ISSN: 2658-8455
Volume 5, Issue 10 (2024), pp. 40-58.

Understanding Moroccan engineers' intentions to adopt AI for Job Application: An Empirical Analysis

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Disclosure Statement :	Authors are not aware of any findings that might be perceived as affecting the objectivity of this study and they are responsible for any plagiarism in this paper.
Conflict of Interest :	The authors report no conflicts of interest.
Cite this article :	ELYOUKDI, K., & ZOHRI, A. (2024). Understanding Moroccan engineers' intentions to adopt AI for Job Application: An Empirical Analysis. *International Journal of Accounting, Finance, Auditing, Management and Economics*, *5*(10), 40-58. https://doi.org/10.5281/zenodo.13888135
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Received: August 16, 2024   *Accepted: October 01, 2024*

International Journal of Accounting, Finance, Auditing, Management and Economics - IJAFAME
ISSN: 2658-8455
Volume 5, Issue 10 (2024)

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Abstract:

Despite the ongoing digitalization of the talent acquisition (TA) practices, there is a significant dearth of research pertaining with the use of AI for TA, leaving a significant gap of understanding of these initial stages of technology adoption. Specifically, end-user perception and readiness to accept the use of this technology.

This study aims to investigate candidates' behavioral intention toward AI for job Application as a component of AI for TA. For this purpose, the constructs of our designed research model are grounded in both UTAUT and the Confidentiality, Integrity and Availability (CIA) framework. A structured questionnaire was used among 183 Moroccan engineers across several disciplines, to assess the impact of performance expectancy, effort expectancy, hedonic motivation, perceived confidentiality, and perceived availability on candidates' behavioral intention to use AI-based job applications. The primary data were analyzed by means of the PLS-SEM method. The findings revealed a significant and positive impact of the constructs in our model on behavioral intention, except for effort expectancy, which did not exhibit a direct influence on our dependent variable. Therefore, the assumed negative impact of Perceived Confidentiality has not been verified. The study suggests that Moroccan candidates are open to using AI for job applications, which could encourage organizations to integrate AI solutions into their talent acquisition processes. The finding can give insight to AI developers to enhance their tools to meet candidate expectations, empowering marketers to promote their innovations effectively.

Keywords: UTAUT, CIA framework, Artificial Intelligence, Talent acquisition, Recruitment, HRM.
JEL Classification : D83 ; M15 ; O33.
Paper type: Empirical research

1. Introduction:

The advent of Industry 4.0 has brought about a shift in talent requirements. Human resources must adapt to the digital and automated nature of modern industries, acquiring new skills and mindsets to thrive in this era and creating a powerful Human-Technology partnership that can drive innovation, productivity, and competitiveness.
According to a recent global survey conducted by Manpower Group, 75% of companies worldwide are experiencing a shortage of skilled personnel (Manpower, 2024). As outlined in the research report "The Future of Talent Acquisition 2023-24" by HR.com, Talent acquisition (TA) continues to be the most critical function of human resources management (Hr.research institute, 2023) . Manifestly, HR managers face TA as one of their most complex challenges (Hongal & Kinange, 2020).
Talent acquisition refers to the strategic process of identifying, attracting, and hiring qualified candidates for specific roles within an organization. This process includes activities such as job posting, candidate sourcing, interviewing (Albert, 2019), and onboarding to ensure the right individuals are brought on board to meet the organization's requirements (Jose, 2019).
HRM fortunately, underwent a considerable transformation because of Industry 4.0. This has drastically changed TA policies and practices, which now align more closely with the rapidly evolving landscape of work and technology, emphasizing digital skills, data-driven decision-making, and a flexible approach to remote and diverse recruitment by incorporating AI into the recruitment process.
AI for TA entails utilizing AI algorithms and technologies like machine learning, natural language processing (NLP), deep learning, cognitive conversations, chatbots, virtual reality, alongside other AI tools to enhance and optimize candidate attraction and recruitment processes (Kumar, 2019; Pillai & Sivathanu, 2020b; Tavana & Hajipour, 2020).
Preliminary, E.T Albert reviews the areas in which AI for TA tools can be used (Albert, 2019). He highlighted specifically, vacancy prediction software; job description optimization software; targeted job and optimization; multi-database candidate search; application platforms; resume pre-screening software; computer-assisted psychometric testing; video pre-screening software; computer-assisted background check.
A study conducted by Hr.Research institute on AI in TA suggests that the use of AI is currently limited but there is a strong anticipation for a substantial increase in its utilization within the coming two years (Hr.research institute, 2019), particularly with the advent of a new wave of startups, offering user-friendly, flexible, cost-effective platforms that can be used by companies of all sizes.
For instance, Morocco, on its path to becoming a prominent African economy experienced a boost in its startup landscape with the "Maroc Digital 2020" program, which gave rise to indigenous AI-based solutions, notably in the HR field.
Press report has revealed that AI recruitment solutions have been available in the Moroccan market since 2019, of which products developed by Moroccan startups. However, AI is still in its infancy as a recruitment tool in Morocco. This raises questions about the rate of adoption of AI for recruitment, which in turn leads us, as researchers, to question the readiness of the Moroccan market for the implementation of AI in the recruitment process.
The decision-making process related to technology acquisition and adoption of innovation is often considered as an organizational decision, while the process of adhering to innovation is considered to be a result of users' intentions to use the technology (Hameed & Arachchilage, 2020). The critical factor to consider in the initial stages of any new technology implementation is User's readiness to accept and use the technology, particularly in the context of talent acquisition, where recruiters give priority to the candidate experience and the employer brand. It's crucial to emphasize that there is a shortage of academic studies that

specifically address the various issues associated with this early stage of AI implementation in the recruitment sector within the Moroccan context.
For ensuring an efficient integration of AI within a task as inherently human and subjective as recruitment, it's of paramount importance at the initial stage, to gain insights into candidates' attitudes and willingness to accept the technology. This implies assessing the candidates' psychological readiness to be involved in an automated recruitment process, specifically, the initial stage of the process 'Job application' (JA). Therefore, the research problem is established as:
What factors could potentially impact the behavioral intention of Moroccan candidates to apply for a job using AI solutions?
While the literature on AI in HRM has been well developed, there remains a dearth of research addressing users' behavior and the psychology of technology use, alongside a scarcity of empirical research within the existing literature.
This empirical investigation sought to analyze the factors influencing acceptance of AI for JA among Moroccan talent, using a research model that integrates elements of the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Confidentiality, Integrity, and Availability (CIA) framework. This integration was undertaken to address the limitations of UTAUT related to perceived security.
This study is structured by a literature review section that incorporates existing literature and theories to establish the theoretical model. From this comes the subsequent section of hypothesis development, to be followed in turn by the research methodology section, which outlines the research design, sampling and data collection methods, the evaluation of the structural model and data analysis, leading to the results section. The discussion section follows, including theoretical and managerial implications, limitations as well as suggestions for future research. Finally, a general conclusion is drawn.

2. Literature review:

2.1. Previous adoption works

AI is increasingly establishing a presence across various sectors, including industries relying on purely Human intelligence and inimitable capabilities. To synchronize with the current technological revolution, research related to different issues of AI implementation spanning various sectors start to be published. Recent studies discuss the adoption decision of AI technologies in Healthcare (Almarzouqi et al., 2022; Alomari & Soh, 2023; Chew & Achananuparp, 2022; Jawad et al., 2023; Kim et al., 2024; Krishnamoorthy et al., 2022; Suroso & Sukmoro, 2021) for AI-powered autonomous vehicles (Huang & Qian, 2021; Kuberkar & Singhal, 2020) (Meyer-Waarden & Cloarec, 2022). In Education (Aziz et al., 2023; Chatterjee & Bhattacharjee, 2020; Jo, 2023; Mohd Rahim et al., 2022; Setiadi & Tjhin, 2021; Wang et al., 2021). In Tourism (Nam et al., 2021; Pillai & Sivathanu, 2020a) and Application of AI in Human Resources Management (HRM) (Hmoud, 2021; Horodyski, 2023; Jose, 2019; Pan et al., 2022; Tanantong & Wongras, 2024).
Artificial intelligence has been instrumental in supporting various HRM functions, including TA. AI-based TA solutions represented a significant advancement, as conventional recruitment relies heavily on social relationships and subjective assessments.
Initial investigations pertaining with AI in TA are predominantly descriptive and lacks substantial empirical studies(Albert, 2019; Gethe, 2022; Upadhyay & Khandelwal, 2018). Their central focus was to assess the accessibility of AI solutions and their potential contributions in diverse areas of HRM. Subsequent researches have addressed the ethical concerns surrounding the use of AI in recruitment (Eerola et al., 2021; Hunkenschroer and Luetge, 2022). Recently, studies on technology adoption started to be issued. These studies

are segmented to give greater focus firstly to the organization with a particular emphasis on decision-makers intention to adopt AI for TA novelty (Pan et al., 2022; Pillai and Sivathanu, 2020a; Shakeel and Siddiqui, 2021) and secondly to the user's intention to be involved in an automated recruitment (Hmoud, 2021; Horodyski, 2023; Tanantong & Wongras, 2024).
The individual as a direct user remains the pivotal factor in the successful integration of any technology(Krishnamoorthy et al., 2022). Studying the conduct of candidates and recruiters as technology users and their acceptance of technology is a critical concern. In the process of TA, significant consideration is given to ensuring candidate satisfaction and creating a positive candidate experience throughout the recruitment process. In this context, it is essential to gain insight into how candidates view the incorporation of AI within the recruitment process with specific emphasis on the initial stage - the application process (Kaoutar & Abdelaziz, 2024). The current literature does not provide a comprehensive understanding of how candidates perceive the integration of AI into the recruitment process, especially within the Moroccan context. For this purpose, we employed an enhanced version of UTAUT, incorporated with the CIA framework to investigate the influence of drawn constructs on Moroccan talent's intention to use AI-based Job application (AI based JA).

2.2. Theoretical Background

2.2.1 Technology adoption models

Many theories and models have been developed to explain and predict the factors influencing the acceptance and diffusion of information technologies. These include the Theory of Reasoned Action (TRA) (Icek & Martin, 1980), Rogers' Diffusion of Innovation Theory (DIT) (Rogers et al., 2014), the Theory of Planned Behavior (TPB) (Ajzen, 1991), the Technology Acceptance Model (TAM)(Davis, 1989) and UTAUT (Venkatesh et al., 2003).
The Technology Acceptance Model (TAM) remains the predominant framework for investigating information technology acceptance and computing behavior (Davis, 1989). It is effective in explaining how external factors influence internal beliefs such as perceived usefulness and perceived ease of use, as well as attitudes and intentions (Davis, 1989; Rogers et al., 2014; Venkatesh et al., 2003) . However, the model has its limitations particularly in addressing moderating and external variables (Bryan and Zuva, 2021; Li, 2008; Schillewaert et al., 2005; Wu, 2011). To address the shortcomings of earlier technology acceptance models, Venkatesh developed the UTAUT model (Venkatesh et al., 2003).

2.2.2 UTAUT

UTAUT theory combines elements of the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory. In order to integrate the structure of perceived usefulness and ease of use components into the original TAM model, UTAUT uses performance expectancy and effort expectancy.
The initial version of UTAUT, as proposed by Venkatesh in 2003 outlines four primary factors which are; performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC) and social influence (SI); that impact the intention and utilization of information technologies (Venkatesh et al., 2003). UTAUT has gone through several revisions, in the 2012 version, three new significant factors; hedonic motivation (HM); price value (PV) and habit (HAB) were incorporated into the model (Venkatesh et al., 2012).
Our research is grounded in the 2012 version of UTAUT to investigate the acceptance of Moroccan talent to be involved in a recruitment process that leverages AI for TA. The strength of this version lies in its integrative approach, which incorporates multiple explanatory variables from the key theoretical frameworks developed to understand technology acceptance and technology usage. In this preliminary investigation, our focus will

be on the examination of the impact of three factors that reflect users' expectations regarding the technology, specifically, PE, EE and HM. One shortcoming of the UTAUT model is the lack of consideration of perceived security and privacy as factors influencing users' acceptance to adopt new technology. To address this issue, the CIA (Confidentiality, Integrity, and Availability) framework was applied by Hartono et al. to investigate security-related issues as factors influencing the actual use of e-commerce in Seoul, South Korea (Hartono et al., 2013). Yigitbasioglu et al. underlines the importance of identifying security factors in the context of cloud computing adoption (Yigitbasioglu, 2014). In a recent study carried out by Salam et al. in 2020, the integration of security factors with the UTAUT model was employed to explore the drivers of cloud adoption in the context of local government in Indonesia (Salam & Ali, 2020).

2.2.3 The Confidentiality, Integrity, and Availability (CIA) framework

The CIA framework is the famous security triangle used for assessing and improving the security of information systems (Taherdoost et al., 2013). By focusing on Confidentiality, Integrity and Availability, organizations can ensure that their systems and data are protected against unauthorized access, use or disclosure, and that they are available to authorized users when they need them (Qadir & Quadri, 2016) (Tsiakis and Sthephanides). NRA Salam et al. introduced “Perceived Confidentiality”, “Perceived Integrity” and “Perceived Availability” as variables, to investigate the perceived security of technology.
Two factors have been considered in this study, Perceived confidentiality and Perceived Availability. Given their alignment with our research context.
In this study, five constructs were proposed to study their direct effect on talent's behavioral intentions to apply for a job position using AI solution for JA.

3. Hypothesis formulation and research model

3.1. Performance Expectancy

PE refers to user's perception of technology performance, and the extent to which using this technology will improve his or her job performance(Venkatesh et al., 2003). Previous studies, have demonstrated a significant effect of PE on Behavioral Intention (BI) across diverse domains, including the adoption of AI for recruitment (Alomari & Soh, 2023; Horodyski, 2023; Jawad et al., 2023; Nikolopoulou et al., 2021; Nordhoff et al., 2020; Shahreki et al., 2020; Sidik & Syafar, 2020; Venkatesh et al., 2003). In the context of AI for JA, PE refers to the extent to which the applicant believes that using AI solutions will help him or her to improve his or her application performance.
Earlier studies have shown that application through AI solutions allows to the candidate diffusing his application to the concerned companies (Albassam, 2023; Albert, 2019; Nordhoff et al., 2020), which increases the likelihood of being hired and allows him to save time and cost. As result this will enhance the candidate's job search performance.
H1: PE will positively impact the BI to use AI based JA.

3.2. Effort Expectancy

EE refers to users' perception of the degree of effort required to use a new technology (Venkatesh et al., 2003). It implies that when new technology is institutionalized, users' behavior is influenced by how they perceive effort needed for processing new complex stimuli.
For our study, the use of AI for job application is associated with the use of a computer or phone or intelligent semantic terminals that are easy to handle, moreover candidates are generally familiar with this kind of technology. Thus, we hypothesize:

ISSN: 2658-8455
Volume 5, Issue 10 (2024), pp. 40-58.

H2: EE positively impacts behavioral intention to use AI based JA.

3.3. Hedonic Motivation

HM is the perceived fun and enjoyment associated with technology use (Venkatesh et al., 2012). This concept describes the satisfaction derived from using a technology while accomplishing routine tasks. Previous studies have shown a significant relationship between HM and BI to use technology (Nikolopoulou et al., 2021; Tsiakis & Sthephanides, 2005; Venkatesh et al., 2012). In the present study, HM would refer to the degree to which using AI to apply for a job is perceived as enjoyable. The fun and enjoyment a person expect to gain from using a specific technology can impact their intention to use this technology. Thus, we expect that a positive HM towards AI based JA will have a positive impact on the BI.
We hypothesize:
H3: HM will have a positive effect on the BI to use AI based JA.

3.4. Perceived Confidentiality (PC)

PC, as part of the CIA framework, is infrequently integrated with UTAUT. This construct refers to the subjective belief that sensitive data are effectively protected and kept private from unauthorized access or disclosure (Tsiakis & Sthephanides, 2005). This concept is a crucial factor influencing people's decisions to adopt and use new technologies, particularly technologies requiring personal data collection, storage and transmission. The user's technology adoption decision is contingent on their judgment of how well an organization or system safeguards their confidential data. Despite the widespread adoption of technology, concerns regarding data confidentiality persist. In the specific context of AI for JA, where the data shared is often sensitive, apprehensions about the security of data storage can deter applicants from adopting these solutions. Hence, the hypothesis can be outlined as follows:
H4: PC will negatively impact the BI to use AI based JA.

3.5. Perceived Availability (PA)

Within the CIA framework, the third element is 'availability,' referring to the continuous and undisrupted access to systems, data, and resources (Tsiakis & Sthephanides, 2005). As for PA refers to how users perceive the reliability and continuity of their access to these resources. PA may be a significant factor influencing the intention to adopt a new technology, as it accurately reflects how users evaluate the technology's reliability. When it comes to AI for JA, perceived availability relates to the way job applicants perceive the system's ability to offer reliable and uninterrupted access to the AI-driven JA platform. The perpetual availability of job application platforms can generate a positive PA, ultimately this can positively affect users' intention to apply through AI-based platforms. This research suggests that the availability of application platforms can positively influence applicants' intention to use AI for JA. Thus, this study proposed,
H5: PA positively affects the intention to use AI based JA.

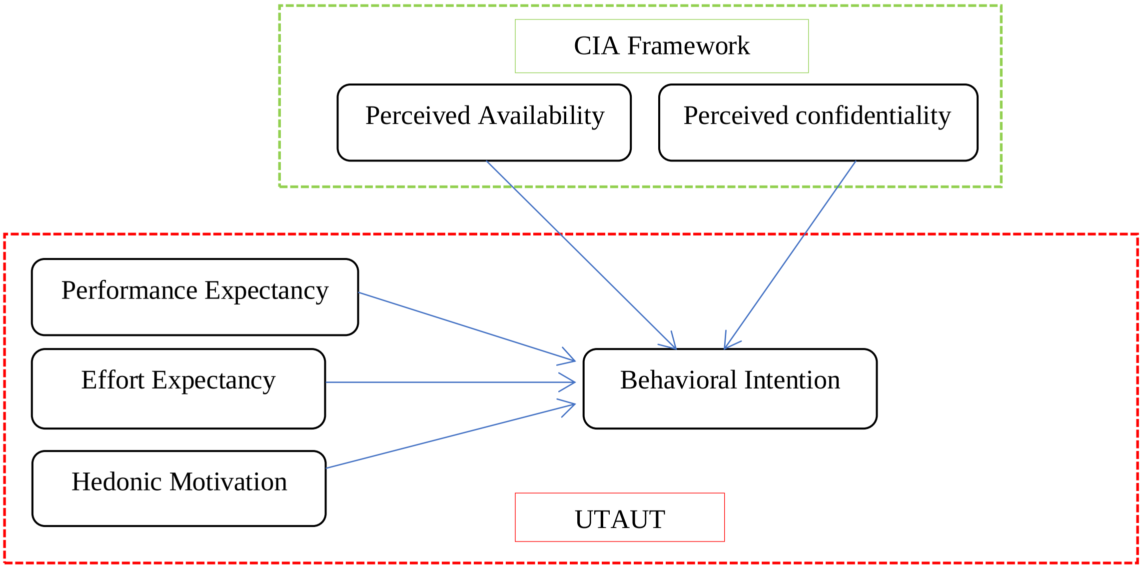
3.6. Behavioral intention

BI, is a construct within the TPB and TRA, represents individual's readiness and willingness to perform a specific action in the future (Venkatesh et al., 2003). It is influenced by "Individual's attitudes" reflecting individual's overall evaluation or perception of the behavior; "Subjective norms" indicating the influence of social pressure or what an individual believes significant others expect in relation to the behavior; "Perceived behavioral control" implying how an individual perceives the ease or difficulty of carrying out the behavior.

In the context of AI-driven JA adoption, applicant's attitudes, subjective norms, and perceived behavioral control can all affect Candidate's intention to rely on AI solutions to apply for a job position.

3.7. Research Model

Figure 1: Research Model



Source: Authors

4. Methodology

4.1. Research design

Through deductive reasoning, we structured a quantitative study to explore the theoretical relationships among various variables resulting from the integration of UTAUT and CIA frameworks. The purpose of this investigation is to understand which factors impact the adoption and utilization of AI for JA among Moroccan engineers. We relied on existing literature pertaining to the UTAUT and CIA frameworks to formulate a quantitative questionnaire as primary tool for data collection, utilizing a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) to measure the operationalized concepts (Likert, 1932).

Before data collection, the survey instruments were sent to tree academics and five professionals, including four human resources professionals, and one AI solutions vender, briefing them on the aims and scope of the research, to validate both the apparent and content validity. Their feedback was incorporated to enhance the questionnaire items.

Subsequently, a pilot study involving 30 PhD students from the Doctoral Training Center in Engineering Sciences was conducted to ensure questionnaire comprehensibility across all respondent groups and to evaluate the operationalized constructs (Table 2). The primary investigation was undertaken after the successful outcome of the pilot study.

4.2. Sampling and data collection

Our study revolves around the acceptance of contribution in a recruitment process using AI for TA. When addressing TA, our target automatically centers on key skills and scarce profiles. To delineate our segment characteristics, we conducted a review of Moroccan press articles published between 2020 and 2023, which anonymously identifies that the scarce profiles in Morocco mainly involve engineering disciplines across different fields. For this purpose, we specifically targeted Moroccan engineers for collecting our primary data.

ISSN: 2658-8455
Volume 5, Issue 10 (2024), pp. 40-58.

We leveraged job fairs organized by five engineering schools in Casablanca, employing smart semantic kiosks for the application process.
A conference was organized on the topic of AI Innovation in Recruitment by a young Moroccan AI startup. Participants at the conference were subsequently invited to respond to our questionnaire. Additionally, we sent the questionnaire via email to individuals who visited the forum. Approximately 329 questionnaires were distributed, only 203 were returned, out of these, only 183 were appropriate for analysis. The details of the respondents are outlined in (Table 1). The response rate reached is 55.62%. In the subsequent step, the non-response bias was assessed using a t-test to compare early and late responses. The result (p = 0.28) suggested the absence of non-response bias according to King and He (King & He, 2005).

TABLE 1. Demographic PROFILE (N=183)

Categories	Dimensions	N	%
Gender	Male	72	39%
	Female	111	61%
Age	Younger than 25 years	8	4%
	25–34 years	168	92%
	35–44 years	7	4%
Education Level	Doctorate	61	33%
	master's	2	1%
	Engineer	120	66%
Specialty	Mechanical engineering	50	27%
	Electrical engineering	44	24%
	Computer engineering	48	26%
	Industrial engineering	33	18%
	Civil engineering	8	4%
Do you know AI based JA software before?	Yes	86	47%
	No	97	53%
Have you experienced AI-driven JA software previously?	Yes	15	8%
	No	168	92%

Source: Authors

4.3. Data analysis

To validate the hypotheses within our conceptual model, we employed the PLS-SEM method (Cite the Use of SmartPLS - SmartPLS, s. d.). PLS-SEM holds significant appeal in social sciences due to its adeptness in handling Complex Models, which was particularly advantageous for our study involving five latent constructs. Moreover, its flexibility to accommodate samples of varying sizes was crucial; our dataset comprised 183 responses, falling below the requisite size for other approaches, additionally, given the exploratory nature of our research, which applied the UTAUT and CIA framework while integrating two theories, a path-modeling method was imperative (F. Hair Jr et al., 2014; Hair et al., 2019, 2021). Hence, the selected approach has been used to confirm the validity and reliability of the model's variables, permitting subsequent analysis of the structural model.

5. Results and interpretation

5.1. Measurement model assessment

Internal consistency or reliability is typically assessed by means of Cronbach's alpha **(α)** (Cronbach & Meehl, 1955) and composite reliability (CR) (Qadir & Quadri, 2016). Hence, values ranging from 0.60 to 0.70 are considered as 'acceptable' in exploratory research, while values between 0.70 and 0.95 are regarded as 'satisfactory to good' (Nunnally, 1978). For our measurement model, the Cronbach's alpha coefficients deemed satisfactory to good (Table 2)

(F. Hair Jr et al., 2014). According to Hair et al, a high level of reliability for all constructs is confirmed by external loadings of composite reliability exceeding 0.6, which is the minimum threshold value.

The scrutiny of validities in SEM is further underlined by convergent and discriminant validity. Convergent validity is established when the Average Variance Extracted (AVE) for a construct surpasses 0.50 (F. Hair Jr et al., 2014). According to table 2, the AVE value of all constructs is strictly greater than 0.6, confirmed the convergent validity of our model.

Subsequently the discriminant validity was assessed according to the Fornell-Larcker criterion. The findings indicated that the squared AVEs values were higher than the inter-construct correlations. It signifies that each variable exhibits a stronger variance with its indicators than with other variables (Table 3). Consequently, the items associated with each of our reflective variables are distinct enough from other items intended to measure other phenomena, ensuring discriminant validity.

TABLE 2. Synthesis of constructs and items

Main construct	Indicator/item	Item loading	Adapted from
(PE) α=0.86 CR=0.86 AVE=0.704	Using AI technology to apply for a job would enable me to accomplish tasks more quickly.	0.863	(Venkatesh et al., 2003)
	Using AI technology would enhance my effectiveness on job application.	0.874	
	Using the AI technology make application to a job easier.	0.893	
	I would find the AI technology useful in my application for a job.	0.818	
(EE) α=0.855 CR=0.858 AVE=0.696	Learning to operate the AI for job application would be easy for me.	0.837	(Venkatesh et al., 2003)
	My interaction with AI solutions would be clear and understandable.	0.856	
	I would find the AI solutions flexible to interact with.	0.835	
	It would be easy for me to become skillful at using the AI solutions for application.	0.81	
(HM) α=0.804 CR=0.819 AVE=0.718	Using AI solutions for job application is fun	0.881	(Venkatesh et al., 2003)
	Using AI solutions for job application is entertaining	0.789	
	Using AI solutions for job application is enjoyable	0.869	
(PC) α=0.853 CR=0.911 AVE=0.690	I feel sure that all of my personal data will be kept secret.	0.899	(Silic & Back, 2016)
	I feel sure that my personal data will never be used against me.	0.738	
	Nobody else besides the recruiters will be able to see my personal data without my approval.	0.738	
	The recruiters are committed to respecting my privacy.	0.785	
(PA) α=0.875 CR=0.881 AVE=0.889	A candidate user can apply through AI for Job application at any time and at any place.	0.948	(Silic & Back, 2016)
	All channels of applying through AI solutions are continuously available to candidates.	0.937	
(BI) α=0.920 CR=921 AVE=0.861	Assuming that I had access to AI solutions for job application, I predict that I would use it in the future	0.936	(Venkatesh et al., 2003)
	If AI solutions for job application become available permanently, I plan to use it	0.934	
	I intend to use AI solutions for job application again during the demonstration period.	0.914	

Source: Authors

The table below presents the reliability and validity statistics for the constructs used in our study. For PE, a strong internal consistency was demonstrated with α=0.86, the CR was also 0.86, indicating a reliable measure, while the AVE was 0.704, suggesting a satisfactory level of convergent validity. EE exhibited a α of 0.855, which is indicative of high internal consistency additionally the CR value was 0.858, further confirming the reliability of the construct while the AVE was 0.696, close to the recommended threshold, indicating acceptable convergent validity. With α=0.804, the internal consistency of HM was deemed acceptable, the CR value was 0.819, demonstrating good reliability and the AVE was 0.718, reflecting strong convergent validity. PC had a α of 0.853, indicating robust internal consistency, the CR was notably high at 0.911, confirming the reliability of the construct and the AVE was 0.690, which is marginally below the ideal threshold but still within an acceptable range for convergent validity. PA showed a high α of 0.875, signifying excellent internal consistency, the CR was 0.881, and the AVE was exceptionally high at 0.889, both indicating very strong reliability and convergent validity. The highest reliability was observed for this BI, with a α of 0.920. The CR was 0.921, underscoring the high reliability of the measure, while the AVE was 0.861, demonstrating very strong convergent validity.

TABLE 3. Fornell–Larcker criterion.

	BI	EE	HM	PA	PC	PE
BI	0.928					
EE	0.370	0.835				
HM	0.470	0.402	0.847			
PA	0.425	0.270	0.250	0.943		
PC	0.318	0.044	0.182	0.402	0.831	
PE	0.426	0.401	0.477	0.250	0.140	0.855

Source: Authors

Table 3 presents the Fornell-Larcker criterion, the square root of the AVE for BI is 0.928, for EE 0.835, for HM 0.847, for PA 0.943, for PC 0.831 and for PE 0.855. Discriminant validity is strongly confirmed considering that their square root exceeds the correlation of each construct with other constructs.

5.2. Assessment of the structural model

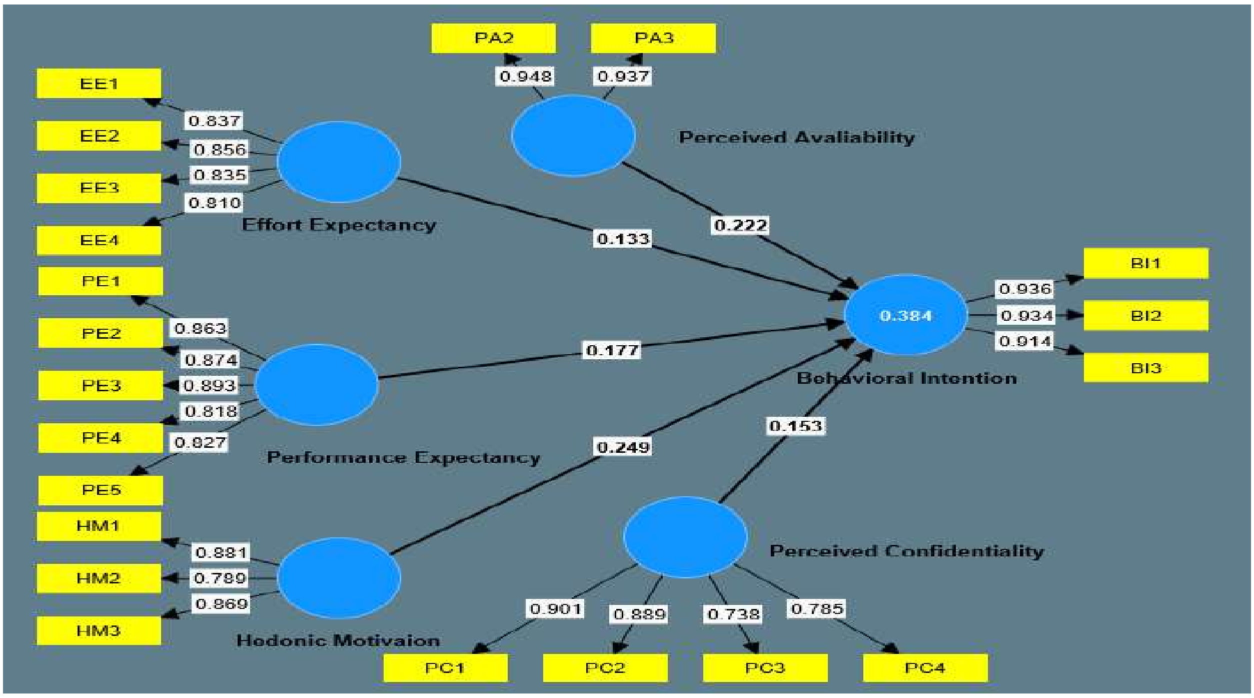
To refine and validate our theoretical model based on empirical data, the evaluation and analysis of the relationships and pathways were performed within this section. The following criteria will be considered for the assessment of our measurement model: R^2, Q^2, hypothesis testing, path coefficients, f^2, as well as the Goodness of Fit (GoF).

For our model, the R^2 value obtained for the adoption of AI for JA was 0.348 indicating that the determinants explained 38.4% of the variance in the adoption of AI for JA, reflecting a significant level of predictive efficacy (Hair et al., 2019). Subsequently, the predictive validity of our model was evaluated through the Stone-Geisser's Q^2 coefficient.

The coefficient is considered acceptable when it exceeds 0, significant when exceeding 0.25, and strong when surpassing 0.5 (Hair et al., 2019; Tenenhaus, 1999). The results related to our structural model display Stone-Geisser Q^2 coefficients greater than 0 it was about 0.341 which entails that the good quality of predictive validity of our model is validated.

For a more robust assessment we considered in addition Goodness of fit to assess the adequacy of our model to describe the underlying structure of the data. Tenenhaus et al. proposed a global fit measure for PLS modeling (Tenenhaus et al., 2005), according to which the GoF index is between 0 and 1 ($0 < GoF < 1$). Hair et al. in 2017 assert that values of 0.02, 0.15, and 0.35 indicating in order, effect sizes categorized as small, medium, and large. With a GoF value of 0.581, surpassing the threshold of 0.36, we can affirm the effective overall validation of our structural model.

Figure 2: Measurement Model



Source: Authors

5.3. Result of Hypotheses Testing

To assess the structural relationships between the model's concepts and to test the research hypotheses, we employed Bootstrapping and Blindfolding procedures conducted in SmartPLS4 with 5000 iterations. The results, including correlations between construction variables, path coefficients (β), T-statistics, and associated p-values, are presented in Table4.
PE (β =0.177, T=2.307, p < 0.021); HM (β =0.249, T= 3.270, p < 0.001); PA (β =0.222, T=2.361, p < 0.018), significantly and positively influence the BI to use AIT, resultantly H1, H3 and H5 was supported.
PC also demonstrates a positive statistical influence on BI. Nevertheless, H4, which suggests that PC will negatively impact candidates' intention to apply using AI technology, can't be supported. Finally, no significant effect was identified regarding EE (β =0.133, T=1.750, p < 0.08), hence H2, was not supported.

TABLE 4. Synthesis of the path coefficients and testing results

Hypothesis	Correlations	Path coefficient	T statistics (|O/STDEV|)	P values	Decision
H1	PE → BI	0.177	2.307	0.021	Supported
H2	EE → BI	0.133	1.750	0.080	Not supported
H3	HM → BI	0.249	3.270	0.001	Supported
H4	PC → BI	0.153	2.883	0.004	Not supported
H5	PA → BI	0.222	2.361	0.018	Supported

Source: Authors

6. Discussion

This study sought to understand the factors influencing the intention to use AIT for JA as part of an automated TA process in Moroccan landscape. The motivation behind this study stems from paucity of existing literature dedicated to investigating the acceptance of artificial intelligence technology in the recruitment process within the Moroccan context. For this purpose, we utilized a theoretical model that integrates both the UTAUT and the CIA framework. The proposed model that was empirically validated incorporates five independent variables: three variables from UTAUT namely PE, EE, and HM and two variables from the CIA framework which are PC and PA.

In light of the findings, a robust statistical correlation was identified between HM and the BI, it stands as the most influential factor explaining the BI of Moroccan candidates regarding the utilization of AI for JA.

This entails that the emotional satisfaction, excitement, or enjoyment that a candidate expect to experience when utilizing AI-driven platforms or tools for job searching impact its BI to rely on it. Hence H2 asserting that HM will positively impact the BI of Moroccan candidates to apply through AIT for JA was strongly supported. These findings are consistent with prior research demonstrating a positive relationship between HM and BI (Nikolopoulou et al., 2021; Nordhoff et al., 2020; Venkatesh et al., 2012).

PE significantly affected the BI to use AIT for JA. Accordingly, H1 was supported, these findings are consistent with earlier results reported in the literature (Alomari & Soh, 2023; Horodyski, 2023; Jawad et al., 2023; Nikolopoulou et al., 2021; Nordhoff et al., 2020; Shahreki et al., 2020; Sidik & Syafar, 2020; Venkatesh et al., 2003). This may be attributed to the efficiency of AIT for JA in saving candidates time and effort, allowing them to focus on more meaningful aspects of their job search and in increasing their likelihood of finding the right job fit by personalizing recommendations and feedback based on individual preferences, skills, and experiences. In conclusion, PE is a significant factor impacting the BI of Moroccan candidates to use AIT for JA.

Conversely, EE has not a statistically significant relationship with BI to use AIT for JA. This leads us to reject H2. The lack of a substantial relationship between EE and BI implies that the PEU of AIT for JA has no direct influence on the BI of Moroccan candidate to use this technology.

In earlier studies, EE was acknowledged as a significant determinant of technology adoption (Albassam, 2023; Jawad et al., 2023; Nikolopoulou et al., 2021; Tanantong & Wongras, 2024; The Power of Artificial Intelligence in Recruitment: An Analytical Review of Current AI-Based Recruitment Strategies | International Journal of Professional Business Review, s. d.; Venkatesh et al., 2003). However, in recent research, the direct relationship of this construct on the BI to use technology is starting to weaken (Alomari & Soh, 2023; Jawad et al., 2023; Nikolopoulou et al., 2021). This could be attributed to increased familiarity with new technologies in addition to the characteristics of the target generation in the research.

Considering security concerns, PA had a statistically significant effect on BI, our finding are comparable to the outcomes of NRA Salam et al. (Salam & Ali, 2020). This suggests that removing time constraints and providing access to intelligent application platforms at any desired time could be a strong determinant in positively influencing the BI of Moroccan candidates to adopt AIT for JA. From the above H4 was supported.

Surprisingly PC demonstrated a positive statically impact on the explained variable. Despite previous findings indicating that confidentiality and security of personal data are major concerns that could negatively influence technology adoption (Derous & De Fruyt, 2016; Goodman, 2017; Pillai & Sivathanu, 2020b). This finding can be attributed to the target demographic of our study, comprising of digital natives who exhibit a notable level of trust in technology. As well as the nature of provided Data, which can be considered by this generation as not highly sensitive information and can be shared publicly in professional social networks. From what has been mentioned H5 which states that perceived confidentiality will negatively impact the BI cannot be supported.

7. Conclusion:

In the present study, we examined the factors that influence the readiness of Moroccan candidates when applying for job positions involving the use of AI technology. To achieve this objective, we expanded the UTAUT model within the psychology of technology adoption, incorporating CIA framework, a cyber security-specific framework. This integration was necessary to accommodate the interdisciplinary nature of our research and to address the shortcomings of the UTAUT model, particularly in considering technology performance factors such as continuous accessibility and the protection of private data through confidentiality and system availability. The incorporation of both these models represents a distinctive addition to the existing literature. The introduced model, empirically validated, will enhance the current literature on technology adoption and serve as a valuable reference frame for researchers in the AIT for TA, especially in the Moroccan context where empirical studies pertaining with AIT for TA are seldom conducted. Overall, to the best of the author's knowledge, this marks the inaugural empirical study scrutinizing the factors impacting the BI of candidate toward using AIT for JA in Morocco. Furthermore, the results of our research validate the positive impact of PE, HM and PA on BI, aligning with previous finding. However, the absence of direct impact for EE unexpectedly notable and was considered as deviation from earlier research findings. Nevertheless, some recent research has yielded similar findings. Finally, it was confirmed that PC from the CIA framework has a positive effect on BI. However, the assumed negative impacts were not verified.

Considering these findings, several research questions need to be explored further to enhance our model and gain insight into the unique aspects of the Moroccan context.

Practical and managerial implications

The outcomes of this study carry substantial practical implications for Organizations, software developers and HR professionals. The optimistic outlook of Moroccan candidates towards utilizing artificial intelligence solutions for JA, as indicated by the absence of any negative impact on their BI to use the technology, may prompt decision-makers to integrate these solutions, thereby improving the efficiency of their talent acquisition process. This in turn can provide reassurance to recruiters, alleviating concerns about biases stemming from candidate’s psychological attitude regarding AI solutions.

On the other side establishing that PE, HM, PA and PC strongly impact candidate BI toward AIT using, may help AI developers enhancing the capabilities of current AI tools to also align with candidates' expectations in terms of performance, enjoyment, confidentiality and availability. This will empower marketers of these technological solutions to prioritize the mentioned factors for effectively promoting their innovation.

Although the study makes original contributions to the field of knowledge, it is subject to certain limitations. First, this was our initial attempt to examine the adoption of AI for TA, an area that still in its early stages of development in Morocco. That's why our initial emphasis was on examining the direct relationships between the latent variables and the explained variable. Future research should consider exploring the relationships between latent variables, particularly those that did not exhibit a direct impact on the dependent variable, in order to assess their indirect effect on behavioral intention. It should also focus on other phases of the recruitment process. Secondly, our study concentrated on a narrow, specific sample, primarily consisting of millennial engineers. This segment is already highly proficient with technology, which may impact the generalization of the study's results to the broader population. In our future research, it is imperative to consider generational diversity and expand our research to include other segments of the labor market beyond talent. Given that the model was exclusively tested in the Moroccan context, it suggests potential avenues for further research in African countries, which represent a potential labor market for Morocco. Finally, studies can also be assessed from a recruiter's perspective to provide a triangulation of results.

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