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Navigating the AI Era: The Crucial Role of Digital Capabilities in Companies Operating in Tunisia

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***Abstract*—Mastery of digital tools, understanding of artificial intelligence (AI) algorithms, and the ability to analyze and leverage data constitute key competencies for promoting the integration of AI. In Tunisia, despite the progressive digital transformation, many companies face challenges related to the adoption of these innovative technologies. Within this context, the research objective is to study the impact of digital capability on AI adoption among businesses operating in Tunisia. To this end, a representative sample of companies was established, including various sectors of activity, sizes, and levels of digital maturity. This study underscores the stakes of corporate digital competencies in leveraging the potential offered by AI. Indeed, the mastery of advanced digital technologies allows companies to optimize their processes, reduce operational costs, and increase their innovation capacity, thereby fostering a competitive differentiation and strengthening their economic position and market competitiveness.**

Keywords*— *Companies Operating in Tunisia- Artificial Intelligence (AI)- Digital Transformation- Digital Capabilities

I. INTRODUCTION

The integration of Artificial Intelligence (AI) within companies constitutes a crucial strategic challenge for their competitiveness and sustainability [5]. Moreover, the adoption of AI by Tunisian companies is strongly influenced by their level of digital capabilities, which include technical competencies, technological infrastructure, and digital culture, which constitute the essential foundation for the successful implementation of AI solutions ([29]; [12]). Nevertheless, the integration of AI continues to be constrained by both structural and human-related barriers, notably low digital maturity and a lack of specialized skills ([23]; [16]). In Tunisia, despite the progressive development of the digital economy, many firms continue to encounter difficulties due to a generally limited digital environment ([20]; [21]). This study seeks to examine the effect of digital capability development covering human skills, technological infrastructure, and digital culture on the adoption of artificial intelligence within Tunisian businesses. This research aims to analyze the impact of digital capability development—encompassing human skills, technological infrastructure, and digital culture on AI adoption within companies operating in Tunisia. Our study is organized as follows: The first section presents a literature review, focusing on the theoretical foundations of digital capability dimensions. The following section describes the methodology used. Then, we present and analyze the results of our analysis. Finally, we highlight the theoretical and managerial implications, as well as avenues for future research.

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II. LITERATURE REVIEW

Digital technologies represent a major asset for organizational transformation [4]. According to [19], this concept refers to the set of changes introduced into the business model through the use of digital technologies. Within this transformation process, Artificial Intelligence (AI) occupies a central role, which can be defined as the pursuit of computer-based solutions capable of performing tasks that traditionally require human intelligence ([41]; [32]), or as "the set of theories and techniques designed to develop machines able to simulate human intelligence" [9]. The adoption of AI relies on digital capability, which is reflected through five main dimensions' customer experience, processes, employee experience, business model, and digital platform ([31]; [25]).

A. Customer Experience and Artificial Intelligence

Digital transformation refers to a set of deep organizational, operational, and strategic changes resulting from the integration of digital technologies within firms [31]. This transformation notably reshapes modes of interaction with customers, making the understanding of their expectations essential to achieving sustainable performance [44].

Within this framework, customer experience constitutes a central pillar of strategies aimed at leveraging new digital technologies to generate substantial business improvements [27]. Artificial intelligence represents a key strategic tool in this regard. It enables advanced analysis of customer data [5], allows for precise identification of individual purchasing behaviors [1], and supports the deployment of highly personalized recommendation systems [40].

This ability to anticipate and understand customer preferences in detail positively impacts the organization's overall operational efficiency and customer loyalty ([2]; [22]). Thus, the following hypothesis is proposed:

H1: Customer Experience has a significant and positive impact on AI Adoption.

B. Operational Processes and Artificial Intelligence

Operational processes can be defined as a set of structured and interdependent activities that organizations implement to design, produce, and deliver goods or services, from the initial conception to final delivery ([18]; [36]). The incorporation of digital technologies is transforming these processes by requiring the development of specific digital skills and the rationalization of work practices ([38]; [34]).

This transformation, which occurs notably through task automation, constitutes an indispensable prerequisite for the strategic adoption of artificial intelligence ([14]; [42]; [26]). As a result, AI plays a key role in enhancing operational processes by improving predictability and speeding up supply chain activities [20]. Accordingly, the following hypothesis is formulated:

H2: *Operational processes have a significant and positive impact on the adoption of AI.*

C. Employee Experience and Artificial Intelligence

Employee experience is described by [35] as the employee's overall perception of their relationship with the organization, shaped by all interactions encountered throughout their professional journey. In addition, [33] highlights three main touchpoints of employee experience: technology, the physical work environment, and cultural experience. Interactions within the digital human resources ecosystem through AI create a norms of reciprocity between HR managers and employees, thereby affecting both the quality of employee experience and the adoption of technological tools [28]. Drawing on these theoretical foundations, the following hypothesis is proposed:

H3: *Employee experience has a significant and positive impact on AI adoption.*

D. Business Model and Artificial Intelligence

The business model is defined by [11] as "the means and methods that assist in the collection, consolidation, modeling, rendering, and analysis of data and information". The expansion of Big Data technologies, along with increased computing capabilities, has reinforced the development of artificial intelligence [10], positioning it as a strategic driver of innovation in business models [25]. Consequently, AI offers a major advantage through the effective optimization and automation of processes ([8]; [3]), thereby creating new and unprecedented opportunities for growth [37]. Based on these arguments, the following hypothesis is formulated:

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H4: *The business model has a significant and positive impact on the adoption of AI.*

E. Digital Platform and Artificial Intelligence

Digital transformation is defined as the set of profound organizational, strategic, and operational changes that a company implements to adapt its core business and reconfigure its processes in response to digital technologies ([24]; [39]). The success of this transformation largely depends on digitalization and automation, which, by relying on robust digital platforms, improve operational efficiency and productivity [42].

These digital platforms constitute strategic infrastructures that foster new forms of collaborative networked work ([41]; [7]) and support the emergence of virtual communities of practice [15]. They standardize interactions and facilitate the sharing and dissemination of skills within the organization, thus providing the essential technological foundation for the integration of artificial intelligence [43]. Consequently, a mature digital platform not only facilitates the adoption of artificial intelligence but also leverages AI's capabilities to optimize its functionalities and enhance the user experience [42]. Thus, the following hypothesis is proposed:
H5: *The digital platform has a significant and positive impact on AI adoption.*

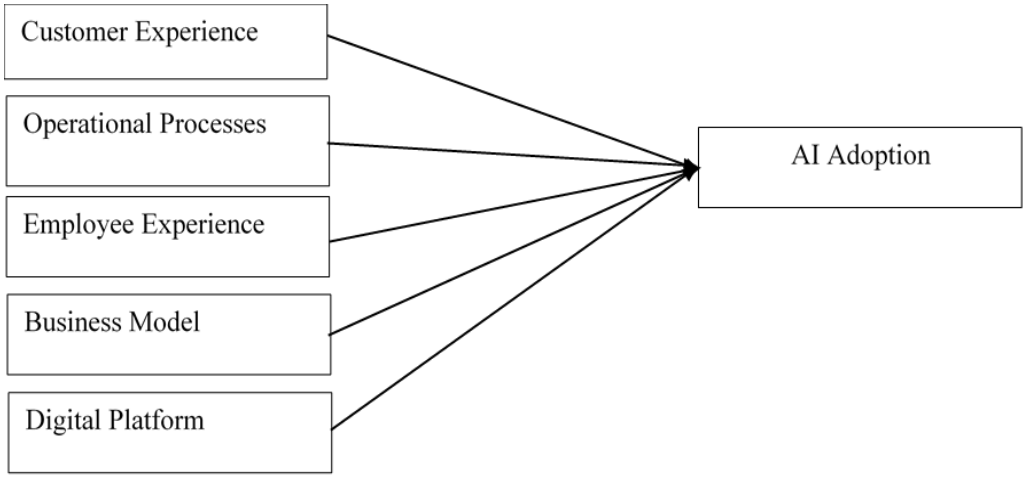

Fig. 1 Conceptual Model

III. RESEARCH DESIGN AND DATA ANALYSIS

A. Data Collection

To study the impact of digital capabilities on AI adoption in businesses operating in Tunisia, an empirical study was conducted using an online and paper-based questionnaire. A total of 102 valid questionnaires were used for the analysis. The sample of businesses consisted of 58.8% private companies, 27.5% public companies, and 13.7% semi-public companies.

Regarding the nature of capital, Tunisian companies overwhelmingly dominate the sample, representing 75.5% of the businesses. Companies with foreign capital (15.7%) or mixed capital (8.8%) constitute a significant minority. In terms of size, the sample focuses on large companies: medium-sized (41.2%) and large (40.2%) companies together make up 81.4% of the surveyed entities. Small businesses (18.6%) are proportionally less represented. Finally, the sector of activity is concentrated around the production and service sectors, with Services (30.4%) and Industry (28.4%) accounting for nearly 60% of the sample. Telecommunications (16.7%) and Public Administration/Community (11.8%) complete this landscape, while Banking/Finance (8.8%) and Agriculture (3.9%) remain the least sought-after sectors.

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TABLE I
DISTRIBUTION OF SAMPLED FIRMS ACCORDING TO ORGANIZATIONAL CHARACTERISTICS (N = 102)

Variable	Category	Frequency (n)	Percentage (%)
Legal Status	Private companies	60	58.8
	Public companies	28	27.5
	Semi-public companies	14	13.7
Ownership Structure	Tunisian capital	77	75.5
	Foreign capital	16	15.7
	Mixed capital	9	8.8
Firm Size	Small firms	19	18.6
	Medium-sized firms	42	41.2
	Large firms	41	40.2
Sector of Activity	Services	31	30.4
	Industry	29	28.4
	Telecommunications	17	16.7
	Public administration / community services	12	11.8
	Banking / Finance	9	8.8
	Agriculture	4	3.9

In terms of job title, the respondents are predominantly managers: Senior Managers (26.5%), Administrative Staff (22.5%), and Engineers/Technicians/Researchers (22.5%). Executive positions (13.7%) and Communication/Marketing Officer roles (6.9%) are the least common. Analysis by age reveals a particularly young workforce: the 30–39 age group is the largest (44.1%), followed by those under 30 (28.4%). Thus, nearly three-quarters (72.5%) of respondents are under 40, indicating strong involvement of younger generations in the surveyed companies. Finally, the gender distribution is almost equal, with a slight predominance of women (52.9%) over men (47.1%).

TABLE II
DEMOGRAPHIC PROFILE OF RESPONDENTS (N = 102)

Variable	Category	Frequency (n)	Percentage (%)
Job Title	Senior Managers	27	26.5
	Administrative Staff	23	22.5
	Engineers / Technicians / Researchers	23	22.5
	Executive Positions	14	13.7
	Communication / Marketing Officers	7	6.9
	Other positions*	8	7.9
Age	Under 30	29	28.4
	30–39	45	44.1
	40 and above*	28	27.5
Gender	Female	54	52.9
	Male	48	47.1

B. Reliability and Validity of Measurements

Table 1 summarizes the main results of the items retained after purging the measurement scales through exploratory analysis. The reliability tests show good results for all the variables adopted in this research. Indeed, all items have an acceptable loading greater than 0.7. Furthermore, the reliability tests show Cronbach's alpha (α) and composite reliability (CR) values greater than the recommended threshold of 0.7 [17]. We used SPSS and PLS-SEM to conduct our statistical analyses.

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TABLE III
RELIABILITY INDICATORS AFTER ITEM PURIFICATION

Measurement Scales		Factor Loading	Reliability Index	
Symbol	**Number of items**	**Loading**	**CR**	**Cronbach's Alpha**
Operational Processes	3		0.913	0.856
Operational_Processes1		0.868		
Operational_Processes2		0.891		
Operational_Processes3		0.885		
Employee Experience	3		0.890	0.815
Employee_Experience1		0.825		
Employee_Experience2		0.867		
Employee_Experience3		0.871		
Customer Experience	3		0.903	0.840
Customer_Experience1		0.876		
Customer_Experience2		0.858		
Customer_Experience3		0.877		
Business Model	3		0.916	0.862
Business_Model1		0.862		
Business_Model2		0.899		
Business_Model3		0.894		
Digital Platform	3		0.934	0.894
Digital_Platform1		0.910		
Digital_Platform2		0.916		
Digital_Platform3		0.897		
AI Adoption	3		0.934	0.894
AI_Adoption1		0.883		
AI_Adoption2		0.946		
AI_Adoption3		0.897		

The results presented in Table 2 show that the convergent validity of the model variables is satisfactory, as the average variance extracted (AVE) for each dimension is greater than 0.5 [29].

As shown in Table 2, discriminant validity was analyzed based on the criteria proposed by [13], as well as cross-loading criteria. The square roots of the AVEs were calculated and compared with their factor correlation values. The bold values on the diagonal of Table 2, which meet the condition of being greater than the correlation values between the constructs and the MEVs (as recommended by [13]), suggest satisfactory discriminant validity.

TABLEAU VI
VALIDITE CONVERGENTE ET DISCRIMINANTE

	AVE	**AI Adoption**	**Customer Experience**	**Employee Experience**	**Business Model**	**Digital Platform**	**Operational Processes**
AI Adoption	0,826	0,909					
Customer Experience	0,757	0,673	0,870				
Employee Experience	0,730	0,756	0,713	0,854			
Business Model	0,784	0,691	0,664	0,787	0,885		
Digital Platform	0,824	0,770	0,673	0,755	0,715	0,908	
Operational Processes	0,777	0,715	0,760	0,757	0,732	0,703	0,881

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C. Hypothesis Testing

The results of the structural model reveal that the Digital Platform variable has a positive impact on AI adoption (β = 0.372; t = 3.333; p < 0.05), thus supporting hypothesis H5. In contrast, the results show that the impact of the following variables; Customer Experience (β = 0.090, t = 0.854, p = 0.393), Employee Experience (β = 0.251, t = 1.788, p = 0.074), Business Model (β = 0.054, t = 0.424, p = 0.671), and Operational Processes (β = 0.156, t = 1.402, p = 0.161) on artificial intelligence adoption is not significant. Therefore, hypotheses H1, H2, H3, and H4 were rejected.

TABLEAU V
RESULTATS DES RELATIONS DIRECTS ET INDIRECTS

Liens	β	t-statistique	p-valeur	Conclusion
Customer Experience -> AI Adoption	0,090	0,854	N.S	Rejetée
Employee Experience -> AI Adoption	0,251	1,788	N.S	Rejetée
Business Model -> AI Adoption	0,054	0,424	N.S	Rejetée
Digital Platform -> AI Adoption	0,372	3,333	P<0.05	Acceptée
Operational Processes -> AI Adoption	0,156	1,402	N.S	Rejetée

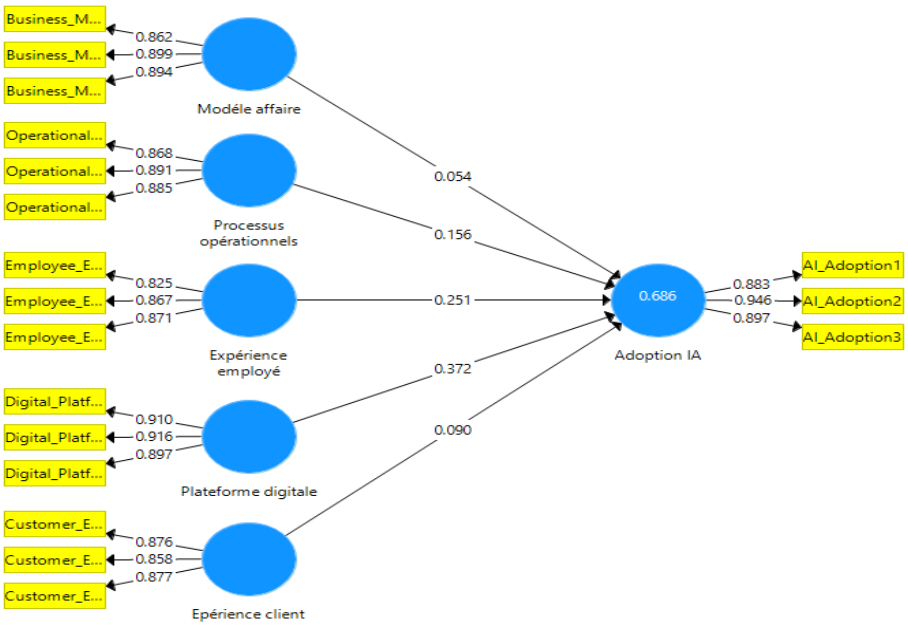

Fig. 2 Path coefficients of hypotheses testing results

IV. DISCUSSION OF RESULTS

The empirical results show that the Digital Platform variable has a positive impact on AI adoption. This aligns with the research of [42]. It can therefore be deduced that the robustness of the Digital Platform, characterized by centralization, process integration, and the use of data platforms for advanced analytics, constitutes the essential foundation and the main catalyst for AI adoption by companies operating in Tunisia.

However, the hypothesis regarding the variable "Customer Experience" was rejected, which corroborates the results of [27]. This lack of a significant relationship is explained by the insufficient maturity of customer data governance. Indeed, despite the presence of digital tools for data collection, this immaturity prevents companies from effectively leveraging customer data for AI projects with high external added value.

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Furthermore, even when customer data are integrated into systems, AI adoption is hampered by more significant organizational incapacity factors. These obstacles include, in particular, a lack of specific data science skills or insufficient data quality for AI models, which limits the possibility of improving customer experience through AI. Consequently, AI adoption in this context is driven by imperatives of internal operational efficiency rather than by the quality or improvement of Customer Experience.

Furthermore, hypothesis H2, which assumed a significant impact of operational processes on AI adoption, was rejected, contradicting the work of [14] and [34]. This result reveals a critical gap between routine automation and innovation through artificial intelligence.

The current state of even digitized and automated processes is not a determining factor in AI adoption in Tunisia because either these processes have not yet been restructured for advanced artificial intelligence, or the quality and interoperability of the data they generate, despite their apparent speed, do not meet the standards of machine learning models. This explains why companies have not overcome the challenges of data governance (quality, labeling) and organizational incapacity (lack of specific data science skills), which are essential to move from simple automation to the strategic adoption of AI.

The rejection of the hypothesis positively linking Employee Experience (EE) to AI adoption suggests that EE is a prerequisite for digital change rather than a direct driver of advanced transformation. The results indicate that employees possess generic digital skills (use of standard tools) but lack the cutting-edge skills (Data Scientists) essential for designing and integrating machine learning-based solutions. This skills gap prevents companies, although digitally mature, from becoming truly “AI-ready.” Furthermore, support for agility and versatility, while creating a favorable environment, is insufficient to compensate for the changing nature of the risk posed by AI. Projects related to these technological innovations require significant investments and a tolerance for uncertainty that go beyond the simple incremental adaptation enabled by employee agility, thus leading to a decoupling between employee performance and the strategic decision to adopt AI.

Hypothesis H4, which posits a significant effect of the business model on AI adoption, was rejected. This result contradicts the study of [25] and [36], which treat AI as a strategic catalyst for business model innovation. This demonstrates a hierarchy of priorities, where AI is perceived as an imperative for infrastructure and efficiency rather than a tool for strategic transformation. The company's intention to reshape its business model by leveraging digital opportunities is insufficient to trigger AI adoption. Such adoption remains contingent upon the prior establishment of solid technical foundations (Digital Platform), relegating the creation of new business models to the status of an objective to be achieved after adoption, rather than the driving force behind the initial investment.

V. CONCLUSION AND IMPLICATIONS

The objective of this research was to examine the impact of digital capabilities, encompassing technology platforms, operational processes, employee experience, customer experience, and business model, on the adoption of Artificial Intelligence (AI) in the specific context of Tunisian companies.

The analysis highlighted the crucial role of a robust Digital Platform as the sole significant and positive catalyst for AI adoption. This result confirms that infrastructural maturity (data centralization and integration) is the essential technical foundation for AI deployment in Tunisian companies. However, the rejection of the assumptions related to Operational Processes, Employee Experience, Customer Experience, and the Business Model suggests that process optimization, the general digital skills of employees, data enrichment of products, and the strategic ambition to transform the business model are insufficient to drive AI adoption. Their effect is neutralized by higher-level implementation barriers, notably a lack of specific data science skills and immature data governance, confirming that companies are "digitally mature" but not yet "AI-ready."

From a theoretical perspective, this research enriches technology adoption models by emphasizing the need to clearly distinguish digital maturity from AI readiness, particularly in emerging markets. It demonstrates that the measured digital capabilities (processes, employee experience, business model) are necessary but not sufficient conditions for AI adoption. Furthermore, this study highlights the critical role of the Digital Platform as the predominant structural variable, relegating the measured organizational and strategic factors to the status of potential consequences of successful adoption, rather than direct causes of the initial investment.

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From a managerial perspective, the results necessitate recognizing AI as an essential infrastructure requirement, not simply an extension of digital transformation. Leaders must consolidate the Digital Platform (the only proven lever), bridge the skills gap by focusing on cutting-edge profiles (Data Science, MLOps) to overcome organizational limitations, and strengthen data governance to ensure the required quality for AI models. Adoption must therefore be initially driven by internal operational efficiency gains, as external strategic objectives (Customer Experience, new business models) are only achievable after these technical and human foundations are established.

Despite its significant contributions, this study has limitations, notably limited generalizability due to the specific economic and institutional characteristics of the Tunisian context. To refine our understanding of AI adoption in emerging countries, future research should focus on exploring non-significant mechanisms. It would be relevant to study the mediating role of data governance and risk culture to explain how existing digital capabilities (operational processes, employee experience) are hindered or facilitated in their impact on AI adoption. Another crucial avenue lies in analyzing technological complexity, distinguishing the impact of simple AI (e.g., advanced RPA) from that of complex AI (machine learning, deep learning) on different variables.

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