study contributes to a mission-driven academic environment where innovative pedagogy ensures long-term information retention and educational sustainability.

Statement of the Problem

The aim of this study was to determine the significance of forecasting Information Retention in Science through the Use of Motives and Utilization of Artificial Intelligence as predictors. Specifically, the following objectives were pursued:

1. To describe the levels of Use of Motives in terms of utility value, expectancy, attainment, intrinsic/interest value, and cost; Utilization of AI in terms of perceptions, current use, impact on learning, future expectations, and concerns; and Information Retention in Science in terms of short-term recall and long-term recall.

2. To determine the significance of the correlation between Use of Motives, and Utilization of AI, and the Information Retention in Science.

3. To determine the significance of the strength of the model for Information Retention in Science as predicted by Use of Motives and Utilization of AI.

Hypotheses

The following were tested at a 0.05 level of significance:

H_{01}: Use of Motives and Utilization of AI do not significantly correlate with Information Retention in Science

H_{02}: The model to predict Information Retention in Science, using Use of Motives and Utilization of AI as predictors, is not significant

Theoretical and Conceptual Framework

This study is grounded in the Technology Acceptance Model (TAM) proposed by Davis (1989), which explains how individuals accept and use technology based on their perceptions of its usefulness and ease of use. It emphasizes that Perceived Usefulness and Perceived Ease of Use lead to the final output through an interacting process of technology integration within the learning environment. This consistent, practical engagement with

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AI tools serves as a bridge to better learning outcomes, especially helping students retain and master scientific ideas.

In this study, the Use of Motives as a predictive variable, indicated by utility value, expectancy, attainment, intrinsic interest, and cost (Yurt & Kasarci, 2024), stands as the Perceived Usefulness (PU) and the view that motivational drive is rooted in the perceived instrumental value of digital tools. The Utilization of AI as a second predictive variable, indicated by perceptions, current use, impact, concerns, and future expectations (Vera, 2023), corresponds to Perceived Ease of Use (PEOU) and reflects evaluations of accessibility, intuitiveness, and the effort required to operate AI platforms. Finally, Information Retention in Science as the criterion variable, indicated by short-term and long-term recall (Royle & Lincoln, 2008; Matolić et al., 2023), relates to the output aspect asserted in the theory, representing the perceived cognitive ability to encode, store, and retrieve scientific principles. Hence, this study is fully grounded in the Technology Acceptance Model (TAM), which posits that these cognitive precursors predict actual usage behavior, which is significantly related to academic outcomes.

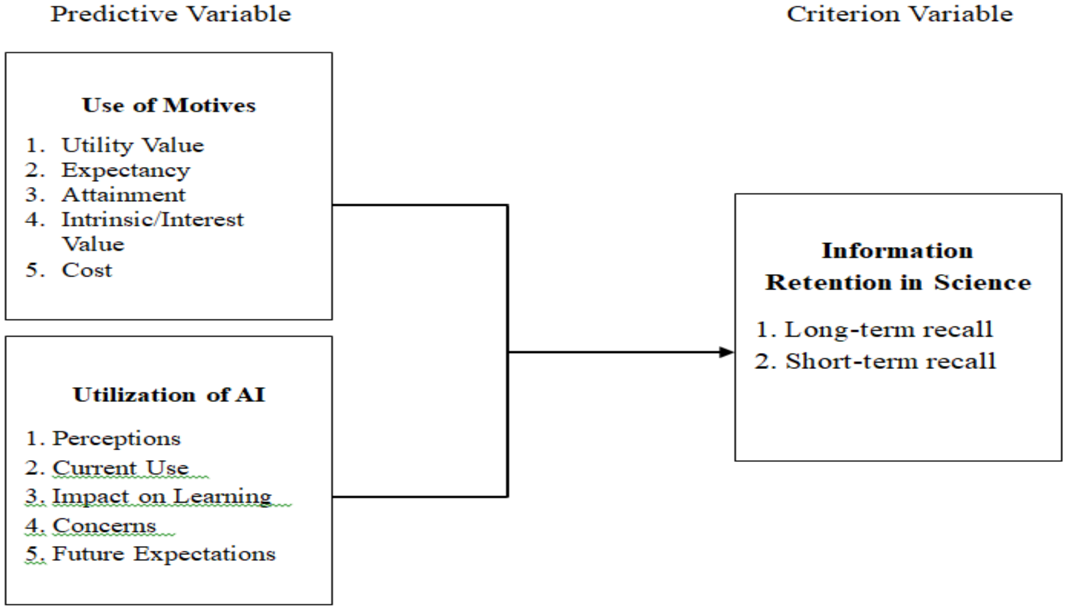

Figure 1. Conceptual Framework of the Study

METHODOLOGY

The research design, locale of the study, the sample and sampling, data gathering technique, data analysis, and the ethical considerations are included in this chapter.

Research Design

This research utilized a predictive research design. It focuses on forecasting future events by analyzing existing or historical data, thereby complementing traditional explanatory research by employing statistical models to generate projections (Sghir et al., 2022). This approach is particularly appropriate for the current study, as it allows researchers to anticipate emerging trends, support evidence-based policymaking, and facilitate early interventions, especially within the fields of education and social sciences (Khalil & Ebner, 2023). Its advantages encompass the detection of latent patterns within extensive datasets, the provision of prospective insights, the enhancement of strategic planning, and the refinement of decision-making accuracy by prioritizing prediction over description (Shmueli et al., 2023).

Locale of the Study

The study was conducted in the public senior high schools of Cluster 1, Division of Davao City, which is under the supervision of the Department of Education in Region XI, Philippines. This cluster includes a pilot school for the Strengthened Senior High School Curriculum, which serves as a model for delivering specialized science programs to a large population of STEM students. The educational setting in Davao City illustrates how national policies and modern pedagogical practices are applied, providing a clear understanding of how the integration of digital tools and students' motivational drivers predicts information retention within the local STEM curriculum.

Sample and Sampling Technique

A total of 266 Grade 12 STEM students from the public senior high schools in Cluster 1, Division of Davao City, were included in this study, representing 100% of the targeted student cohort. According to official enrollment records from the respective school offices for the 2025–2026 school year, these 266 students are enrolled in the specialized science programs within the research locale. All students were officially registered as Grade 12 learners for the current academic year. Given the manageable population size, total enumeration sampling was employed. Total enumeration sampling is a purposive sampling method in which the researcher studies every member of the population who shares the specified characteristics (Laerd Dissertation, 2022). This approach ensures that every member of the study group is included and fairly represented, helping to eliminate any form of bias (Babasola et al., 2024). For this study, the group consisted of students who were at least 18 years of age and had active exposure to AI in their academic activities.

Data Gathering Technique

The data collection was conducted using a survey technique. This systematic approach involves gathering information from a sample through structured questionnaires designed to characterize the attributes, opinions, or behaviors of a broader population. It is commonly employed in research to efficiently evaluate, test, or generalize findings within a specified group (Sheikh et al., 2024). The method offers several benefits, including the ability to access large and heterogeneous populations, generate quantifiable data suitable for pattern analysis, facilitate generalization of results, expedite data collection processes, and ensure reproducibility through standardized procedures (Oranga & Matere, 2025).

In this study, four adapted and modified questionnaires were used. The first instrument, the Use of Motives Questionnaire, was adapted from Yurt & Kasarci (2024). It consists of 20 items designed to assess the level of Use of Motives of students in integrating AI into their scientific learning. A four-point Likert scale was used to describe the degree to which respondents perceived the utility and value of AI in their learning environment. The adapted instruments were pilot-tested for reliability, with the STRS achieving a Cronbach’s alpha of 0.909.

The second instrument, the Utilization of AI Questionnaire, was adapted from Vera (2023). It consists of 25 items designed to assess students' level of AI utilization in integrating these tools into their scientific learning. A four-point Likert scale was used to assess the degree to which respondents used AI in their academic environment. The adapted instruments were pilot-tested for reliability, with the questionnaire achieving a Cronbach’s alpha of 0.888.

The third instrument, the Students’ Information Retention Questionnaire, was adapted from Royle & Lincoln (2008) and Matolić et al. (2023). It consists of 12 items designed to assess the level of Information Retention in Science of students in integrating AI into their scientific learning. A four-point Likert scale was used to describe the degree to which respondents retained and applied scientific principles in their academic environment. This study utilizes a self-report scale to measure perceived information retention in science. This metric captures the students' subjective assessment of their ability to recall and apply scientific concepts. By focusing on perceived retention, the study accounts for students’ internal evaluation of their mastery and confidence in retrieving information in a digital learning context. The adapted instruments were pilot-tested for reliability, with the questionnaire achieving a Cronbach’s alpha of 0.903.

The results yielded an overall Cronbach’s Alpha of 0.953, indicating an "Excellent" internal consistency rating. This confirms that the designed tests were highly consistent in measuring the respondents' perceptions and behaviors.

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Data Analysis Technique

In this study, the data analysis techniques used were descriptive, correlation, and multiple linear regression analyses. Descriptive analysis helps organize and summarize large amounts of data, making it easier for researchers to understand real-world patterns while saving time, no matter the situation or field of study (Costa, 2024).

In this study, the mean and standard deviation were calculated using statistical tools. Moreover, the correlation analysis examines the strength and direction of the relationship between two continuous variables (Rizk, 2023). The Pearson Product-moment correlation statistical tool was used.

Lastly, multiple linear regression Analysis is used to assess how one or more independent variables predict the outcome of a dependent variable, allowing researchers to quantify the influence of specific predictors (Uyanık & Güler, 2013). The beta coefficients and R-squared values were used to assess the predictive power of the determinants.

The matrix presenting the scale, descriptive level, and corresponding interpretation for each study variable was provided, specifically used to describe Use of Motives, Utilization of AI, and Information Retention in Science.

Scale	**Level**	**Use of Motives**	**Utilization of AI**	**Information Retention in Science**
3.26-4.00	Very High	Very strong	Always	Very Good
2.51-3.25	High	Strong	Often	Good
1.76-2.50	Low	Weak	Sometimes	Poor
1.00-1.75	Very Low	Very Weak	Never	Very poor

Standard Deviation Value Ranges and Interpretation

Range	**Description**	**Interpretation**
SD ≤ 0.50	High consistent responses	Strong and uniform perception
SD = 0.51 – 1.00	Moderate Consistent Responses	Acceptable consistency
SD = 1.01 – 1.50	Low consistent responses	Differing views or experiences
SD > 1.50	Very low consistent responses	High variability and lack of consensus

In this study, the significance of the correlation is tested at 0.05 confidence level. The following is the standard measure for the interpretation scale of *r*-value, the following scheme is used:

Computed r	**Descriptive Interpretation**
+/- 1.00	Very High Correlation
Between +/- 0.75 – +/- 0.99	High Correlation
Between +/- 0.51 – +/- 0.74	Moderately High Correlation
Between +/- 0.31 – +/- 0.50	Moderately Low Correlation

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Between +/- 0.01 – +/- 0.30	Low Correlation
0.00	No Correlation

The standard measure for the interpretation to assess the extent of influence and the predictive strength of the independent variables on the criterion variable is as follows:

β Value Range	**Predictive Strength**
±0.00 – ±0.09	Very Weak
±0.10 – ±0.29	Weak
±0.30 – ±0.49	Moderate
±0.50 – ±0.69	Strong
±0.70 and above	Very Strong

Ethical Consideration

Ethical considerations were prioritized in this study. The researcher followed ethical protocols established by HCDC-SMILE, which reviewed the study and instruments. Participation was voluntary, with students aged 18 and above fully informed about the study's purpose, procedures, and minimal risks through signed consent forms. For participants under 18 years old, a letter of assent was obtained from parents and guardians before their participation. Privacy was protected in accordance with the Data Privacy Act of 2012, and all data were securely stored and properly disposed of. Risks were minimized through clear communication, support resources, and collaboration with school authorities. Respondents were fairly selected. The researcher is a licensed teacher.

RESULTS

Included in this chapter were the descriptive, correlation, and regression tabular presentations, along with the corresponding analysis and interpretation of the statistical results. This chapter ended with a summary of findings.

Descriptive Results

Table 1 is a descriptive table. It includes the study's variables: Use of Motives, Utilization of AI, and Information Retention in Science. It also showed the number of respondents, mean, standard deviation (SD), and the descriptive levels for each variable.

Table 1: Descriptive Table (N=266)

Variables	**N**	**SD**	**Mean**	**Descriptive Level**
Use of Motives (IV_1)	***266***	***0.393***	***2.94***	***High***
Expectancy		0.430	3.22	High
Attainment Value		0.542	2.97	High
Utility Value		0.486	3.03	High

Intrinsic/Interest Value		0.528	2.88	High
Cost		0.490	2.61	High
Utilization of AI (IV_2)	***266***	***0.343***	***3.14***	***High***
Perceptions		0.474	3.07	High
Current Use		0.420	2.99	High
Impact on Learning		0.429	3.04	High
Concerns		0.449	3.35	Very High
Future Expectations		0.522	3.25	High
Information Retention in Science (DV)	***266***	***0.418***	***3.03***	***High***
Short-term Recall		0.412	3.05	High
Long-term Recall		0.486	3.00	High

The Use of Motives variable has a mean of 2.94, placing it within the high descriptive level. This suggests that students exhibit a very strong motivation to use AI. All its indicators are described as high. The standard deviation of 0.393 indicates high consistency in responses, signifying a uniformly strong tendency. Moreover, the Utilization of AI variable has a mean of 3.14, putting it within the high descriptive level.

This suggests that students often use AI in Science learning. Four of its indicators are described as high, while only one is described as very high. The standard deviation of 0.343 indicates high consistency in responses, signifying a uniformly strong tendency. Lastly, the Information Retention in Science variable obtained a mean of 3.03, situating it within the high descriptive level.

This suggests that students demonstrate very good information retention in Science. All its indicators are described as high. The standard deviation of 0.418 indicates high consistency in responses, signifying a uniformly strong tendency among the participants.

The Use of Motives, Utilization of AI, and Information Retention in Science are all interpreted at high levels, indicating that students have a very strong motivation to use technology and often apply AI tools to achieve very good scientific recall. This uniform high interpretation suggests a balanced system where students' internal drives and their actual engagement with technology are well-aligned with their cognitive ability to retain science concepts.

Correlation Results

Table 2 presented the results of the correlation analysis among the two predictive variables with the criterion variable. The table detailed the r-values, p-values, and the resulting decision on the null hypotheses.

Table 2: Correlation Table (N=266)

		Information Retention in Science (DV)			
	N	**R**	**p-value**	**Decision on H_0 at 0.05 level of significance**	**Interpretation**

Use of Motives (IV_1)	266	0.674	0.000	Reject Ho	Significant
Utilization of AI (IV_2)	266	0.677	0.000	Reject Ho	Significant

Level of Significance: 0.05

Decision Rule: Reject H_0 if $p < 0.05$

Specifically, the table shows that the correlation between Use of Motives and Information Retention in Science obtained a p-value of 0.000, which is lower than the 0.05 level of significance; hence, the null hypothesis was rejected, indicating that the correlation is statistically significant. The r-value of 0.674 reflects a moderately high positive correlation between Use of Motives and Information Retention in Science. This finding implies that changes in students' motivational drive are significantly associated with variations in their perceived retention of scientific information.

Similarly, the correlation between Utilization of AI and Information Retention in Science yielded a p-value of 0.000, which is also lower than the 0.05 level of significance; hence, the null hypothesis was rejected, indicating that the correlation is statistically significant. The r-value of 0.677 shows a moderately high positive correlation between Utilization of AI and Information Retention in Science. This implies that greater or lesser utilization of AI tools is associated with a higher or lower level of information retention among students, respectively.

Both the Use of Motives and the Utilization of AI show significant positive relationships with Information Retention in Science, indicating that higher motivation or more frequent use is associated with better perceived retention of scientific knowledge. Compared to the Use of Motives, the Utilization of AI has a slightly stronger positive correlation, indicating it may have a marginally greater predictive contribution toward enhancing students' information retention.

Regression Results

Table 3 presents the regression table. Several columns are included in the table, namely, the predictors and criterion variables, B (Unstandardized Coefficient), Beta (Standardized Coefficient), t (t-value), p (p-value), and the Decision on the null hypothesis.

Specifically, the regression analysis showed that the predictive model IRS = 0.403UM + 0.477UAI + 0.342 was statistically significant in predicting Information Retention in Science, as evidenced by r-value of 0.722, and F-value of 143.1.

The corresponding p-value of <0.001, which is less than 0.05 level of significance; thus the null hypothesis was rejected. This signifies that the model outcome for Information Retention in Science is significant. It further indicates that the model provides a good fit to the data and reliably predicts the level of Information Retention in Science.

Table 3: Regression table (N=266)

	Information Retention in Science (DV)						
	Unstandardized Coefficients		**Standardized Coefficients**				
	B	**Std. Error**	**Beta**	**T**	**p value**	**Decision on Ho**	**Interpretation**
Constant	0.342	0.165		2.072	0.039		

Use of Motives (IV_1)	0.403	0.069	0.379	5.845	0.000	Reject Ho	Significant
Utilization of AI (IV_2)	0.477	0.079	0.391	6.031	0.000	Reject Ho	Significant

Model

Summary:

R = 0.722 | R^2 = 0.521 | Adjusted R^2 = 0.517 | F-value = 143.1 | p-value = $p<0.001$

Level of Significance: 0.05

Decision Rule: Reject H_0 if $p<0.05$

The R^2 obtained as shown in the regression table ($R^2 = 0.521$) denotes that the model for Information Retention in Science, having Use of Motives and Utilization of AI as predictors, is a strong model to forecast or calculate Information Retention in Science. In short, the regression model was strong and statistically significant, demonstrating a good fit and reliably predicting Information Retention in Science by showing that changes in Use of Motives and Utilization of AI meaningfully explain variations in Information Retention in Science rather than occurring by chance.

Summary of Findings

Based on the statistical results, it specifically was found that:

1. The Use of Motives and Utilization of AI significantly correlate with Information Retention in Science.
2. The model to predict Information Retention in Science using Use of Motives and Utilization of Artificial Intelligence as predictors is strongly significant.

DISCUSSIONS

In this chapter, the descriptive, correlational, and regression analysis results of the study are discussed. The discussions are made to highlight how the results of the study support previous findings. Here, the conclusion and recommendations based on the results and discussions are also presented.

Use of Motives and Information Retention in Science Correlation

The results showed a significant positive relationship between students' Use of Motives and their Information Retention in Science. This finding aligns with the idea that motivation plays an important role in learning. According to Ryan and Deci (2020), when students see personal or academic value in what they are studying, they are more likely to pay attention, process the information deeply, and store it in their long-term memory. Intrinsic motivation encourages learners to actively participate in learning tasks, which improves their ability to retain knowledge over time.

Likewise, the current finding also affirms the idea that the use of motives is a key pillar in modern learning. Students who possess clear, intrinsic motives for their studies demonstrate higher levels of cognitive engagement and better recall. This underlines the importance of fostering motivation to enhance educational outcomes. (Kovanović et al., 2021).

Furthermore, the present assertion agrees with the study of Higde and Aktamis (2022) explaining that in science education contexts, internal motives serve as the primary engine for active engagement and long-term knowledge acquisition. This suggests that the high motivation observed in the students is a central driver of their cognitive success in science.

On the other hand, these results contrast with the findings of Holmes et al. (2022), which argue that pedagogical design and the quality of classroom instruction remain the primary drivers of student achievement, sometimes overshadowing individual psychological motives. While the current study's larger sample size (N=266) provides strong evidence for the predictive power of motives, the discrepancy highlights elevated motivation and AI use do not automatically guarantee high retention if they are not supported by effective teaching strategies. This suggests that while AI is a powerful tool for STEM students, its effectiveness is likely maximized only when integrated into a high-quality instructional framework, rather than acting as a standalone solution for cognitive gaps (Molenaar, 2022).

Utilization of AI and Information Retention in Science Correlation

The study found a significant positive relationship between the Utilization of AI and students' Information Retention, particularly when AI tools are used for active inquiry. Treating AI as a learning partner encourages deeper thinking and engagement with the material.

The result supports previous findings that AI-powered tools can enhance learning when used effectively. According to Baker and Hawn (2022), AI technologies can improve learning outcomes by offering personalized support and opportunities for retrieval practice. These features help students reinforce what they have learned and bridge the gap between initial instruction and long-term understanding.

Furthermore, the present assertion agrees with the study of Chen et al. (2022). The role of AI in augmenting this process is well-documented; studies have shown that AI-driven learning tools significantly improve information processing efficiency by enabling personalized, interactive retrieval.

Moreover, the current results align with the conclusions of Zawacki-Richter et al. (2020), which indicates that the synergy between a student's internal drive and external AI scaffolding results in more durable knowledge structures, as the technology reinforces the learner's ability to practice and apply scientific concepts effectively.

However, the findings diverge from those of Luckin et al. (2021), who argue that prior knowledge determines how much students benefit from AI. This suggests that the 'AI effect' is not uniform and carries a risk of superficial engagement if students over-rely on automated feedback. While this study empirically validates the predictive power of AI utilization, it acknowledges that technology is most effective when paired with deep-thinking exercises designed by educators to prevent cognitive offloading.

Discussion on the Regression Results

The current finding of the study indicating that the model predicting Information Retention in Science using Motives and Artificial Intelligence as predictors is highly significant aligns with the research of Yurt and Kasarci (2024). Their study confirms that motivational orientations and the perceived usefulness of digital tools are key factors in student engagement, directly affecting the cognitive processes needed to encode and retrieve academic information.

Furthermore, the current finding resonates with the empirical evidence presented by Azawei & Al-Maroof (2023), stating that when AI integration is paired with a strong internal drive, students are better equipped to navigate complex scientific curricula, leading to measurable improvements in retention.

Conversely, Selwyn (2022) argues that without structured teacher guidance, AI reliance can lead to 'passive consumption' rather than long-term retention. While the present data empirically identify AI utilization and motives as significant predictors of success, this relationship likely assumes a level of active engagement. Acknowledging Selwyn's skepticism is vital; the quantified gains in perceived retention may be diminished if students treat AI as a tool for passive retrieval rather than a supplement to guided, active learning.

Although the model explains 52.1% of the variance in perceived retention, the remaining 47.9% highlights the influence of unmeasured variables. Sullivan, et al. (2024) suggests that teacher pedagogical styles and prior scientific knowledge are foundational for information mastery, providing the necessary cognitive 'hooks' for new information to be retained. Additionally, the classroom environment and the specific functionality of AI tools—whether mastery-oriented or task-focused, likely account for the remaining differences in information mastery (Chukwu et al., 2026). Acknowledging these factors highlights the complexity of the digital learning landscape.

CONCLUSION

Based on the findings, the Information Retention in Science is strongly predicted by Use of Motives and Utilization of AI. The significant predictive model suggests that the Information Retention in Science is significantly predicted by the combined strength of Use of Motives and Utilization of AI. This conclusion partially supported the Technology Acceptance Model (TAM), positing that Use of Motives and Utilization of AI are significant predictors of higher levels of Information Retention in Science.

RECOMMENDATION

Based on the conclusions, the following are recommended:

1. This study may be replicated across different locales employing the same variables as utilized herein to enhance the model's generalizability and reinforce the validity of the findings. Future studies could incorporate longitudinal pre- and post-test assessments to triangulate self-perceived retention scores with objective academic performance data.

2. Qualitative research may be explored to generate themes that may be utilized as potential variables needed to account for the remaining 47.9% variance in Information Retention in Science not explained by the current predictive model.

3. The school leaders may exert optimum efforts and allocate resources for motivational strategies and AI integration for students to enhance their Information Retention in Science.

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