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THE DETERMINANTS OF THE ADOPTION OF ARTIFICIAL INTELLIGENCE BY MOROCCAN ENTREPRENEURS

FARSI BOUTAINA
Faculty of Legal, Economic and Social Sciences
University Moulay Ismail, Meknes – Morocco

OUZIF HICHAM
Faculty of Legal, Economic and Social Sciences
University Sidi Mohamed Ben Abdellah, Fez – Morocco

EL IDRISSI LALLA HIND
Higher education teacher
Faculty of Legal, Economic and Social Sciences
University Moulay Ismail, Meknes – Morocco

EL BOUKHARI HAYAT
Professeur chercheur
Faculty of Legal, Economic and Social Sciences
University Sidi Mohamed Ben Abdellah, Fez – Morocco

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ABSTRACT

As Bill Gates has pointed out, "artificial intelligence may be the technology that will most change the global economy". This paper explores the key role of artificial intelligence (AI) in digital entrepreneurship, with a particular focus on entrepreneurs. In this respect, Elon Musk stated that "artificial intelligence is a fundamental risk to the existence of human civilisation". AI is emerging as a significant performance driver and source of differentiation for these entrepreneurs, offering them innovative tools to optimise their operations, improve their decision-making and better respond to changing market needs. We will look at how self-entrepreneurs are using AI in various functional areas of their business, such as marketing, operations and financial management, to increase their operational efficiency and competitiveness. As Sundar Pichai observed, "Artificial intelligence is one of the most important areas to work in. It's deeper than most things people do with their lives". In addition, we will analyse the artificial intelligence factors adopted by entrepreneurs.This study will adopt a quantitative methodology, involving the collection of data using a structured questionnaire distributed to a representative sample of entrepreneurs active in the field of digital entrepreneurship. The data will be analysed using appropriate statistical techniques to identify relationships between the determinants of AI and its adoption by digital entrepreneurs. By exploring these aspects, this paper will contribute to a better understanding of how AI acts as a digital entrepreneurship driver for entrepreneurs, boosting performance and creating crucial differentiation opportunities in an ever-changing business landscape.

Keywords: Artificial intelligence - Digital entrepreneurship- Entrepreneurs- Adoption of AI

1.0 INTRODUCTION

The increasing integration of artificial intelligence (AI) into various economic sectors has led to growing interest in its impact on businesses and the self-employed, especially entrepreneurs. As J. McCarthy points out, "AI is about making computers do things that, when done by humans, are associated with forms of intelligence". These economic players play a crucial role in many fields, contributing significantly to the global economy. As AI continues to evolve and develop, it has become imperative to understand how this technology is transforming entrepreneurial practices and influencing their performance. In this article, we aim to explore the determinants behind entrepreneurs' adoption of artificial intelligence, examining the motivations, barriers and strategies that influence their decision to integrate this revolutionary technology into their business operations. By understanding the factors shaping this adoption, we aim to inform policies and practices to promote more widespread and effective use of AI in the entrepreneurial sector. As Y. Amelin et al, "AI represents an unprecedented opportunity for businesses to automate processes, optimize decisions and improve customer experience." We aspire to analyze how the adoption of AI by entrepreneurs influences their business practices, operational efficiency and market competitiveness. By exploring the different aspects of this relationship, we aim to provide valuable insights for entrepreneurs, researchers and policymakers interested in the growing role of AI in the entrepreneurial context. To achieve this objective, we will present a review of the current literature on the drivers of AI adoption by self-entrepreneurs. As Y. et al. point out, "The existing literature offers varied perspectives on the determinants of AI adoption by entrepreneurs, ranging from perceived usefulness and ease of use to resource availability and individual entrepreneurial characteristics." Next, we will describe the research methodology used to examine these adoption factors, highlighting the relevant variables and data analysis tools. The results of our analysis will be presented in the following section, followed by an in-depth discussion of the practical and theoretical implications of our findings. Finally, we will conclude by summarizing the main findings and highlighting future research directions in this evolving field.

2.0 LITERATURE REVIEW

2.1 Artificial intelligence

Artificial intelligence (AI) has been conceptualized in many different ways by theorists and researchers. Alan Turing (1950), a pioneer of computer science, laid the foundations by introducing the Turing Test. According to him, a machine can qualify as artificial intelligence if, in the course of a conversation, it successfully imitates a human being to such an extent that an observer cannot distinguish the machine from a human. John McCarthy, one of the founders of AI, defined it as the science and engineering of creating intelligent machines, in particular computer programs capable of solving complex problems. Nobel laureate Hebert A. Simon (1957) characterized AI as "the search for ways to make computers work in ways that, for the moment, humans do better". Marvin Minsky (1968), another founder of AI, defined it as "the construction of computer programs to perform tasks which, when performed by humans, require intelligence".Stuart Russell et Peter Norvig (2010) dans leur ouvrage l'intelligence artificielle : ¬A Modern Approach ; Russell et Norvig décrivent l'IA comme « l'étude des agents intelligents, c'est-à-dire des entités capables de percevoir leur environnement, de raisonner, et d'agir en conséquence pour atteindre des objectifs ». Elon Musk (2018) entrepreneur and innovator, has referred to AI as "the automation of human thought". He highlights the potentially risky implications of AI and stresses the importance of regulating its

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development. These different perspectives converge on the fundamental idea that artificial intelligence aims to create machines capable of imitating or reproducing aspects of human intelligence, whether in problem-solving, decision-making, learning, or other cognitive domains. Firstly, digitization is firmly rooted in the socio-economic landscape of business. Defined in management science as "a succession of digital, profound and organizational changes" (Autissier et al., 2014), it stands out as a characteristic indicator of the early 21st century. Indeed, with the digital revolution, companies revised their models, structures, processes and strategies. However, this was only a prelude, as organizations' attention is now focused on artificial intelligence. According to Charlin (2017), artificial intelligence, or AI, was originally a component of computer science, mathematics, engineering, or even statistics. It is understood as "the ability given to a machine to help man solve complex problems [...] it learns and improves autonomously" (Cuillandre, 2018). Some authors, such as Mallard (2018), see AI as being accompanied by a systemic revolution in current business models. The spheres influenced by artificial intelligence are vast, encompassing sectors such as IT, marketing, human resource management, logistics, finance, production, commerce, and strategy.

2.2 Factors in the adoption of artificial intelligence by entrepreneurs

The factors influencing technology use have been extensively studied. Several models have been proposed to explain technology acceptance behavior, including the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), Technology Acceptance Model 2 (TAM2) (Venkatesh and Davis, 2000) and the Unified Theory of Technology Acceptance and Use (UTAUT) . The Technology Acceptance Model (TAM) is one of the most influential models used to test the acceptance of a technological innovation in various contexts. It is praised for its strong predictive power, while maintaining the principle of parsimony. The TAM postulates that two particular beliefs, "perceived usefulness" and "perceived ease of use", are of paramount importance in determining a person's intention to accept and adopt a particular technology. "Perceived usefulness (PU) is the extent to which the user believes that using the technology will improve their performance in accomplishing a task, perceived ease of use (PEOU) is the extent to which the user believes that using the technology will be effortless, i.e. easy to understand or use. Although TAM has generally been a rigorously tested model for predicting user acceptance of an innovation, some have pointed to the need to extend the model and integrate it with other concepts to improve its explanation and prediction of acceptance behavior. Davis' original model is limited in that it takes into account only two variables to determine "behavioral intention" (BI) for a variety of technologies adopted for different purposes. To overcome this limitation, the present study will adopt an "added variables" approach, which involves the incorporation of additional variables tailored to the context and users studied, leading to greater predictive power. The addition of other belief explanatory variables according to the technological context and users studied is a common and acceptable practice in TAM studies. Therefore, this research incorporates an additional construct, studied in previous TAM research that would help us to better predict entrepreneurs' intention to adopt AI. The intention-behavior gap is defined as "the degree of inconsistency between users' intention regarding a specific behavior and their actual behavior" It occurs when users indicate that they intend to adopt the technology but ultimately do not. Many previous studies on TAM have defined technology acceptance as the intention to use it. Turner et al. reported that behavioral intention to use a particular technology was more often measured than actual use, and highlighted instances where the discrepancy between intention and behavior called into

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question the predictive power of TAM when BI was used to assess technology acceptance. An adapted TAM framework (see Fig. 1) was developed to measure Moroccan entrepreneurs' intention to use AI. Based on the literature review, it is hypothesized that perceived usefulness, perceived ease of use and resource availability are positively associated with intention to use AI, Specifically, this study develops the following hypotheses:

Hypothesis 1: Perceived usefulness is positively associated with AI adoption.

Hypothesis 2: Perceived ease of use is positively associated with AI adoption.

Hypothesis 3: Resource availability is positively associated with AI adoption.

3.0 METHODS

For this study, a quantitative approach was adopted to gather quantifiable data on the adoption of artificial intelligence (AI) by entrepreneurs. This approach enables rigorous statistical analysis of the data collected, providing accurate and actionable information. Data collection was carried out using a structured online survey, distributed to a representative sample of entrepreneurs. The survey included questions on the perceived usefulness and ease of use of AI, as well as the adoption of AI in their business activities and overall performance.

Participants in the study were self-employed entrepreneurs operating in a variety of industries, such as commerce, professional services and information technology. The sample included entrepreneurs with different levels of experience and education, in order to capture a variety of perspectives on AI adoption. The data collected was analyzed using specialized statistical software, including SMART PLS 4. Descriptive analyses were performed to examine sample characteristics and general trends in AI adoption. Regression analyses were also carried out to assess relationships between AI adoption determinants and AI adoption by entrepreneurs.

4.0 RESULTS

The proposed model was examined by the partial least squares structural equation modeling (PLS-SEM) method using Smart PLS 4 software.

Variables	Code	Items		Source
Perceived usefulness	**UP1**	I will increase my efficiency at work by adopting AI.	**0.885**	**(Davis 1989 ; Davis et al. 1989)**
	UP2	I'll spend less time doing routine tasks thanks to the adoption of AI.	**0.938**	
	UP3	Using AI in my work would enable me to complete tasks more quickly.	**0.951**	**(Thompson et al. 1991).**
	UP4	Using AI would improve my professional performance.	**0.852**	
Perceived ease of use	**FUP1**	I'd find AI easy to use.	**0.845**	**(Davis 1989 ; Davis al. 1989)**
	FUP 2	I would find AI flexible to use.	**0.921**	
	FUP 3	My interaction with the AI is clear and understandable.	**0.929**	**(Moore et Benbasat1991)**
	FUP 4	I think it's easy to make AI do what I want it to do.	**0.909**	
Availability Resources	**DR1**	I have the necessary resources to use AI in my activities.	**0.866**	**(Ajzen 1991 ; Taylor et Todd 1995a, 1995b)**
	DR2	I was given advice on choosing the right AI for my needs.	**0.862**	

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	DR3	I was able to benefit from specialized AI training for optimal use.	**0.891**	**(Thompson et al. 1991)**
	DR4	The use of AI is compatible with all aspects of my work.	**0.851**	**(Moore et Benbasat1991)**
AI adoption	**AIA1**	Intention to use AI in my future professional activities.	**0.958**	**(Davis 1989 ; Davis et al. 1989)**
	AIA 2	How often I use AI in my daily tasks.	**0.968**	
	AIA 3	Confidence in the effectiveness of AI to improve my professional performance.	**0.980**	
	AIA 4	Overall satisfaction with the use of AI in my work.	**0.959**	

Table 1: Factor loadings, reliability and convergent validity

loadings		Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Resource availability		0.891	0.898	0.924	0.753
DR1	0.866				
DR2	0.862				
DR3	0.891				
DR4	0.851				
Perceived ease of use		0.923	0.934	0.946	0.813
FUP1	0.845				
FUP 2	0.921				
FUP 3	0.929				
FUP 4	0.909				
Perceived usefulness		0.928	0.931	0.949	0.823
UP1	0.885				
UP2	0.938				
UP3	0.951				
UP4	0.852				
AI adoption		0.976	0.977	0.983	0.934
AIA1	0.958				
AIA2	0.968				
AIA3	0.980				
AIA4	0.959				

Table 2: Discriminant validity using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT)

	DR	FUP	UP
DR			
FUP	**0.483**		
UP	0.762	**0.620**	

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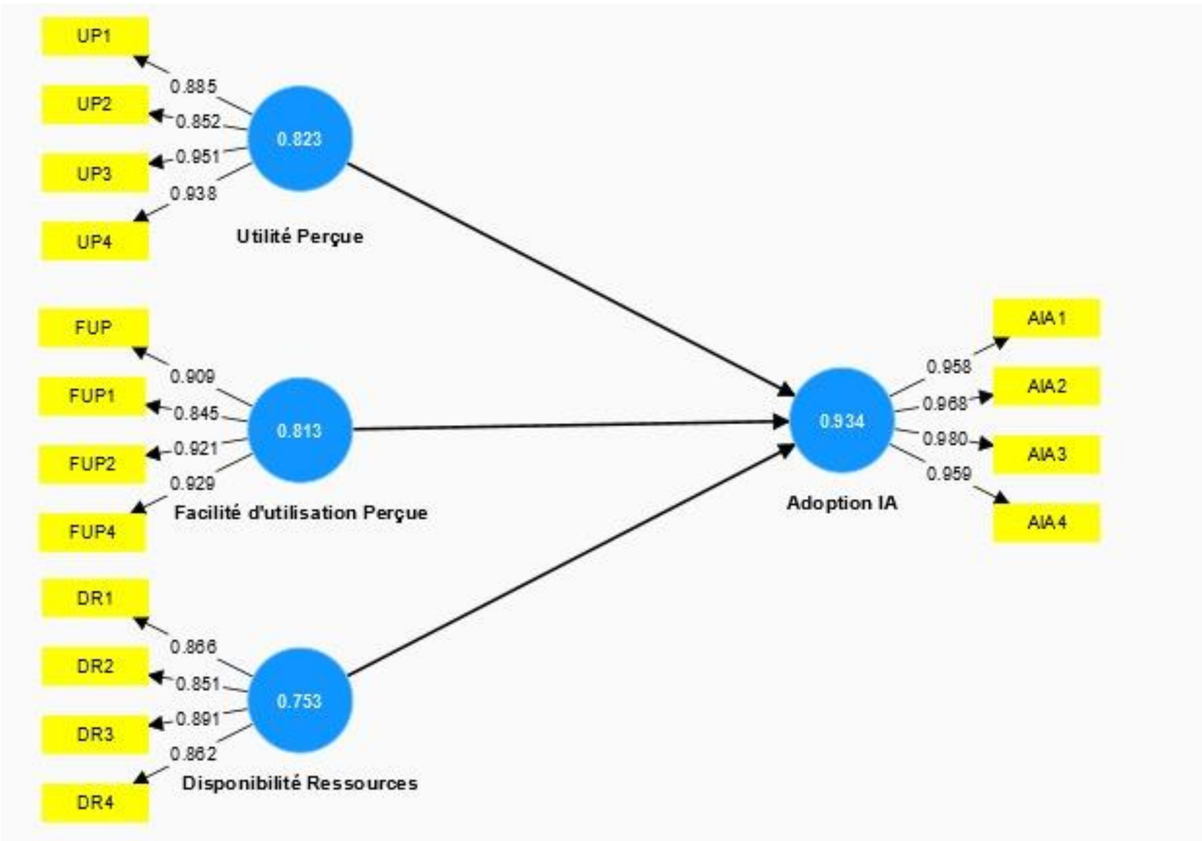
AIA	0.751	0.612	**0.877**

Table 3: Discriminant validity -Fornell-Larcker criterion

	DR	FUP	UP	AIA
DR	**0.868**			
FUP	0.451	**0.902**		
UP	0.702	0.575	**0.907**	
AIA	0.708	0.585	0.835	**0.966**

Table 4: Evaluation of the structural model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Availability Resources -> AI adoption	0.227	0.226	0.064	3.541	0.000
Perceived ease of use -> AI adoption	0.141	0.147	0.066	2.141	0.032
Perceived usefulness -> AI adoption	0.595	0.590	0.055	10.759	0.000



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Research model generated by SMART PLS4 software

5.0 DISCUSSION

5.1 Measurement model evaluation

The first phase of measurement model evaluation was carried out accordingly, to confirm the reliability and validity of the concepts and their dimensions (Hair, 2006). When evaluating the measurement model, no factors were deleted, as all loadings were above or close to the suggested value of 0.60. As a result, all questions were included in the decisive measurement model. Consequently, all questions were included in the decisive measurement model. Table 1 shows that all factor loadings are above the suggested value of 0.60. Similarly, the AVE and CR of all constructs are equal to or greater than the suggested values of 0.50 and 0.70, respectively. Convergent validity and reliability are thus developed. In addition, Table 2 presents the results of discriminant validity (Fornell and Larcker, 1981). To assess discriminant validity, we use the heterotrait-monotrait ratio (HTMT), which compares correlations between heterotrait traits (e.g., the correlation between DR and FUP) with correlations between monotrait traits (e.g., the correlation between DR and DR). HTMT values below 1 indicate acceptable discriminant validity, as this means that correlations between heterotrait traits are weaker than correlations between mono-trait traits, confirming that the traits measure different concepts. The Fornell-Larcker criterion is a commonly used method for assessing discriminant validity in structural component analysis. It compares the square roots of the AVEs (Average Variance Extracted) of each construct with the correlations between the constructs. If the square root of each construct's AVE is greater than its correlations with all other constructs, then discriminant validity is confirmed According to Table 3 :

- For the "AR" (Resource Availability) construct, its square root of the AVE is 0.868. All DR correlations with the other constructs (FUP, UP, AIA) are below 0.868, confirming DR's discriminant validity.
- For the construct "FUP" (Facilité d'Utilisation Perçue), its square root of the AVE is 0.902. All correlations of FUP with the other constructs are below 0.902, confirming FUP's discriminant validity.
- For the "UP" construct (Perceived Utility), its square root of the AVE is 0.907. All UP's correlations with the other constructs are below 0.907, confirming UP's discriminant validity.
- For the "AIA" (Adoption IA) construct, its square root of the AVE is 0.966. All correlations of AIA with the other constructs are below 0.966, confirming the discriminant validity of AIA.

From Table 4 we can conclude the following result:

- Resource availability -> AI adoption: The relationship between resource availability and AI adoption is significantly different from zero, with a t-value of 3.541 and a very low p-value ($p < 0.001$), indicating a statistically significant relationship.
- Perceived ease of use -> AI adoption: The relationship between perceived ease of use and AI adoption is also significantly different from zero, with a t-value of 2.141 and a p-value of 0.032, which is below a typical significance level of 0.05, but above 0.01.

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- Perceived usefulness -> AI adoption: The relationship between perceived usefulness and AI adoption is highly significant, with a t-value of 10.759 and a very low p-value ($p < 0.001$), indicating a strong statistical relationship between these variables.

6.0 CONCLUSION

The first phase of the measurement model evaluation was aimed at confirming the reliability and validity of the concepts and their dimensions, in line with the methodology established by Hair (2006). The results of this evaluation showed that all factor loadings were above or close to the recommended value of 0.60, enabling all questions to be included in the final measurement model. In addition, all factor loadings were above 0.60, and values for Average Variance Extracted (AVE) and Composite Reliability (CR) were at or above the suggested thresholds of 0.50 and 0.70 respectively, confirming the convergent validity and reliability of the measures. With regard to discriminant validity, the results of the HTMT matrix revealed potential problems between certain traits. Correlations between heterotrait traits were greater than 1 for the DR-UP, DR-AIA and UP-AIA pairs, indicating a potential lack of discriminant validity between these concepts. However, correlations between mono-trait traits were below 1, confirming acceptable discriminant validity between these concepts. Another method used to assess discriminant validity was the Fornell-Larcker criterion. The results showed that the square root of each construct's AVE was greater than its correlations with all other constructs, confirming the discriminant validity of each construct. Finally, regression analyses revealed significant relationships between the independent variables (resource availability, perceived ease of use and perceived usefulness) and the dependent variable (AI adoption). In particular, resource availability and perceived usefulness were strongly associated with AI adoption, while perceived ease of use had a significant but slightly weaker association. In conclusion, the evaluation of the measurement model confirmed the reliability and validity of the concepts measured. However, potential problems of discriminant validity were identified between certain traits, suggesting the need for further analysis. The results of the regression analyses highlighted the importance of resource availability and perceived usefulness in entrepreneurs' adoption of AI, underscoring the importance of these factors in the successful implementation of this technology.

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