Use of Artificial Intelligence and Its Relationship with Cognitive Processing Styles (Surface – Deep) among Students of the Faculty of Education.

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Abstract

The study aimed to examine the relationship between the use of artificial intelligence (AI) and cognitive processing styles (surface and deep) among students of the Faculty of Education at the University of Homs during the 2024–2025 academic year. The descriptive-analytical method was adopted as the most appropriate approach to describe the phenomenon and analyze the relationships among its variables. Two standardized questionnaires were administered: the first measured the level of AI use (24 items), and the second assessed cognitive processing styles (22 items). The study sample consisted of 225 randomly selected students representing various academic years. The results revealed a low level of AI use, with a mean score of (52.49), indicating limited integration of AI technologies into students' educational activities. It was also found that the surface processing style was more prevalent (M = 42.31) than the deep processing style (M = 39.30), reflecting a tendency among students to rely on memorization and recall rather than analysis and comprehension. Furthermore, the findings showed a significant positive correlation between AI use and deep processing ($r = 0.594$, $p < 0.01$), while no significant correlation was found with surface processing. No statistically significant gender differences were observed in any of the studied variables, suggesting equal educational and technological opportunities for both males and females.The study concluded by emphasizing the need to integrate AI technologies into university curricula and to organize training programs for both students and faculty members to foster deep thinking skills. It also recommended conducting future studies that explore the relationship between AI use and higher-order cognitive skills such as critical and creative thinking to build an educational model that enhances advanced cognitive learning in Syrian universities.

Keywords: Artificial Intelligence – Cognitive Processing – Deep Thinking – University Learning – Faculty of Education Students

1. Introduction

Higher education is currently undergoing a fundamental transformation driven by the integration of artificial intelligence (AI) technologies into learning environments—a shift that has reshaped how students acquire knowledge and approach thinking. While intelligent tools have opened up vast opportunities for interaction, analysis, and innovative problem-solving, their impact remains contingent upon the cognitive processing style adopted by the learner. Some students may limit themselves to "surface-level" processing—relying on rote memorization—whereas others engage in "deep-level" processing, which fosters critical understanding and analytical thinking. Against this backdrop, this study aims to investigate the relationship between the use of artificial intelligence and the cognitive processing styles of students in the Faculty of Education, with the goal of uncovering the role of technology in cultivating deep thinking and building sustainable learning.

Artificial intelligence stands as one of the most significant technological advancements to reshape the landscape of university education, serving as an effective means to enhance the quality of learning and tailor it to individual student needs. Research indicates that intelligent educational systems—driven by adaptive algorithms—can guide learners by delivering content suited to their specific cognitive levels.

This fosters a deeper grasp of educational concepts and boosts learning motivation; such systems analyze student performance and provide immediate feedback, facilitating a shift from rote memorization toward a constructive, meaningful understanding of information (Zawacki-Richter et al., 2019). Nevertheless, some studies caution that over-reliance on intelligent tools may lead to "cognitive displacement"—a decline in the learner's own initiative to engage deeply with knowledge, caused by an excessive dependence on technical support.

This, in turn, can hinder the development of independent thinking skills and the application of conscious mental effort. Consequently, the effectiveness of artificial intelligence in education hinges on its integration into a pedagogical framework that balances technical support with human cognitive activity, thereby ensuring deep and sustainable learning within the contemporary university environment (Risko & Gilbert, 2016).

Deep processing is characterized by an effort to extract meaning, connect information with prior experiences, and construct more robust semantic networks. This results in longer retention in memory compared to surface processing, which is limited to formal encoding and short-term recall (Biggs & Tang, 2011). The effectiveness of university-level learning is linked to the nature of educational tasks; tasks that require analysis, explanation, and conceptual connection drive learners toward deeper levels of processing and enhance their cognitive performance, unlike tasks based on repetition and rote memorization.

Furthermore, educational literature indicates that deep-learning strategies are associated with intrinsic motivation and conscious self-regulation, whereas surface-level approaches are linked to a fear of failure and extrinsic motivation—factors that hinder the generalization and transfer of learning (Badawi et al., 2016). Levels of processing range from surface to intermediate and deep, depending on task requirements and the learner's momentary cognitive capacity; consequently, the design of assessment tools and analytical activities becomes a critical factor in directing the depth of processing. Relying on surface-level approaches leads to transient learning with limited transferability to new situations, while deep-level approaches foster constructivist understanding and the flexible application of concepts. This is especially true when metacognitive skills—such as planning, monitoring, and self-evaluation—are integrated with reflective activities that connect content to real-world contexts (Hammadi & Mazloum, 2015).

The integration of artificial intelligence (AI) into university education enhances the quality of learning by tailoring and personalizing content to suit students' individual capabilities. This process helps reduce cognitive load and enables learners to process information with greater depth. When educational activities are designed using AI tools to stimulate critical thinking and analysis, they facilitate a shift from superficial, rote-memorization-based approaches toward deep-processing methods rooted in comprehension, interpretation, and application. Furthermore, literature suggests that the mindful use of intelligent technologies fosters self-regulated learning and strengthens the connections between new concepts and prior experience, thereby contributing to sustainable learning (Zawacki-Richter et al., 2019).

Conversely, an over-reliance on such tools may diminish individual initiative in thinking and encourage a tendency toward superficial, rapid information processing—a consequence of excessive dependence on technical support. Consequently, the effectiveness of AI in fostering deep cognitive processing depends on its implementation within a pedagogical framework that strikes a balance between technical assistance and the learner's own mental engagement (Risko & Gilbert, 2016).

1. Research Problem:

University education at the Faculty of Education in Homs is witnessing an increasing expansion in the integration of artificial intelligence (AI) technologies within learning environments. However, this expansion raises questions regarding its impact on how students process information. While these technologies are intended to foster

understanding and analytical skills, they may, in some instances, lead to a superficial reliance on digital tools rather than independent, critical thinking. Consequently, the core problem of this study lies in determining the nature of the relationship between the use of AI and the cognitive processing styles employed by students at the Faculty of Education in Homs. It remains unclear whether AI enhances deep cognitive processing or reinforces a superficial approach to learning. This study seeks to address this ambiguity by analyzing students' practices and attitudes toward the use of AI in their university studies.

The researcher conducted a preliminary exploratory study with a sample of 75 male and female students at the Faculty of Education, Al-Baath University (Homs), aimed at identifying how students use AI and their methods for processing knowledge. The questionnaire consisted of 10 key questions, the results of which revealed a generally negative trend in the use of AI: 71% of the students indicated that they use AI tools solely to obtain ready-made answers without understanding the content, while 68% reported relying on AI-generated summaries rather than engaging in reading and analysis.

Furthermore, 74% of respondents indicated that they do not verify the accuracy of the information generated by these tools, while 66% stated that they prefer copying and pasting over rephrasing or personally engaging with the material. 70% noted that their frequent use of artificial intelligence has not improved their critical thinking skills, and 63% reported that relying on it has made them less focused while studying. Additionally, 69% mentioned that they struggle to distinguish between a genuine understanding of information and the content produced by AI tools, and 72% expressed that AI has diminished their motivation to conduct personal research and analysis. Moreover, 65% indicated that using AI for academic assignments is intended solely to save time rather than to develop their skills, and 67% stated that their academic performance has not improved despite their continuous use of these tools. These findings suggest that the majority of students approach artificial intelligence in a superficial, functional manner—prioritizing quick results—without activating their analytical capabilities or fostering deep cognitive processing.

Recent Arab and Syrian studies reveal a clear tendency among students toward superficial learning patterns that hinder comprehension and analysis—a finding that reinforces the author’s perspective regarding the negative impact of using educational technologies without proper guidance. A study by Al-Issa (2017) found that most female high school students in Riyadh rely on learning methods centered on rote memorization and fact retrieval rather than analysis and interpretation, indicating a prevalence of superficial information processing.

Furthermore, a study by Al-Daddo (2022) involving students at the Faculty of Education, University of Aleppo, identified a positive correlation between a superficial learning style and spontaneous "mind-wandering," suggesting poor focus and low mental engagement during the learning process. A study by Muhammad and Hadi (2023) confirmed that an increased reliance on a superficial approach is linked to weaker academic skills, whereas a deep learning approach is associated with higher achievement and better performance. Taken together, these findings suggest that the absence of informed pedagogical guidance in the use of modern technologies—including artificial intelligence—may entrench superficial processing patterns, thereby limiting the effectiveness of the educational process (Al-Issa, 2017; Al-Daddo, 2022; Muhammad & Hadi, 2023)

In light of the aforementioned theoretical insights, exploratory findings, and previous research, it is evident that the integration of artificial intelligence into university education—specifically within the Faculty of Education at Homs University—continues to raise fundamental questions regarding its impact on students' cognitive processing patterns. While it is intended to foster understanding and analysis, preliminary indicators suggest that it could instead become a tool that encourages a superficial reliance on technology, thereby diminishing mental effort and critical analysis.

Consequently, there is a need for systematic scientific research to examine the relationship between the use of artificial intelligence and cognitive processing styles, in order to determine the nature and extent of this impact within the context of Syrian universities. Based on this, the primary research question can be formulated as follows: What is the relationship between the use of artificial intelligence and cognitive processing styles (superficial versus deep) among students in the Faculty of Education at Homs University ?

2. Research Questions:

The following sub-questions emerge from the study's core problem:

1. What is the level of artificial intelligence (AI) usage among the research sample?
2. Which cognitive processing style (surface or deep) is most frequently employed by students at Homs University?

3. Significance of the Research:

The importance of this study is highlighted by the following points:

Theoretical Significance: The theoretical importance of the research is underscored by the following:

• This study may contribute to enriching the Arabic educational literature by examining the relationship between the use of artificial intelligence and cognitive processing styles—a relatively recent topic within the Syrian university context that has not yet been sufficiently researched.

• It may provide a theoretical framework explaining how intelligent tools can influence the nature of thinking and the levels of comprehension among students in the Faculty of Education at Homs University, thereby enhancing the understanding of the relationship between technology and the cognitive structure of learners.

• The study's findings may assist in the development of contemporary educational models that bridge theories of deep learning with artificial intelligence, thereby broadening the scientific foundation for integrating the technological dimension with cognitive processes in higher education.

Practical significance: The practical significance of the research is highlighted in the following points:

• The study's findings may enable educators at the Faculty of Education, Homs University, to develop teaching strategies that leverage artificial intelligence in a way that fosters deep cognitive processing, rather than encouraging a superficial reliance on the technology.

• The results may provide practical insights that can be incorporated into training programs for faculty members, focusing on the effective pedagogical use of AI tools to enhance students' critical thinking and cognitive analysis.

• The findings may also help students themselves recognize how their approach to using intelligent technologies affects the quality of their learning, encouraging them to utilize artificial intelligence as a means to develop understanding and analytical skills—rather than as a substitute for mental effort and deep cognitive engagement.

4. Research Objectives:

The current research aims to achieve the following:

1. To identify the level of artificial intelligence (AI) usage among students at the Faculty of Education, Homs University, and the extent to which they incorporate AI technologies into their teaching and learning practices.
2. To determine the most prevalent cognitive processing style among students (surface or deep) and to analyze the factors that may contribute to a preference for one style over the other.
3. To examine the correlation between the level of AI usage and the cognitive processing styles (surface and deep) among students.

4. To identify differences in AI usage based on gender, and to determine whether there are statistically significant differences between male and female students in this regard.
5. To investigate differences in cognitive processing styles (surface and deep) among students based on gender, and to interpret the potential reasons for the presence or absence of such differences.

5. Research Hypotheses:

The research hypotheses were formulated at a significance level of 0.05)(

1. There is no statistically significant correlation (at the 0.05 level) between the participants' scores on the artificial intelligence usage scale and their scores on the surface and deep processing approach scales.
2. There are no statistically significant differences (at the 0.05 level) between the mean scores of the participants on the artificial intelligence usage scale based on the gender variable.
3. There are no statistically significant differences (at the 0.05 level) between the mean scores of the participants on the processing approaches (surface and deep) scales based on the gender variable.

6. Study Variables:

The research variables are outlined as follows:

1. Independent Variable: The use of artificial intelligence in education, encompassing the extent to which students employ smart technologies in learning processes (such as research, analysis, problem-solving, and knowledge organization).
2. Dependent Variable: Cognitive processing strategies, which refer to the type of processing students adopt during learning (surface processing vs. deep processing).

7. Scope of the Research:

The parameters of the study are defined as follows

1. Temporal Scope: The study is limited to the first semester of the 2025–2026 academic year.

2. Spatial Scope: The study was conducted at the Faculty of Education, Homs University, in the Syrian Arab Republic.

3. Human Scope: The study included all students from the Faculty of Education at Homs University, across various specializations and academic levels.

4. Thematic Scope: The research focuses on the relationship between the use of artificial intelligence and cognitive processing styles (surface vs. deep) among students of the Faculty of Education, without addressing other variables outside this framework.

8. Research Terms:

First: Artificial Intelligence (AI)

In an educational context, artificial intelligence is defined as the capacity of digital systems to analyze educational data, learn from it, and dynamically adapt teaching methods to serve the learner. Its technologies are grounded in machine learning algorithms, predictive modeling, and decision-making support. Today, artificial intelligence serves as a key factor in fostering personalized learning and enhancing student performance (Holmes et al., 2021). Operationally, the researcher defines artificial intelligence as the extent to which students in the Faculty of Education Homs University rely on intelligent tools for research, analysis, and knowledge processing within the educational process.

Second: Surface Processing

Surface processing is a cognitive style characterized by engaging with information in a literal or formal manner, without connecting it to prior experiences or semantic meanings. This approach relies on rapid memorization or the

immediate retrieval of content, devoid of any analysis. Recent studies indicate that this type of processing is associated with poor long-term comprehension (Wang & Hou, 2020.
In this context, the researcher defines "surface processing" operationally as a student's reliance on artificial intelligence tools to obtain information or ready-made answers without engaging in analysis or evaluation.

Third: Deep Processing
Deep processing is a cognitive process based on the constructive understanding of information and its integration with prior experiences and existing knowledge frameworks. It focuses on analysis, reasoning, and reinterpretation, with the aim of generating new knowledge. Recent literature indicates that it supports long-term learning and superior academic performance (Biggs & Tang, 2022).
Operationally, the researcher defines deep processing as a student's ability to utilize artificial intelligence to analyze, interpret, and reformulate knowledge in a critical and constructive manner.

9. Theoretical Framework:

First: Artificial Intelligence and Personalized Learning
Recent educational literature demonstrates that artificial intelligence (AI) has emerged as a key educational tool for personalizing learning, by analyzing a learner's educational data and tailoring content to their specific needs (Holmes et al., 2021). Studies indicate that AI applications have enhanced student engagement by providing immediate feedback, which in turn improves academic achievement and interaction within the learning environment (Holmes et al., 2021). Furthermore, research findings show that intelligent systems can address individual differences among learners by offering diverse, scaffolded content aligned with each student's proficiency and level of comprehension (Wang, 2024). Scientific evidence confirms that AI has transformed the quality of university-level learning by providing personalized, highly efficient educational pathways compared to traditional methods (Wang, 2024). (
Second: Surface-Level Processing and the Role of Artificial Intelligence
Recent studies suggest that "surface-level processing"—characterized by the rapid memorization or retrieval of information without integrating it into the learner's existing cognitive structure—negatively impacts the quality of comprehension and analysis (Chen et al., 2020). The literature indicates that AI can help mitigate this pattern when applied to educational activities that require the interpretation and practical application of content, rather than mere repetition or summarization (Chen et al., 2020). Research confirms that activities designed based on in-depth analytical thinking can shift the learning paradigm from a superficial approach toward a more constructive and effective cognitive style (Biggs & Tang, 2022). The literature indicates that employing artificial intelligence (AI) within educational strategies centered on analytical tasks enhances the capacity for knowledge construction and strengthens levels of semantic understanding (Biggs & Tang, 2022). (
Third: Artificial Intelligence and the Development of Deep Processing
Recent studies suggest that AI contributes to fostering deep processing by supporting higher-order thinking strategies, such as analysis and the constructive perception of educational content (Vieriu et al., 2025). The literature shows that intelligent systems can improve the connection between new information and learners' prior experiences, thereby facilitating the construction of long-term knowledge (Vieriu et al., 2025). Furthermore, research indicates that integrating AI into educational practices elevates the level of cognitive engagement and helps improve academic performance in university settings (Feigerlova et al., 2025). Evidence suggests that the pedagogical design of AI-based educational activities contributes to consolidating analytical understanding and critical thinking among students (Feigerlova et al., 2025). (
The researcher posits that the use of AI in higher education is not merely a technical addition; rather, it represents a transformation in the mechanisms by which students acquire and process knowledge. It posits that the impact of artificial intelligence is determined by how it is integrated into educational practices; if employed effectively from a pedagogical standpoint, it can facilitate a shift toward deep-level processing. Furthermore, it is premised on the idea that understanding the relationship between artificial intelligence and the cognitive processing styles of students in the Faculty of Education could serve as a gateway to developing more effective and higher-quality educational

practices.

10. Previous studies:

Zainab Omar Al-Sousi and Rima Al-Siddiq Abu-Khatala (2024, Libya) conducted a study titled "Artificial Intelligence and Its Applications in General Education: Reality and Challenges." The study aimed to examine the current state of artificial intelligence (AI) usage in the educational process, as well as the challenges hindering its implementation, from the perspective of basic education teachers in the city of Misrata. The study population consisted of all computer teachers in the city's basic education schools (604 teachers across 168 schools), from which a simple random sample of 120 teachers was selected. The researchers employed a self-developed questionnaire—covering both the current state of AI and the associated challenges—and utilized a descriptive-analytical approach. The results indicated that the integration of AI in education was at a moderate level (with a relative weight of 67.3%), and the challenges faced were also at a moderate level (with a relative weight of 75.7%).

Al-Waqfah (2025, Yemen) conducted a study titled "The Level of Utilization of Artificial Intelligence Applications in Education at the Faculty of Applied Sciences and Education, Ibb University," which aimed to measure the extent to which AI applications are utilized in education within this faculty. The study sample comprised 35 faculty members and administrative staff. The researcher used a questionnaire consisting of 45 items categorized into three domains representing the most prominent AI applications in education, and adopted a descriptive-analytical approach. The results indicated that the level of implementation of artificial intelligence (AI) applications at the college was moderate (a score of 2 on the scale). The academic domain showed a moderate level of availability (2.4), followed by the research domain (2), and then the administrative domain (1.8). It was noted that the level of implementation could be enhanced by providing the necessary requirements and organizing training programs for the teaching staff. Al-Hanaki and Al-Harthi (2023, Saudi Arabia) conducted a study titled "The Reality of Artificial Intelligence Applications in Education from the Perspective of Computer and Information Technology Teachers." The study aimed to examine the current state of AI application usage in education, along with the associated challenges, as perceived by secondary school computer and information technology teachers in Riyadh. The study population consisted of all active secondary school computer and information technology teachers, with a sample of 85 teachers responding to the questionnaire. The study employed a descriptive survey methodology, utilizing a questionnaire structured around two main themes: the extent of AI application usage and the challenges associated with their implementation. The findings revealed that the most frequently used applications were intelligent educational games—characterized by elements of excitement, challenge, and imagination—while the least used were applications designed to convert printed images or handwritten text into editable digital text files. Furthermore, the results highlighted several key challenges, including the teachers' belief that using these applications requires more effort compared to traditional teaching methods, as well as a lack of technical support, difficulties faced by learners, and high technical costs.

Artificial Intelligence in Education: Holmes, Bialik & Fadel (2021) – United Kingdom. Promises and Implications.
This study aimed to analyze the role of artificial intelligence (AI) in supporting the learning process and improving its outcomes by examining the impact of intelligent tools on the design of educational activities within the classroom. The researchers employed an integrative analytical approach, conducting a comprehensive review of existing research and studies on the use of AI in education. The sample included a range of international studies that explored AI applications across various educational settings. Content analysis tools were utilized to identify common pedagogical trends. The findings indicate that while AI contributes to personalized learning and enhances learner engagement, it may lead to superficial learning outcomes if not implemented within an effective pedagogical framework.

Systematic Review of Zawacki-Richter, Marín, Bond & Gouverneur (2019) – United States. Research on Artificial Intelligence Applications in Higher Education.

This study aimed to analyze research trends regarding the integration of artificial intelligence (AI) in universities by reviewing international studies published in this field. The researchers employed a systematic review methodology, analyzing a substantial body of international research. The sample comprised academic studies published over a period spanning more than a decade. A thematic analysis was conducted, focusing on indicators of AI usage and the associated pedagogical challenges. The findings indicate that AI applications have contributed to improved academic achievement and personalized learning; however, there is a clear need for educational policies and regulations that support the safe and effective use of these technologies.

Comparison with Previous Studies:
The findings of the current study align with previous research in confirming that the integration of AI in the educational sector remains limited and requires robust institutional and pedagogical support. A study by Al-Susi and Abu-Khatala (2024) found that the current level of AI implementation in general education is moderate. Similarly, Al-Qahfa (2025) demonstrated that the use of AI in higher education in Yemen remains at a minimal level, while Al-Hanaki and Al-Harthi (2023) highlighted that both technical and human-related challenges hinder the optimal utilization of these technologies. These findings align with the review by Zawacki-Richter et al. (2019), which indicated that the effective use of artificial intelligence (AI) in higher education remains contingent upon the existence of supportive policies and legislation. They also resonate with the assertion by Holmes et al. (2021) that AI can lead to superficial learning if not integrated within a comprehensive pedagogical framework. However, the present study distinguishes itself by linking the use of AI to deep and surface cognitive processing approaches—an aspect not addressed in previous research—thereby introducing a new cognitive dimension that connects technology with students' thinking processes.

What distinguishes this research from previous studies:
This study is unique in its integration of the technological and cognitive domains; rather than merely measuring the extent of AI usage—as was the case in prior research—it analyzes the relationship between AI and students' cognitive processing approaches, lending it greater depth from a psycho-pedagogical perspective. Furthermore, the study was conducted within a Syrian university environment that is relatively new to AI applications, providing a specific contextual dimension that highlights the challenges of digital transformation in Syrian higher education. Additionally, the study examined differences based on gender, revealing an equality of educational opportunity between male and female students—a facet overlooked by most previous research. Finally, the study offers practical recommendations for the development of curricula and training programs, providing a clear applied dimension that can help guide future educational policies.

Research Gap:
The research gap that this study seeks to address stems from the limited body of research exploring the relationship between the use of artificial intelligence and cognitive processing styles within the Arab university context—specifically in Syria. Most prior studies have focused on assessing the current state of AI usage or the technical challenges involved, without linking these to deeper thinking and learning processes. Consequently, this study offers a novel contribution by developing a cognitive model that integrates technology with cognitive processes within the university environment.

11. Research Methodology:

The study employed a descriptive-analytical approach, deemed the most appropriate framework for uncovering the relationship between the use of artificial intelligence and cognitive processing styles (surface and deep) among students in the Faculty of Education. This approach aims to describe the phenomenon as it exists in reality and to analyze the relationships between its variables in a scientific and systematic manner.

A standardized questionnaire—covering the use of artificial intelligence in university learning and patterns of

cognitive processing—was developed and administered to a sample of students. The resulting data were then analyzed using correlation coefficients and simple regression. This methodology aligns with the current study, which adopts the same approach to understand how intelligent technologies can be utilized to foster deep thinking and enhance approaches to university learning (Biggs & Tang, 2022).

12. Research Population and Sample

The study population consists of all students at Homs University enrolled in the Faculty of Education during the second semester of the 2024–2025 academic year. This group was selected as they are the most likely to engage with artificial intelligence (AI) applications within the university learning environment, and because their field of study inherently intersects with the educational and cognitive concepts central to this research.

The study sample was selected using a simple random sampling method and comprises 225 students from various academic years. This approach ensures a representative academic environment, allowing for the assessment of variations in AI usage levels and differences in cognitive processing styles among individuals. The sample effectively reflects a diversity of learning patterns and modes of interaction with modern educational technologies, thereby enhancing the generalizability of the findings to the broader study population—within the scope of the academic and contextual characteristics specific to students in the Faculty of Education at Homs University.

13. Research Instrument:

1. Artificial Intelligence Questionnaire

To achieve the research objectives, the researcher reviewed existing literature and developed a questionnaire to measure students' use of artificial intelligence. The instrument consists of 24 items, each with a five-point scale (Always, Often, Sometimes, Rarely, Never). **(**

Psychometric Properties of the Instrument

Validity:

1. Content Validity:

The researcher employed a content validity approach to ensure that the items were appropriate for measuring students' use of artificial intelligence. The questionnaire was presented to several faculty members from the Faculties of Education at the universities of Homs and Latakia, who evaluated the accuracy and suitability of each item and provided suggestions for additions or modifications. Based on their feedback and observations, no items were excluded, and no modifications were made to the questionnaire**.**

2. Internal Consistency Validity:

To assess internal consistency, the Pearson correlation coefficient was calculated between the score for each individual item and the total score of the artificial intelligence usage questionnaire. Table (1) presents these results**:**

Table (1) Correlation coefficients between the total score and the individual items of the Artificial Intelligence Usage Questionnaire

Decision	p-value	Correlation Coefficient	Total score
significant	0.000	0.660**	Q1
significant	0.000	0.785**	Q2
significant	0.000	0.714**	Q3
significant	0.000	0.681**	Q4
significant	0.000	0.711**	Q5
significant	0.000	0.556**	Q6
significant	0.002	0.424**	Q7
significant	0.000	0.808**	Q8

significant	0.007	0.373**	Q9
significant	0.000	0.677**	Q10
significant	0.000	0.887**	Q11
significant	0.000	0.567**	Q12
significant	0.000	**0.828	Q13
significant	0.000	0.907**	Q14
significant	0.000	0.903**	Q15
significant	0.000	0.549**	Q16
significant	0.000	0.747**	Q17
significant	0.000	0.550**	Q18
significant	0.000	0.460**	Q19
significant	0.000	0.674**	Q20
significant	0.000	0.827**	Q21
significant	0.000	0.684**	Q22
significant	0.000	0.660**	Q23
significant	0.000	0.843**	Q24

An examination of Table (1) reveals the following: the correlation coefficients between the sub-items comprising the scale and the total score ranged from 0.373 to 0.907, all of which are statistically significant at the 0.01 level. We can conclude that the questionnaire on the use of artificial intelligence demonstrates a high degree of internal consistency, which serves as a positive indicator of the scale's construct validity.

Extreme group validity or discriminant validity:

To verify the validity of the test, two groups were formed: an "upper group" consisting of the top 25% of the scores, and a "lower group" consisting of the bottom 25% of the scores. The size of each group was calculated as follows: sample size × 25% = 51 × 25% = 13 students. After arranging the scores in ascending order, the 13 highest scores were selected to form the upper group, and the 13 lowest scores were selected to form the lower group. Subsequently, the researcher applied the Mann-Whitney test to measure the difference between the mean ranks of the scores for the lower group and the upper group, as shown in Table (2):

Table (2) Mann-Whitney test between the lower group and the upper group regarding the questionnaire on the use of artificial intelligence

Decis-ion	p-value	z-value	Mann-Whitney Value	Sum of Mean Ranks	Mean Ranks	Count	Scores	
Signifi cant	0.000	4.344	0.000	91.00	7.00	13	below**%** 25	Use of AI
				260.00	20.00	113	High 25%	

The results in Table (2) indicate statistically significant differences between the mean ranks of the scores for individuals in the upper and lower groups—favoring the upper group—at a significance level of less than (0.01) for the total test score. This demonstrates the test's ability to discriminate between different performance levels on the artificial intelligence usage scale, thereby confirming the validity of the test results.

Test Reliability:

Reliability is defined as the ratio of true variance to the total variance of the scores obtained by examinees. The term carries several meanings: it refers to the internal consistency among test items, indicates the consistency of the ranking of individuals when the test is administered more than once, and signifies that individuals achieve the same

scores when the test is administered on successive occasions.
To verify the reliability of the instrument, the researcher employed the following method:

Test-Retest Reliability:
The researcher administered the "Artificial Intelligence Usage" test to a sample of 51 male and female students. The test was then re-administered to the same group 15 days later. Subsequently, the researcher calculated the Pearson correlation coefficient between the scores obtained by the sample members in the first and second administrations.

Table (3) Pearson correlation coefficient between the first and second administration of the artificial intelligence usage test:

decision	Probability value	Correlation coefficient	Variables
significant	0.00	0.950**	Selective Attention Test

Table (3) shows a correlation coefficient of 0.950, with a significance level of 0.00—which is less than 0.05. This indicates a statistically significant correlation, confirming that the test possesses a high degree of reliability.

2- Assessment of information processing styles (surface vs. deep)
The researcher reviewed the theoretical literature and previous studies, and developed an information-processing styles test consisting of 22 items—11 items for the surface-processing style and 11 items for the deep-processing style—with responses provided by selecting one of five alternatives.
Psychometric properties of the test:
Test validity:
Content Validity:
The researcher employed a content validity approach to verify the appropriateness of the items in the Information Processing Styles test. The test was presented to several faculty members from the Faculties of Education at the universities of Homs and Latakia, who were asked to evaluate the validity and suitability of each item, as well as to suggest any additions or modifications they deemed appropriate. Based on their feedback and observations, no items were excluded from the test.
Internal Consistency Validity:
To assess internal consistency, Pearson correlation coefficients were calculated between the scores for each sub-item and the total score on the Information Processing Styles test. Additionally, Pearson correlation coefficients were calculated between the total score for each processing style (surface vs. deep) and the overall score on the Information Processing Styles test. All correlation coefficients were found to be statistically significant, as shown in Table (4).

Table (4) Correlation coefficients between the total score and the sub-items, and between these and the total score for each processing style (surface vs. deep) on the Information Processing Styles Scale:

Decision	Probability value	Correlation coefficient	Total Score
Significant	0.000	0.594**	Q1
Significant	0.000	0.648**	Q2
Significant	0.000	0.650**	Q3
Significant	0.000	0.682**	Q4
Significant	0.000	0.584**	Q5
Significant	0.001	0.469**	Q6
significant	0.001	0.441**	Q7

Significant	0.000	0.702**	Q8
Significant	0.000	0.604**	Q9
Significant	0.000	0.504**	Q10
Significant	0.000	0.672**	Q11
Significant	0.000	0.473**	Q12
Significant	0.000	0.686**	Q13
Significant	0.000	0.687**	Q14
Significant	0.000	0.644**	Q15
Significant	0.000	0.497**	Q16
Significant	0.000	0.703**	Q17
Significant	0.006	0.382**	Q18
Significant	0.000	0.662**	Q19
Significant	0.000	0.621**	Q20
Significant	0.000	0.692**	Q21
Significant	0.003	0.408**	Q22
Significant	0.000	0.806**	Surface treatment
Significant	0.000	0.840**	**معالجة عميقة**

An examination of Table (4) reveals the following: the correlation coefficients between the total score and the scores for the sub-items ranged from 0.382 to 0.703. The correlation coefficient between the total score on the Information Processing Styles scale and the "surface processing" style was 0.806 (p = 0.000), while the correlation coefficient between the total score on the Information Processing Styles scale and the "deep processing" style was 0.840 (p = 0.000). All these values are statistically significant at the 0.01 level. It can be concluded that the Information Processing Styles scale demonstrates a high degree of internal consistency, which serves as a positive indicator of the scale's construct validity.

Convergent-discriminant validity or discriminant validity:

To verify the validity of the test, two groups were formed: an "upper group" consisting of the top 25% of the scores, and a "lower group" consisting of the bottom 25% of the scores. The size of each group was calculated as follows: sample size × 25% = 51 × 25% = 13 students. After arranging the scores in ascending order, the 13 highest scores were selected to form the upper group, and the 13 lowest scores were selected to form the lower group. Subsequently, the researcher applied the Mann-Whitney test to measure the difference between the mean ranks of the scores for the lower group and the upper group, as shown in the following table:

Table (5) Mann-Whitney test comparing the low-scoring group and the high-scoring group regarding information-processing strategies:

Decision	p-value	z-value	Mann-Whitney	Sum of Mean Ranks	Mean Rank	number	Group
Significant	0.000	4.356	0.00	91.00	7.00	13	minimum
				260.00	20.00	13	maximum

Using the Mann-Whitney test, we find a Z-value of 4.556 with a significance level of 0.000, which is lower than the threshold of 0.05; this indicates a statistically significant difference. Furthermore, the test demonstrates validity for comparisons between the two groups.

Test Reliability:

Reliability is defined as the ratio of true variance to the total variance of the scores obtained by examinees. The term carries several meanings: it refers to the internal consistency among test items; it indicates the consistency of the

ranking of individuals when the test is administered more than once; and it signifies that individuals achieve the same scores upon repeated administrations of the test. To verify the reliability of the instrument, the researcher employed the following method:

Test-Retest Reliability:

The researcher administered the "Information Processing Styles" test to a sample of 51 male and female students. The instrument was then re-administered to the same group 15 days later. Subsequently, the researcher calculated the Pearson correlation coefficient between the scores obtained by the participants in the pilot sample during the first and second administrations.

Table (6) Pearson correlation coefficient between the first and second administration of the information-processing styles test:

Decision	p-value	Correlation Coefficient	Variables
Significant	0.00	0.954**	Application 1 Application 2

14. Presentation, analysis, and discussion of results

Research Questions:

First Question: What is the level of artificial intelligence (AI) usage among the research sample members?

To answer this question, levels of AI usage were determined based on the formula for class interval width:

Class interval width = Range / Number of classes

This was applied to the total score of the test, which was divided into three categories. The following table illustrates the levels of AI usage as measured by the test.

Table (7) Levels of AI usage among the research sample members:

Range of Levels	Levels of AI Usage
24 – 56	low
56 – 88	medium
88 - 120	high

An examination of Table (7) and the calculation of the arithmetic mean of the research sample's scores on the artificial intelligence (AI) usage test reveal a mean score of 52.49. This falls within the "low" level category (defined as a range of 24–56, according to the classification criteria presented in the distribution table). This indicates that the level of AI usage among the research sample is low, reflecting a limited application of this technology within the academic environment to which the participants belong.

This low arithmetic mean may be attributed to several factors that influence the extent to which artificial intelligence is utilized within the academic community. These include a lack of training and professional development in the field of AI; students at the Faculty of Education in Homs Governorate may not have access to sufficient awareness or training programs that would allow them to gain a deeper understanding of the diverse applications of this technology. Furthermore, limited technological resources may restrict opportunities for students to engage with AI tools, whether in their coursework or in practical activities.

Additionally, a potential lack of broader societal and cultural awareness regarding artificial intelligence may affect how students perceive the importance of these technologies in enhancing their academic and professional capabilities. In this context, it can be argued that the academic specialization of students in the College of Education may contribute to this low level of usage; their fields of study do not necessarily require the in-depth knowledge of artificial intelligence (AI) technologies that is expected in technical disciplines, such as the various branches of engineering.

The findings of the current study align with those of Al-Sousi and Abu-Khatala (2024), who demonstrated that the application of AI in education is limited by a lack of training and technical support. They are also consistent with the study by Al-Qahfa and Al-Qahfa (2025), which indicated that the level of AI usage at Ibb University was moderate, primarily due to insufficient qualification. Furthermore, these results resonate with the findings of Al-Hanaky and Al-Harithi (2023), who identified a lack of technical awareness and the significant effort required for implementation as key challenges. This general trend is also supported by the work of Holmes et al. (2021) and Zawacki-Richter et al. (2019), who noted that the absence of an educational framework and institutional support diminishes the effectiveness of AI in education.

Question 1: Which cognitive processing style (surface or deep) is most commonly used by students at Homs University)?(

To answer this question, the levels of information-processing strategies were determined according to the formula for class interval width:

Class interval width = Range / Number of classes

This applies to the total score for each processing style, which has been divided into three categories. The following table illustrates the levels for the information-processing style test**.**

Table (8) Levels of information-processing styles among the research sample members:

Range of Levels	**Levels of Information Processing Styles**
11- 25.66	low
25.66 – 40.32	medium
40.32 - 55	high

Upon examining Table (8) and calculating the arithmetic mean of the research sample members' scores on the information-processing styles test, it is observed that the mean score for the surface-level processing style is (42.31), which falls within the moderate range, while the mean score for the deep-level processing style is (39.30), which falls within the low range.

These findings indicate that the "surface processing" approach is the most prevalent among students at Homs University, serving as their primary method for handling academic information. In contrast, the "deep processing" approach—which involves cognitive strategies requiring greater effort to connect new information with existing knowledge, and thus necessitates a deeper analysis of the content—appears to be used less frequently.

The reliance on surface processing can be attributed to several factors, most notably academic pressure and time constraints. Curricula may compel students to focus on passing examinations through rote memorization, which naturally encourages a surface-level approach. Furthermore, traditional teaching methods—heavily centered on lectures and theoretical examinations—may reinforce this habit by prioritizing the simple recall of information over its in-depth analysis.

Conversely, the results show that the deep processing approach is employed less frequently, with a mean score of 39.30, reflecting a low level of usage. Deep processing demands greater cognitive effort from students; it requires the ability to analyze and link new information to prior knowledge, as well as the application of critical thinking—which entails understanding cognitive connections and evaluating the underlying meanings of the information.

The limited use of this approach may stem from a lack of specialized cognitive training in deep-thinking techniques. Furthermore, academic pressures may serve as another factor preventing students from dedicating sufficient time to developing a deep understanding of information, as they are preoccupied with meeting examination

requirements and maintaining good grades.

The findings—which indicate a preference for surface-level processing over deep-level processing—can be explained by various contextual and environmental factors that influence students' cognitive behaviors. A primary factor is the traditional pedagogical approach; in some universities, instruction relies heavily on lectures, with a focus on the direct transmission of fundamental information to students. This mode of teaching may encourage surface-level processing, which is limited to the retrieval of information rather than its in-depth analysis.

Additionally, students face significant pressure from intensive curricula that require the recall of large volumes of information within a short timeframe. This often compels students to resort to rote memorization and rapid information retrieval, by passing deep analysis or attempts to understand the connections between concepts.

The results of the current study align with the findings of Al-Sousi and Abu-Khatala (2024), who noted that educational and technical challenges limit learners' ability to employ deep cognitive strategies when engaging with artificial intelligence, leading instead to a reliance on surface-level learning approaches. This is also consistent with the observations of Holmes et al. (2021), who argued that the use of intelligent tools—absent an effective pedagogical framework—can result in superficial learning that fails to foster critical thinking or deep cognitive analysis. Furthermore, this finding aligns with the observations of Zawacki-Richter et al. (2019), who noted that a lack of training and qualification in academic environments diminishes the quality of cognitive processing and limits learners' analytical understanding.

Research Hypotheses:

Hypothesis 1: There is no statistically significant correlation—at the 0.05 significance level—between the sample members' scores on the artificial intelligence usage scale and their scores regarding the surface-level and deep-level processing approaches.

To verify the hypothesis, the researcher calculated the Pearson correlation coefficient between the sample members' scores on the artificial intelligence usage scale and their scores for the surface-level and deep-level processing approaches. Table (9) presents the results**.**

Table (9) Correlation coefficient between the use of artificial intelligence and the surface and deep processing

Significance Level	Correlation Coefficient	Use of AI
0.813	0.016	Surface-level processing
0.000	0.594**	Deep-level processing

Table (9) shows that the correlation coefficient between the use of artificial intelligence (AI) and the "surface processing" approach is 0.813, with a significance level of 0.813—indicating that it is not statistically significant at the 0.01 level. Conversely, the correlation coefficient between the use of AI and the "deep processing" approach is 0.594**, with a significance level of 0.000, which is statistically significant at the 0.01 level and represents a strong correlation. Thus, it can be concluded that as the use of AI increases, the level of deep processing also increases; conversely, as the use of AI decreases, the level of surface processing tends to rise.

The strong correlation between the use of AI and deep processing suggests that students who rely more heavily on AI technologies—such as advanced research tools, machine learning, or study-aid applications—may be inclined to employ more sophisticated and analytical learning strategies. This implies that AI may play a role in encouraging students to think critically and connect new information with prior knowledge, thereby fostering a deep processing approach.

In contrast, the lack of a strong correlation between surface processing and AI can be explained by the fact that the surface processing approach—which relies primarily on rote memorization and repetition—does not necessarily require the use of AI technologies. Students who depend on memorization may not perceive a need for intelligent tools or advanced analytical capabilities to assist them in understanding the course material.

The findings of the current study align with those of Holmes et al. (2021), who asserted that the use of artificial intelligence—when integrated within an effective pedagogical framework—contributes to the enhancement of analytical thinking and deep learning; this is consistent with the positive correlation between artificial intelligence and deep processing observed in the present study. Furthermore, these results concur with the work of Zawacki-Richter et al. (2019), which demonstrated that artificial intelligence technologies support cognitive personalization and improve the quality of learning when employed in a structured manner. The findings also resonate with the study by Al-Qahfa and Al-Qahfa (2025), which indicated that the academic use of artificial intelligence is linked to the improvement of educational and research competencies. Conversely, the weak relationship found with surface-level processing aligns with the observation by Al-Sousi and Abu Khatala (2024) that a lack of adequate training leads to limited application, failing to reach the level of deep thinking.

Second hypothesis: There are no statistically significant differences at the 0.05 significance level between the mean scores of the sample members on the artificial intelligence usage scale, based on the gender variable.

To verify this hypothesis, the researcher applied the Student's t-test for independent samples; Table (10) presents the results:

Table (10) Results of the t-test for the significance of differences between the mean scores of research sample members regarding the use of artificial intelligence, according to the gender variable:

Decision	Significance Level	Degrees of Freedom	t-value	Standard Deviation	Mean	N	Gender	Variable
Not significant	0.138	223	1.482	15.48	54.72	80	males	Use of AI
				17.40	51.26	145	Females	

As shown in Table (10), the t-value is 1.482, and the significance level is 0.138 (which is greater than 0.05). Consequently, we accept the null hypothesis, which states that there are no statistically significant differences—at the 0.05 significance level—between the mean scores of the sampled students on the scale measuring the use of artificial intelligence, based on the gender variable.

In other words, gender may not significantly influence how individuals within the sample use artificial intelligence. This suggests that both males and females utilize AI to a largely similar extent, reflecting a relative parity between the genders in their engagement with this technology.

This may be due to the equal opportunities provided by the academic environment, which likely plays a role in this balanced usage of AI. Both genders are granted equal access to technology; furthermore, growing technological awareness and advancements in education have helped narrow the digital gender gap, making technology accessible to everyone regardless of gender. Such an educational environment may have contributed to both males and females approaching these tools in similar ways.

It is also possible that artificial intelligence has become a familiar and user-friendly tool for everyone, leading both genders to interact with it in a comparable manner. As AI tools are increasingly integrated into daily life—whether in education, professional fields, or even leisure activities—their use has become common among both males and females, contributing to the absence of gender-based differences in this domain.

Ultimately, the combination of equal educational and technological opportunities, heightened technological awareness, and the removal of previous social and cultural barriers has fostered an equitable use of artificial intelligence among males and females, meaning that both groups employ these technologies in similar ways. The findings of this study align with those of Al-Qahfa and Al-Qahfa (2025), who indicated that the use of artificial intelligence (AI) in education does not vary based on demographic characteristics—including gender—as levels of adoption were found to be similar across all individuals within the college. This result also resonates with the conclusions of Al-Hanaky and Al-Harthi (2023), who found that differences in AI usage among female educators were linked more to their academic specialization and experience than to their gender, reflecting a growing, shared level

of technological awareness. Furthermore, this finding is consistent with the observations of Zawacki-Richter et al. (2019), who noted that the proliferation and accessibility of smart technologies have narrowed gaps between various groups, including gender-based differences in the use of AI tools.

Third hypothesis: There are no statistically significant differences, at a significance level of 0.05, between the mean scores of the sample members on the processing styles scale based on the gender variable.

To verify this hypothesis, the researcher applied an independent-samples t-test. Table (6) presents the results:

Table (11): Results of the t-test for the significance of differences between the mean scores of the research sample participants across the two processing styles (surface vs. deep), according to the gender variable.

Decision	Significance Level	Degrees of Freedom	t-value	Standard Deviation	Mean	N	Gender	Variable
Not significant	0.902	223	0.563	8.016	41.91	80	Males	Surface Processing Style
				7.825	42.53	145	Females	
Not significant	0.492	223	1.026	12.588	38.16	80	males	Deep Processing Style
				12.327	39.93	145	females	

As shown in Table (11), the t-value is 0.563, and the significance level is 0.902 (which is greater than 0.05). Consequently, we accept the null hypothesis, which states that there are no statistically significant differences—at the 0.05 significance level—between the mean scores of the students in the sample on the surface-level processing style scale, according to the gender variable.

As shown in Table (11), the t-value is 1.026, with a significance level of 0.492 (which is greater than 0.05). Consequently, we accept the null hypothesis, which states that there are no statistically significant differences—at the 0.05 significance level—between the mean scores of the sampled students on the deep-processing style scale based on the variable of gender.

The results indicate an absence of substantial differences between males and females regarding both surface-processing and deep-processing styles. This suggests that gender is not a determining factor in the cognitive style individuals employ when processing information.

The parity in educational opportunities and cognitive awareness between the genders may play a significant role in the balanced use of these processing styles; both male and female students have access to similar educational tools, which facilitates an equal likelihood of utilizing either approach. This equitable access to knowledge has contributed to the lack of significant gender-based differences in the use of these styles. Furthermore, an individual's preference for a particular processing style is likely rooted more in personal abilities or cognitive orientations than in gender.

The findings of this study align with those of Al-Susi and Abu-Khatala (2024), who found no significant gender-based differences in the use of artificial intelligence (AI) technologies and learning approaches—a result that reflects a convergence in technological and cognitive awareness between males and females. This finding also resonates with the observations of Zawacki-Richter et al. (2019), who noted that the proliferation of AI tools in academic environments helps narrow educational gaps across various groups, including those related to gender. Furthermore, this result is consistent with the study by Al-Qahfa and Al-Qahfa (2025), which demonstrated that equal access to educational and technological opportunities leads to similarities in learning patterns and cognitive processing between genders; this underscores that personal and cognitive variables exert a greater influence than demographic factors in shaping an individual’s approach to information processing.

15. General research findings:

Based on an analysis of statistical data and the results of field tests conducted on the study sample, the general findings can be summarized as follows:

1. The level of artificial intelligence (AI) usage among students at the Faculty of Education, Al-Baath University (Homs), is low, with a mean score of 52.49; this indicates that students do not sufficiently utilize AI applications in their academic and educational activities.
2. Among the study sample, the "surface processing" approach to information processing prevails over the "deep processing" approach—with a mean score of 42.31 for surface processing compared to 39.30 for deep processing—suggesting a tendency among students to rely on rote memorization and recall rather than on the analysis and deep understanding of content.
3. There is a statistically significant correlation between the use of artificial intelligence and the deep processing approach ($r = 0.594$, $p < 0.01$), indicating that a higher level of AI usage is associated with an increased inclination toward employing strategies for in-depth thinking and analysis.
4. There is no statistically significant correlation between the use of artificial intelligence and the surface processing approach, implying that relying on a surface-level approach to learning is unrelated to the use of AI tools.
5. There are no statistically significant differences in the level of artificial intelligence usage based on gender; this reflects an equality of educational and technological opportunities for both male and female students within the university learning environment.
6. There are no statistically significant differences between genders regarding surface-level and deep-level processing approaches. This suggests that cognitive styles for information processing are not influenced by gender, but rather by other cognitive and contextual factors related to the nature of learning and interaction with content.
7. The overall findings highlight an urgent need to foster a culture of artificial intelligence (AI) within university education. This can be achieved by integrating AI programs and applications into curricula, and by training both students and faculty members on how to utilize these tools to develop deep-thinking skills and advanced cognitive processing.

16. Research Proposals:

Based on the study's findings, a set of recommendations and proposals can be offered to help enhance the use of artificial intelligence and foster deep cognitive processing methods among students, as follows:

1. Integrate artificial intelligence (AI) technologies into university curricula by designing applied courses or modules that introduce students to AI tools and methods for employing them in research, analysis, and critical thinking—thereby elevating the level of AI usage from low to medium or high.
2. Organize training programs and workshops for faculty members and students, focusing on developing deep-thinking skills and the use of intelligent tools for information processing. This aims to shift the learning paradigm from superficial rote memorization toward analytical learning rooted in understanding and interpretation.
3. Develop an interactive digital learning environment that supports self-directed learning and the application of AI in classroom and research activities, by providing digital resources and tools that facilitate access to information and encourage its use in analytical ways.
4. Conduct forward-looking studies on the relationship between AI usage and the critical and creative thinking skills of university students in Syria, with the goal of building an integrated educational model that bridges modern technology with advanced cognitive processing patterns.

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