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Assessing the Determinants of AI Integration in Tourism SMEs

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ABSTRACT: *This study explores the factors influencing the adoption of Artificial Intelligence (AI) technologies among tourism Small and Medium-sized Enterprises (SMEs) in Marrakech, Morocco. Given the critical role of AI in enhancing productivity and competitiveness, understanding its adoption in the tourism sector, particularly among SMEs, is essential. Using Structural Equation Modeling (SEM) and data collected from 233 respondents, the research examines the impact of Organizational Readiness (OR), Top Management Commitment (TMC), External Support (ES), Employee Adaptability (EA), and Competitive Pressure (CP) on AI adoption. The findings reveal that TMC and EA significantly influence AI adoption, underscoring the importance of leadership and workforce adaptability. These insights are valuable for practitioners, policymakers, and researchers aiming to develop targeted strategies to enhance AI integration in the tourism sector.*
KEY WORDS: *Artificial Intelligence , SMEs, Tourism, TOE*

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I. INTRODUCTION AND LITERATURE REVIEW

In recent years, artificial intelligence (AI) has been growing very quickly (Dwivedi et al., 2023). As businesses face more competition, it becomes essential for them to use the latest technologies. AI offers many solutions that make hard tasks easier and repetitive tasks faster, greatly improving productivity (OECD, 2019). Numerous sectors can benefit from AI. In fact sectors like business, finance, health, manufacturing, public service, education, agriculture, energy, environmental, construction, entertainment, investigation, forestry, and transportation. can gain a lot from AI (Espina-Romero et al., 2023). Artificial intelligence can improve operations and help with marketing decisions (Davenport et al., 2019), providing significant benefits to businesses of all sizes. However, evidence shows that an uneven spread of AI can create inequalities between different sectors, companies, and regions, and may even widen these gaps (Brynjolfsson & McElheran, 2016). The timing of technology adoption is crucial. Early adopters typically see the most significant benefits, while those who adopt later often experience fewer or no benefits at all (Nemoto et al., 2010). This can create an issue for the tourism industry where SMEs make up about 80% of all businesses worldwide (UNWTO, 2022). In the tourism sector, AI is already changing how businesses operate. For example, travel agencies use AI-powered chatbots to help travelers with planning and recommendations. These innovations have greatly improved service processes, product quality, and customer satisfaction in the travel industry (Lalicic & Weismayer, 2021). Understanding what affects AI adoption in SMEs is crucial for making the most of this technology in the tourism sector. There is a need for more research on AI adoption in the hospitality and tourism industry (Rafiq et al., 2022). This research endeavors to address this critical gap in the literature by offering a comprehensive exploration of the factors influencing the uptake of AI technologies by tourism SMEs.

In the context of Marrakech (Morocco), a city renowned for its rich cultural heritage and vibrant tourism industry, the integration of AI technologies by SMEs holds particular significance. Marrakech serves as a unique backdrop where traditional charm converges with modern tourism demands. By shedding light on this understudied domain, the study aims to provide valuable insights for practitioners, policymakers, and researchers alike, contributing to the enhancement of the adaptive capacity and competitiveness of the tourism industry in an era increasingly defined by technological innovation.

The integration of artificial intelligence (AI) in the tourism industry has been a subject of extensive research and discussion. AI offers transformative potential for augmenting and potentially replacing human tasks across various industrial, intellectual, and social applications (Dwivedi et al., 2021). In the context of tourism, AI applications encompass a wide range of areas, including robotics, big data analytics, and customer service. The tourism industry has witnessed a growing number of real-world applications of robotics and AI, with examples such as biometric identification, meal planning, voice-steered information searches, and the use of intelligent robots to provide services for hotel guests (Gössling, 2020). Furthermore, AI technologies, such as intelligent chatbots and virtual reality-enabled applications, have been explored for their potential to enhance customer experiences and service quality in the post-COVID-19 revival of the tourism industry (Van et al., 2020). The potential benefits of AI in tourism are not limited to customer-facing applications. AI has also been recognized for its role in improving tourism forecasting accuracy, with the introduction of AI-based models such as support vector regression neural networks (SVRNN) to enhance forecasting capabilities (Jiao & Chen, 2019). Additionally, AI technologies have been implemented to improve talent management practices, impacting service quality and customer satisfaction in the hospitality and tourism industry (Ruel & Njoku, 2020).

The adoption of AI technologies presents unique challenges and barriers for SMEs across various industries (Dwivedi et al., 2021; Espina-Romero et al., 2023). Several studies have highlighted the factors that hinder the adoption of new technologies, including AI, in SMEs (Badghish & Soomro, 2024; Lada et al., 2023a). Studies have highlighted the importance of overcoming knowledge barriers, pointing out that enhancing users' skills and knowledge can significantly facilitate and accelerate the adoption of new technologies, such as information systems (Ghobakhloo et al., 2011). Similarly, research into SMEs in the West Midlands found that these businesses often struggle to develop new workflow processes, adapt their organizational structures, and transition from old to new cultural practices when implementing information and communications technology (Chibelushi & Costello, 2009). These insights suggest that SMEs in the tourism sector may encounter distinct challenges when it comes to adopting AI technologies.

Many studies identified and examined crucial factors that play a pivotal role in shaping the landscape of AI adoption in SMEs (Ingalagi et al., 2021; Lada et al., 2023a; Rawashdeh, 2022; Wang et al., 2021). These variables encompass a spectrum of elements ranging from top management commitment to external environmental support, each contributing uniquely to the overall dynamics of AI implementation (Ingalagi et al., 2021; Lada et al., 2023a).

Top Management Commitment: TMC refers to the involvement, enthusiasm, motivation, and encouragement provided by top management towards the acceptance of IS innovations, including AI and other emerging technologies (Ifinedo, 2011). Research has shown that top management support facilitates the relationship between openness of technology adoption and service innovation, indicating its significant influence on fostering innovation through technology adoption (Hsu et al., 2018). In the realm of AI adoption for talent acquisition, top management support is particularly crucial. Recognizing the challenges of talent acquisition in today's landscape, leveraging AI effectively becomes imperative (Pillai & Sivathanu, 2020). Fu et al (2023) emphasized that top management support is a major factor affecting a company's decisions regarding the adoption of AI technologies. A study by Alsheibani et al (2020) indicated that top management support has emerged as one of the strongest determinants of AI adoption.

H1: Top Management Commitment (TMC) influences AI adoption within tourism SMEs.

Employee Adaptability: The successful implementation and utilization of new technologies like AI in the tourism industry hinge on employees' adaptability (Sahadev et al., 2017). To understand the factors that determine an individual level technology adoption and use, the Technology Acceptance Model (TAM) emphasizes perceived usefulness and perceived ease of use (Venkatesh & Bala, 2008). As technology rapidly evolves, tourism businesses must keep pace to enhance services and maintain customer relationships (McIntyre, 2016). This involves utilizing technology to change how the industry interacts with consumers and promotes sustainable practices (Rafiq et al., 2022; Zimeng et al., 2023). For employees to adapt to industry changes, continuous training and improvement in technological competencies are essential (Poddubnaya et al., 2020; Premović et al., 2021; Wu et al., 2021). By prioritizing skill development, employees can effectively navigate evolving technological landscapes and contribute to the industry's success.

H2: Employee Adaptability (EA) influences AI adoption within the tourism SMEs.

Organizational Readiness: Organizational readiness emerged as a comprehensive variable, encapsulating technological, financial, and human resource aspects. Research by Jöhnk et al (2021) provides a conceptualization of organizational AI readiness, offering relevant factors and indicators to understand and assess the measures required for successful AI adoption (Jöhnk et al., 2021). Moreover, research suggests that organizational readiness positively influences top management support, indicating the interconnectedness of organizational readiness with other factors crucial for AI adoption (Maroufkhani et al., 2022).

H3: Organizational Readiness (OR) influences AI adoption within the tourism SMEs.

External Environmental Support: Research has indicated that external support plays a crucial role in shaping SMEs' decisions to adopt new technologies such as AI (Ghobakhloo et al., 2011; Igbaria et al., 1997). In the

context of cloud-based enterprise resource planning (ERP) systems, external support has been identified as one of the main factors influencing SMEs to adopt new technology, emphasizing the role of external stakeholders in shaping technological adoption decisions (Jaffa & Salim, 2020). The external environment has been recognized as a significant determinant of technology adoption in various contexts. For instance, 's study on e-commerce adoption by SMEs in developing countries emphasized the influence of environmental factors on technology adoption (Rahayu & Day, 2015).
H4: External Environmental Support (EES) influences AI adoption among tourism SMEs.

Competitive Pressure: Several studies have highlighted the impact of competitive pressure on technology adoption, including AI (Low et al., 2011; Sharma et al., 2024; Tyler et al., 2020). Competitive pressure is a key driver for the adoption of innovative technologies, as organizations strive to gain a competitive advantage (Yang et al., 2015) (Yang et al., 2015). The integration of AI into an organization is seen as a significant way to achieve this advantage due to AI's ability to create new opportunities and foster innovation (Fast & Horvitz, 2017). This competitive edge has a socio-environmental dimension, as the adoption of AI technologies not only transforms business operations but also influences the organizational culture and work environment (Makridakis, 2017).
H5: Competitive Pressure (CP) influences tourism SMES for AI adaptation.

1.2 Research Objectives

The objective of the research is to explore the factors influencing the uptake of AI technologies by tourism SMEs.

1.3 Research Methodology and Data Analysis

Building upon the foundation laid by these prior investigations, our research seeks to test a model to assess AI adoption specifically among SMEs operating within the tourism industry. This method enables us to examine the distinct challenges and opportunities that tourism-focused SMEs encounter when incorporating AI technologies into their business operations. This research methodology closely follows the framework in studies by Ingalagi et al.(2021) with modifications added by Lada et al. (2023), who utilized comprehensive models from the literature to measure AI adoption in various industrial sectors.

A series of hypotheses that are grounded in existing theoretical models and the findings of previous research studies, enabling us to comprehensively assess the dynamics of AI adoption. To test these hypotheses, we will rely on a quantitative method, employing structural equation modeling (SEM) to analyze the data collected. The selected model provides a robust framework for analyzing key determinants : Employee Adaptability (EA), Organizational Readiness (OR), External Support (ES), Top Management Commitment (TMC), and Competitive Pressure (CP).

3.1 Research instruments

The proposed model is grounded in six key variables that form its conceptual foundation: Employee Adaptability (EA), Top Management Commitment (TMC), Organizational Readiness (OR), External Support (ES), and Competitive Pressure (CP). Figure 1 illustrates our proposed research model, which integrates these key factors based on the theoretical frameworks examined. To assess the six variables in this study, a four-point Likert scale was used, where responses ranged from 1 (strongly disagree) to 4 (strongly agree). The measurement items were sourced and adapted from Lada (2023). An expert academic reviewed the draft survey, and based on her feedback, the survey was refined for a pilot study to ensure its reliability and understandability. Data analysis was conducted using SmartPLS 3, chosen for its suitability in analyzing small sample sizes and its focus is on confirming theoretical frameworks from a predictive standpoint. (Hair et al., 2019). The Path model within SmartPLS 3 was used to test the hypotheses through regression coefficients.

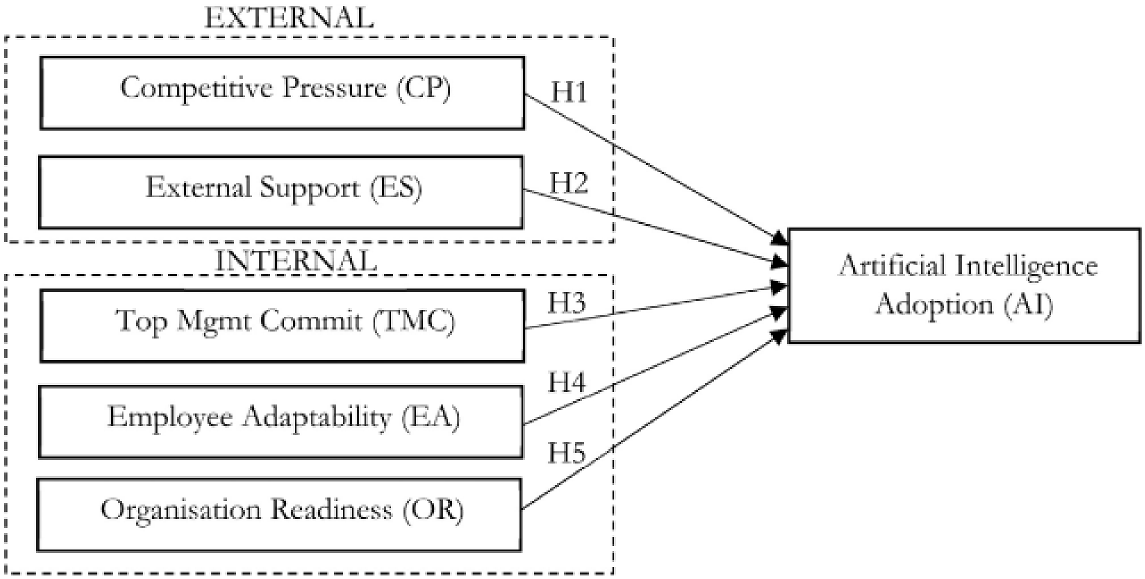

Fig. 1. The modified conceptual framework of AI adoption.
Source: (Lada et al., 2023)

3.2 Data Collection and Sampling

The study targeted owners, managers, and employees of tourism Small and medium enterprises operating in Marrakech, Morocco. The survey was created using Google Forms and distributed via email. To encourage participation, follow-up emails and phone calls were made. Data collection occurred between May and July 2024. Considering the sufficiency of this sample size to run the model, The required sample size was calculated using G*Power software (Faul et al. 2009). Since the model has five predictors, with an effect size of 0.15 and a desired power of 0.95, the minimum required sample size was calculated to be 138. This is in line with the recommendation of a minimum acceptable power of 0.8 commonly used in business and social science research. (Gefen et al., 2010; Hair et al., 2013). Ultimately, 233 valid responses were collected. So this sample size should suffice to run the model. This study utilized a judgmental sampling technique, focusing on several types of tourism SMEs that primarily cater to tourists.

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IV. Results

4.1 Respondents profile

The study sample comprised respondents from various sectors within the tourism SMEs industry in Marrakech, Morocco. Table 1 shows the distribution included 32.2% from lodging, 10.3% from restaurants, 15.0% from transport, 27.5% from travel agencies, and 15.0% from attractions. The businesses varied in age, with 9.4% being 1 to 3 years old, 21.0% between 4 to 7 years, 27.0% between 8 to 10 years, and 42.5% having been established for more than 10 years. Regarding the respondents' positions within their businesses, 40.3% were owners, 28.3% were managers, and 31.3% were employees.

Table 1: Profile of respondents by sector.

SMEs sector	Frequency	%
Lodging	75	32.2
Restaurant	24	10.3
Transport	35	15.0

Travel agency	64	27.5
Attractions	35	15.0
Age		
1 to 3 years	22	9.4
4 to 7 years	49	21.0
8 to 10 years	63	27.0
More than 10 years	99	42.5
Position		
Owner	94	40.3
Manager	66	28.3
Employee	73	31.3

4.2 Validity of measurement model

A measurement model's validity indicates how well it represents the construct it aims to measure. This aspect is essential to ensure that the instruments used provide reliable results. Kline (2010) and Hoyle (2011) suggest that measurement models focus on evaluating latent or composite variables. To assess the validity of these models, researchers rely on three important criteria: construct validity, convergent validity, and discriminant validity (Hair et al., 2019; Ahmad et al., 2016).

4.3 Convergent validity

To evaluate the convergence of constructs, several metrics were computed, including composite reliability (CR), factor loadings, average variance extracted (AVE), and reliability using Cronbach's Alpha (Fornell & Larcker, 1981). Convergent validity refers to the concept that different measures of the same construct should show strong correlations (Bagozzi & Yi, 2012). This is confirmed when the average variance extracted (AVE) for all constructs exceeds the threshold value of 0.50 (Fornell & Larcker, 1981; Hair et al., 2014). Cronbach's alpha values for the six factors (Table 2) all surpassed the recommended threshold of 0.7, as suggested by Nunnally and Bernstein (1994) for a desirable reliability coefficient. Composite reliability represents the internal consistency of items that measure the same underlying constructs (Fornell & Larcker, 1981). Typically, a composite reliability value above 0.7 is considered acceptable (Hair et al., 1998; Nunnally & Bernstein, 1994).

As shown in Table 2, the measurement model meets the criteria for CR, standardized factor loadings, AVE, and Cronbach's Alpha, confirming construct reliability.

Table 2 : Construct validity and reliability.

Construct	Code/Items	Loadings	AVE	CR	Crobach's Alpha
Artificial Intelligence Adoption (AI)	AI1	0.963	0.789	0.918	0.864
	AI2	0.806			
	AI3	0.889			
Competitive Pressure (CP)	CP2	0.723	0.639	0.840	0.727
	CP3	0.896			
	CP4	0.769			
Employee Adaptability (EA)	EA1	0.888	0.825	0.950	0.930
	EA2	0.916			
	EA3	0.961			
	EA4	0.865			
External Support (ES)	ES2	0.941	0.761	0.905	0.874
	ES3	0.854			
	ES4	0.817			

Organization Readiness (OR)	OR1	0.828	0.763	0.928	0.901
	OR2	0.921			
	OR3	0.844			
	OR4	0.897			
Top Management Commitment (TMC)	TMC1	0.759	0.730	0.915	0.881
	TMC2	0.911			
	TMC3	0.914			
	TMC4	0.825			

Table 2 presents the results of the convergent validity assessment. The factor loadings for all items ranged from 0.723 to 0.963, surpassing the minimum threshold of 0.5. The AVE values for all constructs were above the recommended 0.5 threshold, with values ranging from 0.639 to 0.825, indicating that a substantial amount of variance is captured by the constructs. The CR values exceeded the 0.7 criterion for all constructs, ranging from 0.840 to 0.950. Additionally, Cronbach's Alpha values for all constructs were well above the acceptable level of 0.7, indicating high internal consistency, with values ranging from 0.727 to 0.930.

4.4 Discriminant validity

The purpose of evaluating discriminant validity is to verify that each reflective construct is more closely related to its own indicators than to those of other constructs within the PLS path model (Hair et al., 2019). Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations, following the recommendations of Henseler et al. (2015). Discriminant validity is confirmed when HTMT values are below the threshold of 0.90. Table 3 presents the HTMT values for the constructs in this study.

Construct	AI	CP	EA	ES	OR	TMC
Artificial Intelligence Adoption (AI)						
Competitive Pressure (CP)	0.095					
Employee Adaptability (EA)	0.647	0.127				
External Support (ES)	0.272	0.142	0.223			
Organization Readiness (OR)	0.125	0.051	0.128	0.077		
Top Management Commitment (TMC)	0.726	0.096	0.507	0.47	0.189	

Table 3 : Discriminant validity: Heterotrait-Monotrait ratio (HTMT).

In the evaluation of the structural model using PLS-SEM, the focus is on the significance of the path relationships, along with the model's ability to explain and predict outcomes. Key metrics for this evaluation include the R^2 and Q^2 values. R^2 serves as an indicator of the model's explanatory power (Shmueli & Koppius, 2011). It is also known as predictive power (Rigdon, 2012). R^2 values range from 0 to 1, with higher values indicating stronger explanatory power.

Based on the results presented in the figures, the R^2 value for the model is 0.554, indicating that 55.4% of the variability in AI adoption can be explained by the independent variables included in the model. This suggests a substantial level of explanatory power, as the R^2 value exceeds the 0.1 threshold recommended by Falk and Miller (2014). Additionally, the adjusted R^2 value is 0.544, which supports the robustness of the model.

The Q^2 values for the indicators AI2, AI1, and AI3 are 0.346, 0.437, and 0.478 respectively, all of which are above zero. This confirms the predictive relevance of the model for these endogenous constructs. However, the evaluation of model fit indices showed that the Standardized Root Mean Square Residual (SRMR) values for both the saturated model and the estimated model were 0.104. The SRMR values exceeding the recommended threshold of 0.10 suggest that the model fit is not entirely satisfactory (Hair et al., 2016). Other indices, such as Chi-Square (2321.285) and Normed Fit Index (NFI) at 0.555, provided further insights into the model fit, indicating areas for potential improvement.

Table 4 : Path Coefficient

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CP -> AI	0.003	-0.007	0.05	0.055	0.956
EA -> AI	0.326	0.322	0.051	6.431	0.000
ES -> AI	-0.031	-0.017	0.04	0.769	0.442
OR -> AI	-0.001	0.01	0.049	0.018	0.985
TMC -> AI	0.545	0.537	0.035	15.373	0.000

Table 4 provides the results of the path coefficient analysis. The findings indicate that Top Management Commitment (TMC) and Employee Adaptability (EA) have significant impacts on AI adoption, with path coefficients (TMC – AI: $\beta = 0.545$, $t = 15.373$, $p < 0.001$) and (EA – AI: $\beta = 0.326$, $t = 6.431$, $p < 0.001$), supporting hypotheses H1 and H2. However, Organizational Readiness (OR), External Support (ES) and Competitive Pressure (CP) did not show significant impacts on AI adoption, leading to the rejection of hypothesis H3, H4, and H5.

1.4 Findings and Interpretation

This study aimed to examine the influence of various factors on the adoption of AI technologies among tourism SMEs in Marrakech, Morocco. The findings indicate that Top Management Commitment (TMC) and Employee Adaptability (EA) are significant predictors of AI adoption, confirming hypothesis H1 and H2. However, Organizational Readiness (OR), External Support (ES) and Competitive Pressure (CP) did not show significant effects, leading to the rejection of hypothesis H3, H4, and H5.

The positive impact of TMC on AI adoption aligns with existing literature, underscoring the crucial role of leadership in fostering technological innovation within organizations (Lada et al., 2023a). This suggests that tourism SMEs in Marrakech can enhance their AI adoption rates by prioritizing and demonstrating strong managerial commitment to technology integration. Leaders in these businesses must actively support AI initiatives, ensuring that necessary resources and strategic guidance are available to facilitate successful implementation.

Similarly, the significant relationship between EA and AI adoption highlights the importance of workforce adaptability in embracing new technologies. Employees' willingness and ability to adapt to AI technologies are essential for their effective utilization. This finding suggests that ongoing training and development programs aimed at improving technological competencies can be beneficial. Tourism SMEs should invest in continuous learning opportunities to enhance their employees' skills, thereby facilitating smoother transitions and greater acceptance of AI tools.

The tourism industry, particularly in sectors such as lodging and restaurants, heavily relies on employees to perform labor-intensive jobs such as housekeeping, waitressing, and cooking. These roles require a significant human element, and the implementation of AI in these areas may be limited due to the high costs associated with AI technologies and the financial constraints of SMEs. For instance, while AI services that handle reservations could be beneficial, their adoption might be hindered unless these technologies become more affordable for small businesses in Marrakech.

Contrary to expectations, CP, ES, and OR did not significantly influence AI adoption among the surveyed SMEs. An important consideration is that the model used in this study is being applied for the first time in the context of tourism SMEs. This novelty might explain why only two variables showed a significant effect on AI adoption.

Moreover, previous studies have shown that Morocco is in the very early stages of AI adoption, with no specific investigations into AI adoption among tourism SMEs (Yousra & Khalid, 2021). However, other sectors such as banking, agriculture, and the chemical industry have been identified as fertile grounds for AI integration. This early stage of AI adoption presents unique challenges and opportunities for the tourism sector in Morocco. Future research should focus on exploring these aspects in more detail, particularly how AI can be integrated into labor functions beyond management roles.

The unique environment and challenges of the tourism sector in Marrakech might necessitate the inclusion of other variables that were not considered in this initial model. The poor fit indicated by the SRMR value also suggests that the model could benefit from refinement. This measure points to potential gaps in the model, indicating that additional or alternative factors might play a significant role in AI adoption in this context. The poor SRMR highlights the need to explore other variables that could influence AI adoption among tourism SMEs.

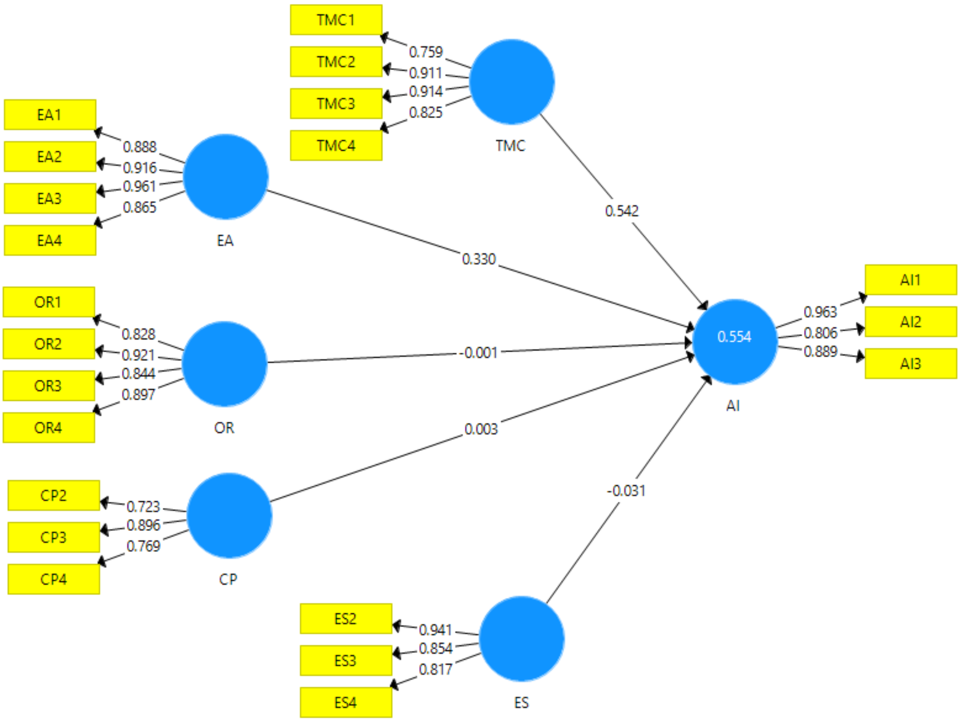

Fig. 2. Path coefficient.

V. Conclusion

This study explored the factors influencing the adoption of AI technologies among tourism SMEs in Marrakech, Morocco, utilizing SmartPLS 3 and data from 233 respondents. The findings indicate that Top Management Commitment (TMC) and Employee Adaptability (EA) significantly impact AI adoption, highlighting the critical roles of leadership and workforce adaptability in embracing new technologies. Given the findings, organizations are encouraged to strengthen their focus on TMC (Top Management Commitment) and EA (Employee Alignment) to improve AI-related outcomes. Since tourism SMEs in Marrakech are still in the early phases of adopting AI, this study mainly focuses on the overall application of AI technology. In comparing the findings of the current study with the previous research, a notable contrast emerges regarding the influence of Employee Adaptability (EA) on AI adoption. The previous study suggested that Employee Adaptability (EA) did not significantly affect AI adoption, emphasizing instead the importance of Top Management Commitment (TMC) and Organizational Readiness (OR) for successful AI integration. However, the current study reveals that both TMC and EA significantly influence AI adoption among tourism SMEs in Marrakech, underscoring not only the critical role of leadership but also the adaptability of the workforce in adopting new technologies. This contrast suggests that while previous research downplayed the impact of EA, the current findings indicate that in certain contexts, such as tourism SMEs in Marrakech, workforce adaptability plays a vital role alongside management commitment in driving AI adoption.

Future research could explore AI adoption from a more specialized perspective, examining its role in specific labor functions within tourism beyond just management. It's also important to recognize that SMEs in other regions may encounter distinct opportunities and challenges related to AI adoption. Differences in aspects like regulatory market conditions, frameworks, cultural influences, and resource availability across various countries can greatly impact both the adoption process and its outcomes. As a result, the conclusions drawn from this study may not fully capture the experiences of SMEs operating outside of Marrakech.

One of the limitations of this study is that the model we adopted had a Standardized Root Mean Square Residual (SRMR) score that is not entirely satisfying. The SRMR value exceeding the recommended threshold of 0.10 suggests that the model fit is not entirely satisfactory. This poor SRMR highlights the need to explore other variables that could influence AI adoption among tourism SMEs. The unique environment and challenges of the tourism sector in Marrakech might necessitate the inclusion of other variables that were not considered in this initial model. Future research should consider refining the model to add additional or alternative factors that might play a significant role in AI adoption in this context. Additionally, the sample size, while adequate for the study, limits the generalizability of the results to other regions or sectors. Economic conditions, such as access to capital and economic stability, were also not considered but could significantly impact the ability of SMEs to adopt AI technologies.

To improve the external validity of the study, future research should aim to broaden its scope by including SMEs from a wider range of countries. Taking a broader approach would provide a more in-depth understanding of the factors driving AI adoption and their impact in varying contexts. While this study offers valuable contributions to understanding AI adoption in the tourism sector, there remains a need for further research to refine the model and explore additional determinants. These efforts will better capture the complexities of AI adoption in tourism SMEs and support the development of targeted strategies to foster technological integration and sustainable growth.

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