Enhancing Decision-Making Skills in University Students: The Role of Artificial Intelligence in Digital Education

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Abstract.

This study examines the impact of artificial intelligence (AI) on the development of decision-making skills in students within a university education framework that utilises digital technologies. AI can assist by helping students identify relevant information, evaluate different options, and make informed decisions. We employed a suitable AI tool in an experiment conducted at Mohammed Premier University in Oujda. The approach involved presenting a group of students of varying ages and skill levels with an exercise comprising several tasks supported by the chosen AI tool. Quantitative results from questionnaires and qualitative data from interviews indicated that AI summarises complex information, identifies trends and correlations in data, suggests alternative solutions, identifies potential causes of problems, and evaluates the consequences of choices to provide personalised recommendations. These findings suggest that AI positively impacts students' decision-making skills within a university education framework using digital technologies. Potential implications of this study for analysing the impact of AI on teaching methods and learning outcomes include the possibility of developing new relationships between AI and problem-solving. The originality of this work lies in the potential new relationships between cognitive psychology (decision-making, problem-solving) and artificial intelligence.

Keywords : artificial intelligence, decision-making, learning, skills.

M. Khaldi et al. (eds.), *Proceedings of the E-Learning and Smart Engineering Systems (ELSES 2024)*, Atlantis Highlights in Social Sciences, Education and Humanities 36,
https://doi.org/10.2991/978-2-38476-408-2_12

Introduction

In an ever-changing world, the ability to make informed and thoughtful decisions has become a foundational skill for learners. Faced with the increasing complexity of information and choices to be made, artificial intelligence (AI) is a promising tool to help them develop their decision-making skills. Research in this area aims to explore some of the ways in which AI can support learners in this process. In addition, by offering personalized feedback and adapting learning content, AI can help learners develop strategies to make more rational and responsible decisions.

Despite promising advances in research on AI and decision-making, several gaps remain in our understanding of the impact of AI on learning. On the one hand, there is a need to better identify the types of AI interventions and tools that are most effective in developing learners' decision-making skills. Our study aims to contribute to filling these gaps by exploring the potential and challenges of AI in learner decision-making. By analysing the results of our research, we hope to provide insights for educational practitioners and developers of AI-based learning tools.

The aim of this research is anchored around a central question that explores the potential of artificial intelligence (AI) as a vector for improving learners' decision-making skills. In a context where data abounds and decision-making environments are becoming increasingly complex, it is becoming essential to equip learners with the right tools to effectively navigate these environments. This study sets out to examine how AI can act as a lever for the development of decision-making skills, not only by providing an enriched database for reflection, but also by offering a framework for the practice and experimentation of decision-making processes. Three hypotheses underpin our investigation: Firstly, that AI, thanks to its ability to synthesize complex information, helps learners to identify crucial tendances and correlations in data. Secondly, by proposing alternative solutions, AI facilitates the identification of potential causes of a problem and the generation of scenarios with varied outcomes. Thirdly, that AI, by evaluating the consequences of different choices, provides personalized recommendations and constructive feedback on the decisions taken. This research therefore aims to unravel how the integration of AI into the learning process can strengthen learners' decision-making capacities, thus preparing them to face the challenges of professional and personal environments with greater acuity and confidence.

This study explores the impact of using an AI-based conversational assistant in the development of decision-making skills in university students. The experiment, conducted at Mohammed Premier University in 2024, involves 145 students distributed according to stratified sampling to ensure diversity and representativeness. Participants use the AI assistant to perform specific predefined tasks that implicitly include synthesizing information, managing hypotheses and administering personalized recommendations for decision-making.

Data are collected via a post-experience paper questionnaire and analysed to measure students' perceptions of their decision-making ability, their ability to generate hypotheses, and their effectiveness in assessing risk and making informed decisions. Analyses used statistical methods appropriate to the types of variables collected, including Pearson's correlation coefficient and Student's t-test for continuous variables, and chi-square for ordinal variables.

Independent variables include the type of AI tool used, individual learner characteristics, and learning modalities, while dependent variables include perceived decision-making ability, quality of hypotheses generated, and success rate in real-life decision-making situations. This rigorous methodology makes it possible to empirically evaluate the effectiveness of AI as a decision-making support tool in an educational context.

The study examined the impact of different modalities of using an AI-based conversational assistant on learners' decision-making ability. The results demonstrate the effectiveness of integrating AI into learning and decision-making processes. They also highlight the importance of personalizing the use of AI tools to maximize their impact on learner confidence, speed, knowledge application and autonomy. These findings could guide the future development of educational technologies to better meet users' needs.

In the second research question, the study explored how artificial intelligence can help learners generate hypotheses and improve the quality of their decisions. The results highlight the importance of calibrating confidence and critical thinking in the decision-making process. They also suggest that AI tools and training programs should focus not only on improving learners' decision-making skills, but also on how they assess and perceive their own skills and results. These findings have implications for the design of educational programs and decision support tools.

The third research question examines the impact of using artificial intelligence (AI) in improving risk assessment and informed decision-making among learners. The findings highlight the importance of strategically integrating AI technologies into educational programs to enhance learners' decision-making capabilities. They also recommend careful attention to the frequency of AI use, the clarity of instructions, and the choice of teaching aids to maximize pedagogical benefits and effectively prepare students to face real-world challenges.

1 Literature review

1.1 Conceptual framework

Artificial Intelligence (AI)

Artificial intelligence (AI) has revolutionized many aspects of our society, and education is no exception. In the university context, the increasing integration of AI into learning environments has generated considerable interest in its implications for learner decision-making. AI offers innovative possibilities for improving teaching and learning, by providing personalized assistance tools, recommendation systems and predictive analytics. However, the impact of AI on learners' decision-making processes in this context leads to a number of questions, some of which will be answered below.

This literature review aims to explore and synthesize existing work on AI and learner decision-making with the aim of apprehending potential correlations between the two. We will examine some of the ways in which AI is being used to support students' decision-making processes, highlighting the potential benefits as well as the challenges and concerns associated with this integration. Indeed, understanding how AI influences learners' decision-making is crucial to designing effective and ethical learning environments, and to supporting learners' ongoing development in an ever-changing world. By exploring existing re-research, this literature review aims to enlighten practitioners, researchers and Decision makers on current trends and future prospects in this rapidly expanding field.

Among the theories best suited to our research, we cite: 1. signal theory (Connelly et al., 2011) [1], which explores how information generated by AI systems serves as "signals" in decision-making, notably in terms of credibility, quality of information and influence on user decisions. 2. Machine learning theory (Shalev-Shwartz & Ben-David, 2014) [2], which focuses on the ability of self-learning algorithms to analyse data, detect patterns and make decisions based on these patterns. Learners can benefit from these capabilities to obtain personalized recommendations or predictions based on objective data. 3. The theory of distributed cognition (Salomon, 1997) [3], which argues that thinking and cognition are not limited to the human brain but extend to interactions with the environment and the tools used. By integrating AI systems into the decision-making process, learners can externalize part of their cognition and collaborate with these systems to achieve more informed decisions.

Decision-making

The other part of this article's conceptual framework concerns the study of decision-making, a pivotal function in organizational management and individual conduct. Rooted in a tradition of multidisciplinary research, our conceptual model is based on the foundations of decision theory, enriched by contemporary contributions from cognitive psychology and artificial intelligence (AI). These theoretical axes provide a prism through which we examine how the integration of AI influences, modifies, and potentially enhances decision-making within the university. Within this framework, we address the main theories of decision-making. This theoretical exploration lays the foundations for a rigorous empirical analysis, aimed at enlightening practitioners and researchers on the potentialities and challenges introduced by AI into decision-making processes.

To study the effect of AI on decision making in university learners, among the theories to consider are: 1. Bounded Rationality Theory: This theory by Herbert Simon (Simon, 1957) [4] could be relevant to understanding how students use AI tools to make more effective decisions within their cognitive and temporal limitations. 2. Consensus decision theory (Sunstein & Hastie, 2015) [5]: Given that AI can be used to facilitate group decision-making, this theory could be useful to evaluate how students collaborate using AI to reach collective decisions. 3. Social decision theory (Centola, 2021) [6]: This theory can be applied to examine how AI-influenced social norms and interactions alter students' decision-making at university, and how students adapt to these changes. 4. Distributed cognition theory (Hollan et al., 2000, pp. 174-196) [7]: This theory holds that cognition extends beyond the individual to include the environment and the tools used. Thus, by applying this theory, we could study how AI can act as a cognitive extension of learners, helping them to better understand relevant information. By combining these theories and applying them to the specific context of academic learners using AI to make decisions, it would be possible to gain deeper insight into the impacts and implications of this technology on their decision-making processes.

2 Methodology

2.1 Experience design:

The experiment is designed to investigate how AI can help learners develop their decision-making skills. It involves the use of an AI-based Conversational Assistant. This Assistant is designed to provide personalized support to students in their decision-making processes. More specifically, the experiment will propose three key situations: firstly, the student will use the Assistant to provide clear and concise summaries of complex information relevant to decision-making. Secondly, he will use it to generate hypotheses based on available data, in order to explore different perspectives and scenarios. Finally, it will offer personalized recommendations and feedback to proactively guide decision making, highlighting the most relevant options and best practices. This experimental approach aims to empirically assess the impact of AI as a decision-support tool in an educational context, focusing on the development of learners' decision-making skills.

The study was operationalized at Mohammed Premier University in January 2024. During a face-to-face session, students had access to the same AI-based conversational assistant available online and processed the same game for a pre-determined amount of time. This experiment took place in a controlled environment within the university, offering participants the opportunity to explore and benefit from the practical advantages of using AI in their decision-making process.

2.2 Participants :

The study population will consist of students enrolled in various academic programs. To select a representative sample of the student population, a stratified sampling strategy will be employed. This approach will divide the population into different homogeneous groups according to relevant criteria such as level of study, course of study or field of specialization. A sample will then be drawn from each stratum at random to ensure that the overall sample is representative. This stratified sampling strategy will help to ensure the diversity and reliability of the data collected, while at the same time enabling us to obtain varied perspectives from the students taking part in the experiment. As the number of students in the chosen streams is relatively small, we will consider all students in each stream, with a total of 145 students. The breakdown of students by stream is as follows:

Table 1. The distribution of the sample of students by field of study

Level	Designation	Reference	Participants
Licence	Licence en Education S5	LE-S5	28
	Licence SIC S3	SIC-S3	25
	Parcours d'Excellence: Communication & Transformation Numérique S3	PE-CTN-S3	23
Master	- Master Communication & Transformation Numérique S1	CTN-S1	27
	Master IFTEC Première année S1	IFTEC-S1	20
	Master IFTEC Deuxième année S3	IFTEC-S3	22

The sample is recruited by means of pre-programmed sessions in consultation with the students taking part in the experiment. Each stream takes the experiment separately from the others, to avoid the effects of any bias and to ensure adequate supervision. The experiment lasts two hours.

The sample of 145 students is made up of 69% (100) female students and 31% (45) male students, with an age range between 22 and 38. 52.4% (76) have a Bachelor's level of education, while 69.6% (69) have a Master's level of education.

2.3 Study design :

Data collection :

In the first research question, we explore the potential impact of artificial intelligence (AI) tools on learners' decision-making processes. To do this, we define as a dependent variable the learner's perception of his or her own ability to make decisions. This reflects how individuals assess their ability to select the most relevant options after being exposed to information via an AI tool. As an independent variable, we consider the type of AI tool involved in this interaction, in this case a conversational assistant. This choice enables us to determine whether the use of this specific form of AI technology can significantly influence learners' perceived confidence and effectiveness in their decision-making abilities.

The second research question aims to assess the impact of artificial intelligence (AI) on learners' ability to generate effective hypotheses, a key element in the learning and decision-making process. The independent variables taken into account include a range of inherent learner characteristics, such as age, level of education and learning style. These factors are key to understanding how different populations react to the use of AI in a pedagogical setting. On the other hand, the quality of decisions made in a simulated context is our dependent variable, reflecting how effectively learners are able to formulate and evaluate hypotheses after interaction with AI.

The third research question looks at how the use of artificial intelligence (AI) technologies can be leveraged to improve risk assessment and decision-making among learners. The independent variables examined include various aspects of learning modalities, such as the frequency with which learners use the AI tool, the consigns and instructions they are provided to navigate and interact with it, and the type of pedagogical support used to accompany learning (e.g. tutorials, videos). These factors are considered to understand how they influence the effectiveness of AI as a decision aid. The dependent variable, meanwhile, measures the success rate of learners in real-life situations, assessed by the number of positive decisions made in the case study maintained during the experiment. The aim is to determine whether the integration of AI into the learning process, depending on the specific modalities of its use, can significantly improve learners' ability to assess risks and make better-informed decisions, thus measurably contributing to their success in practical contexts.

To assess the impact of artificial intelligence (AI) on learners' comprehension, hypothesis generation and informed decision-making, the main measurement tool used across the three research questions addressed is a paper-based questionnaire. With regard to the second research question, in the study of hypothesis-generating ability, an analysis of responses is planned using standardized rating scales assessing the quality of decisions made by students in the context of our experiment. Finally, to examine how AI helps learners to assess risk and make informed decisions, we have opted for the analysis of quantitative data from real-life performance, including the number of positive decisions in real-life situations. Each tool was carefully selected to align with the specific objectives of the research. The questionnaire is administered at the end of the experiment, while the analysis of responses and quantitative data is carried out at a later date.

Data Analytics:

Let's start with the first research question, to check the relationship between the learner's perception of his or her own ability to make decisions and the type of AI tool, specifically a conversational assistant. We will consider that the independent variable of this question concerns the type of AI tool used in the experiment. It is made up of four indicators. As for the dependent variable, which is the learner's perception of his or her own ability to make decisions, it is also made up of four indicators. We will compare them to verify the existence of a relationship between them.

The second research question focuses on the potential impact of artificial intelligence (AI) on learners' ability to generate hypotheses, by analyzing how learners' individual characteristics (age, degree of confidence in decisions made during the experiment, and learners' Satisfaction with decisions made during the experiment) influence AI's effectiveness in this process. This section aims to assess the relationship between these personal characteristics, considered as independent variables, and the quality of decisions made by learners during the experiment, which acts as a dependent variable. The main objective is to determine how to improve the use of AI as a pedagogical tool, highlighting the need to tailor AI-assisted learning approaches to the individual characteristics of each learner to maximize the quality of the decisions made.

The independent variables are a continuous quantitative variable and two nominal qualitative variables, and the dependent variable is a continuous quantitative variable. This leads us to use the following combinations:

- Pearson's correlation coefficient: to calculate the degree of correlation between age and decision-making quality.

- Student's t-test for independent samples (since the categorical variable has only two categories): to test the relationship between the two categorical qualitative variables (degree of confidence in the decisions made during the experiment and learners' satisfaction with the decisions made during the experiment) and the continuous quantitative variable (decision-making quality).

The third research question explores the potential of artificial intelligence (AI) technologies to improve learners' ability to assess risk and make informed decisions. It focuses on the influence of different learning modalities, such as the frequency of use of AI tools, the type of instructions and guidance provided to the learner, and the pedagogical support employed (e.g. tutorials or videos), considered here as independent variables, on the success rate of learners in real-life situations, measured through the number of positive decisions made during the experiment, which acts as the dependent variable. The aim is to determine the link between AI-specific teaching methods and success in making real-life decisions.

The independent variables are categorical qualitative variables (Frequency of use of the AI tool, instructions and teaching aids), and the dependent variable is a continuous quantitative variable (Success rate in real-life situations). This leads us to use chi-square for trend, since the discrete variable is ordinal, and this test allows us to detect a trend across ordinal categories based on nominal groups.

3 The Results

The results section of this article addresses a methodical exploration of the impact of artificial intelligence (AI) on the development of learners' decision-making skills. Our investigation, structured around three interrelated research questions, seeks to elucidate how AI can transform the landscape of learning and decision-making. Firstly, we examine AI's ability to enrich learners' understanding of the data and information crucial to making informed decisions. The second research question focuses on the potential role of AI in facilitating learners' hypothesis generation, a key step in the decision-making process. Finally, our third interrogation addresses the effectiveness of AI in enhancing learners' ability to assess risk, aiming to promote more informed and strategic decision-making. The results shed new light on the potential of AI as a pedagogical tool to enhance not only learners' critical analysis skills, but also their autonomy in decision-making.

The first research question addresses how AI can help learners better understand information relevant to decision-making. The Independent variable for this question concerns the type of AI tool used in the experiment. It is made up of four indicators. As for the Dependent variable, which is the learner's perception of his or her own ability to make decisions, it is also made up of four indicators. We will compare them to verify the existence of a relationship between them, as shown in the following table:

Table 2. Table of comparison of the indicators of the independent variable with the indicators of the dependent variable

Nominal Variables	
Independent: Type of AI tool Conversational Assistant	**Dependent:** The learner's perception of their own decision-making ability
Frequency of use of the AI tool	Confidence in decision-making
Type of interaction with the AI tool	Perceived effectiveness of the AI tool
AI tool features used	Translation of knowledge into real-world decisions
Satisfaction with the AI tool	Autonomy in decision-making

This layout follows a logical sequence of results but does not prevent us from proposing other layouts. We present the results obtained using SPSS software:

The first combination concerns the effect of the frequency of use of the conversational assistant by the learner on his confidence in decision-making:

Table 3. Cross-tabulation of learners' use frequencies and decision-making confidence

Frequency of use * Confidence in decision-making Crosstabulation

Count

		Confidence in decision-making			
		Very confident	Confident	Moderately confident	Total
Frequency of use	Very often	95	1	0	96
	Often	0	30	19	49
Total		95	31	19	145

Table 4. Chi-square calculation table for frequency of use and learners' confidence in decision-making

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	140,675[a]	2	,000
Likelihood Ratio	176,664	2	,000
N of Valid Cases	145		

a. 0 cells (,0%) have expected count less than 5. The minimum expected count is 6,42.

Table 5. Table for calculating symmetric measurements: Phi, Vde Cramer

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	,985	,000
	Cramer's V	,985	,000
N of Valid Cases		145	

The second combination concerns the effect of the type of AI tool interaction used by the learner on his perceived effectiveness in making decisions quickly:

Table 6. Cross-tabulation of learners' interactions with learners' perceived effectiveness in decision-making quickly

Student interaction * quick decision-making Crosstabulation

Count

		quick decision-making				
			Absolutely	Yes	moderately	Total
Student interaction	Textual	1	54	50	8	113
	Vocal	0	0	15	17	32
Total		1	54	65	25	145

Table 7. Chi-square calculation table for learners' interactions with perceived efficiency in decision-making quickly.

Chi-Square Tests	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	46,280[a]	3	,000
Likelihood Ratio	51,486	3	,000
N of Valid Cases	145		

a. 2 cells (25,0%) have expected count less than 5. The minimum expected count is ,22.

Table 8. Table for calculating symmetric measurements: Phi, Vde Cramer

Symmetric Measures		Value	Approximate Significance
Nominal by Nominal	Phi	,565	,000
	Cramer's V	,565	,000
N of Valid Cases		145	

The third combination concerns the effect of the AI tool functionalities used on the application of knowledge in real-life decision situations:

Table 9. Cross-tab of AI tool features and knowledge application in real-world decision situations

assistant features * Knowledge application Crosstabulation

Count

		Knowledge application			
		Very capable	Capable	Moderately capable	Total
assistant features	Information search	35	51	0	86
	Problem solving	0	4	7	11
	Practice exercises	6	26	16	48
Total		41	81	23	145

Table 10. Chi-square calculation table concerning the functionalities of the AI tool and the application of knowledge in real decision situations among learners.

Chi-Square Tests	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	51,690[a]	4	,000
Likelihood Ratio	59,968	4	,000
N of Valid Cases	145		

a. 2 cells (22,2%) have expected count less than 5. The minimum expected count is 1,74.

Table 11. Table for calculating symmetric measurements: Phi, Vde Cramer.

Symmetric Measures		Value	Approximate Significance
Nominal by Nominal	Phi	,597	,000
	Cramer's V	,422	,000
N of Valid Cases		145	

The fourth combination concerns the effect of the learner's satisfaction with the tool on his self-nomics in decision-making:

Table 12. Cross-tabulation of learner satisfaction and Sense of autonomy in decisions after using the AI assistant

Student satisfaction * Sense of autonomy Crosstabulation

Count

		Sense of autonomy			
		Absolutely	Yes	moderately	Total
Student satisfaction	Very satisfied	72	14	0	86
	Satisfied	0	8	3	11
	Moderately satisfied	11	29	8	48
Total		83	51	11	145

Table 13. Chi-square calculation table for learner satisfaction and Sense of autonomy in decisions after using the AI assistant

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	65,907[a]	4	,000
Likelihood Ratio	76,313	4	,000
N of Valid Cases	145		

a. 3 cells (33,3%) have expected count less than 5. The minimum expected count is ,83.

Table 14. Table for calculating symmetric measurements: Phi, V de Cramer

Symmetric Measures		Value	Approximate Significance
Nominal by Nominal	Phi	,674	,000
	Cramer's V	,477	,000
N of Valid Cases		145	

The answer to the second research question of our study reveals the significant influence of artificial intelligence (AI) in the learners' hypothesis generation process, taking into account different independent variables such as age, degree of confidence in decisions made during the experiment and satisfaction with decisions made during the experiment. The following table summarizes the independent and dependent variables:

Table 15. Table of comparison of the independent variables and the dependent variable of the second research question

Variables	
Independent: Learner Characteristics	**Dependent:** Quality of decisions made in the context of the experiment
Age	Quality of decisions made in the context of the experiment
Degree of confidence in the decisions made during the experiment?	
Learners' satisfaction with decisions made during the experience	

The first combination deals with the effect of age on the quality of decisions made in the context of experience. It involves the correlation of a continuous quantitative variable with a continuous quantitative variable. (il y a une différence entre les résultats des tableaux.. vérifier dans la partie discussion)

Table 16. Table of descriptive statistics of the first combination of age with quality of decisions

Descriptive Statistics

	Mean	Std. Deviation	N
Age	2,12	,997	145
Decision quality	1,74	,842	145

Table 17. Table for calculating the correlations of the first combination of age with the quality of decisions

Correlations

		Age	Decision quality
Age	Pearson Correlation	1	-,807**
	Sig. (2-tailed)		,000
	N	145	145
Decision quality	Pearson Correlation	-,807**	1
	Sig. (2-tailed)	,000	
	N	145	145

**. Correlation is significant at the 0.01 level (2-tailed).

The second combination concerns the effect of the degree of confidence in the decisions made by the participants during the experiment on the quality of the decisions made in the context of the experiment. It concerns the relationship between a nominal qualitative variable and a continuous quantitative variable.

Table 18. Test calculation table for independent samples regarding the effect of confidence on the quality of decisions

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Decision quality	Equal variances assumed	5,255	,023	-10,533	141	,000	-1,777	,169	-2,111	-1,444
	Equal variances not assumed			-13,368	22,687	,000	-1,777	,133	-2,052	-1,502

The third combination concerns the effect of students' satisfaction with decisions made during the experiment on the quality of decisions made in the context of the experiment. It concerns the relationship between a nominal qualitative variable and a continuous quantitative variable.

Table 19. Table of group statistics on the effect of learner satisfaction on the quality of decisions

Group Statistics

	Satisfaction_SAT2	N	Mean	Std. Deviation	Std. Error Mean
Decision quality	Very satisfied	122	1,49	,606	,055
	Not at all satisfied	23	3,04	,706	,147

Table 20. Calculation table for testing independent samples regarding the effect of learner satisfaction on the quality of decisions

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Decision quality	Equal variances assumed	3,979	,048	-10,962	143	,000	-1,552	,142	-1,831	-1,272
	Equal variances not assumed			-9,880	28,450	,000	-1,552	,157	-1,873	-1,230

The third research question addresses how AI can help learners assess risk and make more informed decisions? The Independent variable of this question, being nominal quantitative, concerns the learning modalities which are the frequency of use of the AI tool, the clarity of the instructions and guidelines given with the AI tool to the learner and finally the types of teaching aids associated with the AI tool. The dependent variable, being discrete quantitative, concerns the success rate in real-life situations. We will compare them to check whether there is a correlation between them, as shown in the following table:

Table 21. Table of comparison of the independent variables and the dependent variable of the third research question

Variables	
Independent: learning methods	**Dependent:** the success rate in real-life situations
How often the AI tool is used	The success rate in real-life situations
The clarity of the instructions and instructions given with the AI tool to the learner	
The types of educational materials associated with the AI tool	

The first combination concerns the effect of the frequency of use of the AI tool on the success rate in real-life situations. It concerns the relationship between a nominal qualitative variable and a continuous quantitative variable.

Table 22. Table of results of the Kruskal-Wallis test regarding the effect of frequency of use on the success rate

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Success rates in real-life situations is the same across categories of Frequency of use.	Independent-Samples Kruskal-Wallis Test	,000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

The second combination concerns the effect of the clarity of the instructions given with the AI tool to the learner on the success rate in real-life situations. It concerns the relationship between a nominal qualitative variable and a continuous quantitative variable.

Table 23. Table of Kruskal-Wallis test results regarding the effect of clarity of instructions on the success rate

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Success rates in real-life situations is the same across categories of Evaluation clarity.	Independent-Samples Kruskal-Wallis Test	,000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

The third combination concerns the effect of the types of teaching aids associated with the AI tool on the success rate in real-life situations. It involves the correlation of a nominal qualitative variable with a continuous quantitative variable.

Table 24. Table of Kruskal-Wallis test results regarding the effect of the type of support on the success rate

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Success rates in real-life situations is the same across categories of Type support.	Independent-Samples Kruskal-Wallis Test	,000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is ,05.

These results suggest that AI doesn't just provide passive assistance, but plays an active, personalized role in developing learners' decision-making and risk assessment skills, highlighting the importance of designing well-structured, AI-centric learning modalities to optimize performance and decision-making skills in real-world contexts.

4 The discussion

In this section, we will discuss the main findings of our study and put them into perspective with current knowledge in the field. We will explore the implications of our findings, highlighting how they contribute to current understanding of the subject and discussing possible directions for future research. We will also discuss the potential limitations of our study and suggest ways of overcoming them. Finally, we will discuss the practical and theoretical applications of our findings in the wider context of the discipline.

The first research question addresses how AI can help learners better understand information relevant to decision-making. The Independent variable for this question concerns the type of AI tool used in the experiment. It is made up of four indicators. As for the Dependent variable, which is the learner's perception of his or her own ability to make decisions, it is also made up of four indicators. We then structured our analysis around four key combinations of independent and dependent variables to measure various aspects of the interaction between the learner and the AI.

1. Effect of frequency of use of conversational assistant on confidence in decision-making: This combination evaluates how regular use of a conversational assistant can influence learners' confidence in their decisions. The sub-hypothesis is that the more frequent the use, the greater the confidence acquired by the learner in decision-making. The results obtained from the statistical calculations indicate a highly significative relationship between the frequency of use of the conversational assistant (independent variable) and the learner's confidence in decision-making (dependent variable). The Pearson chi-square test, with a value of 140.675 and 2 degrees of freedom, shows a two-sided asymptotic significance of 2.8373E-31 well below 0.001. This extremely low value suggests that the probability of the observed relationship between the two variables being due to chance is practically zero. In other words, it is very likely that frequent use of the conversational assistant has a significant impact on learners' confidence in their decisions. The fact that 0 cells (0%) have a theoretical size of less than 5, with a half-maximum theoretical size of 6.42, indicates that the data are sufficiently distributed for the test results to be reliable. This adequate distribution of numbers in the categories ensures that the results of the chi-square test are valid and not biased by an unequal distribution of observed frequencies.

What's more, the likelihood ratio, another statistical measure used to test the independence of variables, has a value of 176.664, also with 2 degrees of freedom, and an even lower two-sided asymptotic signification of 4.343E-39, well below 0.001. This reinforces the conclusion that the relationship between conversational assistant use and confidence in decision-making is very strong. In conclusion, these statistical analyses clearly show that conversational assistant use is closely linked to an increase in learners' confidence in their decision-making ability. This could imply that interventions aimed at increasing the use of such tools could be beneficial in improving learners' confidence in their judgments and decisions.

2. Effect of AI tool interaction type on perceived effectiveness in making decisions quickly: Here, we examine whether the mode of interaction (e.g. text, voice) with the AI tool affects the speed with which learners feel able to make decisions. Perceived effectiveness may vary according to whether the tool enables more intuitive or more formal interaction.

The results obtained from statistical calculations show a significant relationship between the type of interaction with the conversational assistant and users' ability to make decisions quickly. The Pearson chi-square test gives a value of 46.28 with 3 degrees of freedom and an extremely low two-sided asymptotic significance of 4.9453E-10 at 0.001. This value indicates that the probability that the observed relationship between interaction type and decision-making speed is due to chance is practically zero. This suggests a significant influence of interaction mode on rapid decision-making ability.

The likelihood ratio, another statistical measure for assessing the independence of variables, confirms these results with a value of 51.486 and an even lower significance of 3.8542E-11 (very low at 0.001). This concordance of results reinforces the validity of the association between interaction type and decision-making speed.

However, it is important to note that 2 cells (25.0%) have a theoric count of less than 5, with a minimum of 0.22. This could indicate that certain categories of data are less well represented, potentially affecting the precision of chi-square estimates. To enrich and strengthen the interpretation of results obtained from chi-square tests, we adopt symmetrical measures such as Phi, Cramer's V and the Contingency Coefficient. Phi and Cramer's V, having the same value in this context, indicate a medium to strong association between variables. Phi and Cramer's V are measures of the strength of association for contingency tables. Here, a value of 0.564952 suggests that the type of interaction with the conversational assistant has a significant and non-negligible impact on users' decision-making speed. The approximate significance of 4.9453E-10 (well below 0.001) for these two measures confirms the very low probability that this association is due to chance.

The contingency coefficient (0.491882), while indicating a significant association (with the same approximate significance of 4.9453E-10 much lower than 0.001), is slightly lower than Cramer's Phi and V values. The contingency coefficient, adjusted for table size, also shows a strong relationship, but it is important to note that it is limited by a theoretical maximum of less than 1, which may explain why it is lower than the other measures. This indicates a notable dependence, but it also recognizes the limits of the strength of the association due to the structure of the contingency table.

These measures, by being consistent with the results of the chi-square test, reinforce the conclusion that the type of interaction (text or voice) plays a crucial role in how quickly users can make decisions using a conversational assistant. The presence of a strong and significant association suggests that conversational assistant designers should consider these results when designing their systems, optimizing the type of interaction to facilitate fast and efficient decision-making.

3. Effect of the AI tool's functionalities on the application of knowledge in real-life decision-making situations: This analysis aims to determine whether the tool's specific functionalities (such as data analysis or summary generation) improve learners' ability to apply what they have learned in real-life decision-making scenarios.

In assessing the impact of the artificial intelligence tool's functionalities on the application of knowledge in real-life decision-making situations, our statistical analyses provide significant findings. Pearson's chi-square tests reveal a value of 51.69 with a degree of freedom of 4 and an extremely low two-sided asymptotic significance at 0.001 (1.6015E-10), indicating a highly significant relationship between AI functionalities and the effectiveness of knowledge application in real-life decision-making contexts. Although 22.2% of cells have a theoretical size of less than 5, which might suggest caution in interpreting the results, the likelihood ratio of 59.96 with an even lower significance (2.9457E-12) reinforces the robustness of these conclusions. The null hypothesis is thus rejected.

Complementary symmetrical measures such as Phi (0.597), Cramer's V (0.422) and the Contingency Coefficient (0.513) confirm the strength of this association. These indices, all significant at the same level (1.6015E-10), illustrate a moderate to strong correlation between the AI tool's functionalities and users' ability to effectively apply the knowledge acquired in practical situations. These results suggest that certain AI tool functionalities could be particularly effective in improving knowledge-based decision-making in real-life contexts, underlining the importance of judiciously integrating these technologies into decision-making processes. This analysis should prompt further exploration of the specific features that contribute most to this enhanced capability, in order to guide the future development of AI tools to maximize their effectiveness in practical applications.

4. Effect of learner satisfaction with the tool on autonomy in decision-making: Finally, we explore how overall satisfaction with the AI tool influences learners' sense of autonomy in decision-making. High satisfaction could be associated with greater independence in decision-making.

The results obtained from statistical calculations indicate a significant relationship between learner satisfaction with the tool and autonomy in decision-making. The Pearson chi-square test shows a high value of 65.9 with a degree of freedom (ddl) of 4, and an extremely low two-sided asymptotic significance (1.6569E-13), suggesting that the relationship between these two variables is statistically significant and not due to chance. However, it is important to note that 33.3% of the cells have a theoretical size of less than 5, with a minimum of 0.83, which may affect the reliability of the interpretation of the results obtained from the statistical calculations. The likelihood ratio, with an even higher value of 76.3 and a very low significance of 1.0512E-15, reinforces this conclusion, indicating a strong dependency between these two variables.

Symmetrical measures such as Phi (0.674), Cramer's V (0.477), and the Contingency Coefficient (0.559) also show very low significant values (1.6569E-13), indicating a notable correlation between learner satisfaction and autonomy in decision-making. The Phi, in particular, reveals a relatively strong association, while Cramer's V and the Contingency Coefficient, though slightly lower, also confirm a significant relationship. These results suggest that the more satisfied a learner is with the tool, the more likely they are to feel autonomous in their decisions. This finding could have important implications for the design and improvement of educational tools, underlining the importance of positive user experience in empowering learners.

The second research question in our study explores the potential of artificial intelligence (AI) in assisting learners to generate hypotheses. This question focuses on AI's ability to propose alternative solutions, identify the possible causes of a problem, and generate scenarios with varied outcomes. The underlying hypothesis is that AI, by providing these capabilities, can enrich learners' thinking processes and improve the quality of their decisions. To examine this hypothesis, we consider learners' individual characteristics as independent variables, including age (a continuous variable), education level (a categorical variable) and learning style (a categorical variable). The dependent variable in our study is the quality of decisions made by learners in the experimental context, measured quantitatively. This approach enables us to assess how learners' personal characteristics interact with AI tools to influence their ability to formulate effective and relevant hypotheses. We confronted the three constituents of the independent variable with the dependent variable according to the following combinations:

The first combination deals with the effect of age on the quality of decisions made in the context of experience. It is the correlation of a continuous quantitative variable with a continuous quantitative variable.

The results show a strong positive correlation (0.760) between the age of the participants and the quality of their decisions, with a very low two-way significance (1.5753E-28). This positive correlation indicates that, in the context of this experiment, as participants' age increases, the quality of their decisions also improves. On the other hand, descriptive statistics provide additional context for this analysis. With a mean age of 2.12 (and a standard deviation of 0.997) and a mean decision quality of 1.74 (and a standard deviation of 0.842), the two variables show a moderate dispersion around their respective means. The number of participants (N = 145) provides a solid basis for the reliability of the statistical results.

Interpreting this positive correlation could suggest several potential mechanisms. On the one hand, it could be that older individuals have accumulated more experience or knowledge, which helps them to make better decisions. Alternatively, it could indicate that cognitive abilities related to decision-making, such as practical wisdom or the ability to manage ambiguity, improve or stabilize with age. These findings have important practical implications, not least for the design of training and development programs, where the age of participants can be taken into account to tailor methods and content. In addition, it may influence how AI-based decision support tools are adapted to different age groups, exploiting the strengths of older users while supporting their decisions.

The second combination concerns the effect of the degree of confidence in the decisions made by learners during the experiment on the quality of decisions made in the context of the experiment. It concerns the relationship between a nominal qualitative variable and a continuous quantitative variable.

The results obtained from Student's t-test for independent samples show a significant difference in the quality of decisions made as a function of the degree of confidence expressed by participants during the experiment. Group statistics indicate that participants who felt "extremely confident" in their decisions had a mean decision quality of 1.54, while those who were "not at all confident" had a significantly higher mean of 3.31. This suggests that less confident participants made better quality decisions, which is counterintuitive.

Levene's Test confirmed a significant difference in variances between the two groups (sig = 0.023), indicating that the variances were not equal. This led to the use of the unequal variances hypothesis for the t-Test, which also showed a significant difference between the groups with a t-value of -13.368 and an extremely low two-sided significance (3.0654E-12), reinforcing the validity of the results. In addition, the confidence interval for the difference in means (with unequal variances) ranged from -2.052 to -1.502, confirming that the difference was not due to chance and that the less confident participants did indeed make better quality decisions than their more confident counterparts.

This relationship can be interpreted in several ways:

1. Confidence calibration: Less confident participants may be more cautious or meticulous in their decision-making, leading to better quality choices. On the other hand, those who are extremely confident could be prone to overconfidence, which can often lead to errors of judgment.

2. Dunning-Kruger effect: This psychological phenomenon where low-skilled individuals overestimate their ability could explain why those who felt extremely confident performed less well. They may be unaware of their shortcomings, and therefore uninterested in improving their decisions.

3. Impact of reflection: Participants who doubt their abilities may spend more time thinking and considering different options before making a decision, which could lead to better results.

These results suggest that training programs and decision support tools should eventually focus not only on improving decision skills, but also on calibrating decision-makers' confidence to more accurately assess their own skills and limitations.

The third combination deals with the effect of learners' satisfaction with decisions made during the experiment on the quality of decisions made in the context of the experiment. It concerns the relationship between a nominal qualitative variable and a continuous quantitative variable.

The results obtained from Student's t-test for independent samples show a significant difference in the quality of decisions made as a function of students' satisfaction with the decisions they made during the experiment. Participants who were "very satisfied" with their decisions recorded a significantly lower mean decision quality (1.49) compared to those who were "not at all satisfied" (3.04). This observation is counterintuitive, as we might expect those who are satisfied with their decisions to have made better decisions.

Levene's Test indicated a significant difference in variances between the two groups (sig = 0.048), justifying the use of the unequal variances hypothesis for the t-Test. The results of the t-test under this assumption show a significant difference (t = -9.880; sig = 1.0622E-10) with a mean difference of -1.552, confirming that this difference in decision quality is not due to chance. Furthermore, the confidence interval for the difference in means, under the assumption of unequal variances, ranges from -1.873 to -1.230, reinforcing the robustness of these results.

Among the possible interpretations of this unexpected relationship could include:

1. Complacency effect: Participants who are highly satisfied with their decisions may be less critical of themselves and less inclined to question or re-evaluate their choices, which could lead to poorer quality decisions.

2. Correlation with confidence: As seen above with confidence, satisfaction could also be linked to overconfidence, where satisfied participants might not perceive flaws in their decisions due to confirmation bias.

3. Subjective satisfaction criteria: Satisfaction could be based on criteria that are not necessarily aligned with objectives or objectively measured outcomes of decision quality. For example, a student might feel satisfied if the decision made corresponds to personal preferences or subjective expectations rather than rational or optimal decision criteria.

Practical implications of these findings include the need to train participants to be more critical and reflective about their own decisions, even when they feel satisfied, to avoid complacency and promote better quality decision-making. Specific workshops or training modules could be developed to help align personal satisfaction with objective indicators of decision quality.

The third research question in this article explores the potential role of artificial intelligence (AI) in enhancing risk assessment and informed decision-making among learners. We postulate that AI, by assessing the consequences of choices and providing personalized recommendations and feedback on decisions made, can play a decisive role in increasing learners' success rates in real-life situations. This research looks at learning modalities as independent variables, including the frequency of use of the AI tool, the instructions and guidelines given to learners, as well as the pedagogical support used, to examine their influence on the percentage of positive decisions made by learners. By deciphering these interactions, we hope to draw conclusions about how AI technologies can be integrated into educational processes to enhance learners' decision-making capabilities. We compared the three components of the independent variable with the dependent variable in the following combinations:

The first combination concerns the effect of the frequency of use of the AI tool on the success rate in real-life situations. It involves a relationship between a nominal qualitative variable and a continuous quantitative variable. Since the discrete variable is ordinal, a chi-square test for trend can be used to detect a trend across ordinal categories based on nominal groups.

Statistical analysis using the Kruskal-Wallis test rejected the null hypothesis, indicating that the distribution of the success rate in real-life situations varies significantly with the frequency with which learners use the AI tool. This result, with a significance well below 0.001, suggests a strong association between intensity of engagement with the AI tool and improved success rate in real-life contexts.

This relationship can be interpreted in several ways. Firstly, more frequent use of the AI tool could enable learners to acquire a better understanding of the risks associated with different decisions, thanks to repeated exposure to personalized feedback and recommendations based on assessment of the consequences of their choices. Indeed, by providing in-depth analysis and tailored advice, the AI tool can improve learners' ability to anticipate the outcomes of their actions and choose options that maximize the chances of success. Secondly, the increase in success rates could also be attributed to the improvement in learners' decision-making skills over time, facilitated by ongoing interaction with the AI. This implies that the AI tool not only provides instant solutions, but also contributes to long-term learning and skills development.

In conclusion, the results highlight the importance of integrating AI technologies into educational programs, not only as assistive tools, but also as means of strengthening learners' analytical and decision-making capabilities. These propositions could encourage educational establishments to consider more robust and frequent AI implementation strategies in their curricula, to maximize pedagogical benefits and effectively prepare students to face complex real-world challenges.

The second combination concerns the effect of the clarity of the instructions given with the AI tool to the learner on the success rate in real-life situations. It concerns a relationship between a nominal qualitative variable and a continuous quantitative variable. We'll use the same test as above: chi-square test for trend.

The results obtained from the Kruskal-Wallis test show a significance much lower than 0.001, leading to the rejection of the null hypothesis. This means that the clarity of instructions given to learners significantly affects their success rate in real-life situations. Different categories of instructional clarity do not produce a uniform distribution of success rates, indicating that the way in which information is presented and explained plays a crucial role in the effectiveness with which learners can apply their knowledge and skills in practice.

This interpretation underlines the importance of clarity in pedagogical communication. Clear, well-structured instructions help learners to better understand the tasks at hand, reducing ambiguities and misunderstandings that could hamper their performance. Clear instructions enable learners to focus on the essential aspects of the problems to be solved, facilitating more effective and precise application of the skills acquired.

For educators, these findings suggest that improving instructional clarity could be an effective strategy for increasing learners' success rates in real-world contexts. This could involve using precise language, structuring information logically, and confirming that learners fully understand instructions before proceeding with complex tasks.

In conclusion, educational institutions could benefit from integrating specific training for teachers on clear and effective communication techniques. In addition, regular assessments of the clarity of teaching materials and instructions could help maintain a high level of learner understanding and engagement, which is essential for their success in practical applications.

The third combination concerns the effect of the types of teaching aids associated with the AI tool on the success rate in real-life situations. This is a relationship between a nominal qualitative variable and a continuous quantitative variable. We will treat it using the same test: chi-square test for trend.

The rejection of the null hypothesis in the results obtained from the Kruskal-Wallis test, where the significance is well below 0.001, indicates that the type of teaching aids associated with the artificial intelligence (AI) tool significantly influences the success rate of learners in real-life situations. This means that the way in which information is presented and structured through the teaching aids has a significant impact on learners' ability to effectively apply their knowledge and skills in practical contexts.

This interpretation suggests that certain types of teaching aids are more effective than others in facilitating learning and the application of knowledge in real-life situations. For example, written tutorials and videos are more engaging and effective for 65% of learners, compared with other media such as Interactive Exercises (19%) or live webinars (16%). Interaction and multimodality could help to better retain information and develop more robust practical skills. For educators and designers of learning programs using AI, these results underline the importance of choosing or developing teaching aids that are not only adapted to the content being taught, but also to the way learners absorb and use information. It could be beneficial to incorporate a variety of teaching aids and allow learners to choose those that best suit their learning styles.

In conclusion, educational institutions and educational technology developers should consider investing in the research and development of innovative teaching aids that maximize the effectiveness of learning via AI tools. This could include interactive media, simulations, educational games, or explanatory videos, all of which are likely to enhance learner engagement and improve performance in real-world applications. Ongoing evaluation of the effectiveness of these aids in various learning contexts should also be an integral part of improving modern pedagogical practices.

5 Conclusion

In conclusion, this study explored the significant impact of using artificial intelligence (AI) on the development of learners' decision-making skills in a university educational setting. The results obtained show that:

The first research question explores how artificial intelligence (AI) can improve learners' understanding of information essential for decision-making. AI, through different tools and interactions, offers summaries and analyses of complex data, helping to identify crucial trends and correlations. The study examines the effect of the frequency of use of conversational assistants, the type of tool interaction (text or voice), specific AI features, and learners' satisfaction with these tools on their confidence, speed, decision-making efficiency, and autonomy. The results show that increased use of AI strengthens learners' confidence, speeds up and improves the quality of their decisions, and increases their autonomy, underlining the importance of designing AI tools that are user-friendly and efficient for practical educational and decision-making applications.

The study's second research question focuses on the ability of artificial intelligence (AI) to help learners generate hypotheses by proposing alternative solutions, identifying possible causes of a problem and generating scenarios of varied outcomes. The study analyses the effect of learners' age, confidence and satisfaction on the quality of their decisions. The results reveal that older individuals tend to make better decisions, possibly due to an accumulation of experience or an improvement in cognitive abilities with age. Less confident participants made better quality decisions, possibly due to greater caution or better calibration of their confidence. On the other hand, those who were very satisfied with their decisions tended to make lower-quality decisions, possibly indicating complacency or overconfidence. These observations suggest that AI tools should be adapted to help users assess their skills and limitations more accurately, and be more critical and reflexive in their decision-making.

The third research question addresses how artificial intelligence (AI) can improve risk assessment and informed decision-making among learners. By assessing the consequences of choices and providing personalized recommendations and feedback on the decisions taken, AI significantly helps to increase learners' success rates in real-life situations. The results show that frequent use of the AI tool improves learners' understanding of risk and decision-making skills, thanks to repeated exposure to in-depth analysis and tailored advice. In addition, the clarity of the instructions provided with the AI tool and the type of teaching aids used are crucial to learner success, indicating that clear instructions and well-tailored teaching aids increase the effectiveness of knowledge application in practice. These findings suggest the integration of AI technologies into educational programs to enhance learners' analytical and decision-making capabilities, effectively preparing students to face complex real-world challenges.

The implications of this research are far-reaching. Firstly, it highlights the importance of integrating AI technologies into educational curricula to prepare students to respond effectively to real-world challenges. However, it is crucial to note that the results vary according to learners' age, confidence and satisfaction, indicating that AI tools need to be personalized to meet the specific needs of individuals. This study therefore invites reflection on the design and implementation of AI tools that are not only technologically advanced but also pedagogically relevant.

The contributions of this research to understanding the use of AI in education are significant. It provides empirical evidence that AI can indeed improve learners' decision-making skills, while also highlighting the factors that influence the effectiveness of these tools. However, the limitations of the study should be acknowledged, notably the need to broaden the sample to include a wider diversity of educational and cultural contexts. Future research should also examine the long-term impact of AI use on decision-making skills.

In summary, this research confirms that the judicious integration of AI into education can significantly transform the way learners apprehend and solve complex problems, preparing them to excel in a world increasingly governed by technology. These findings strengthen the case for innovative pedagogy that fully embraces the potential of artificial intelligence.

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