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Understanding Candidates' Behavioral Intentions toward AI for Talent Acquisition: A Conceptual Study Using UTAUT and CIA Frameworks .

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Abstract

The objective of this conceptual study is to propose an enhanced model of factors that impact candidates' behavioral intention (BI) to accept the use of AI solutions for TA, including factors related to the privacy and security of this new technology. By integrating the Unified Theory of Technology Acceptance and Use (UTAUT) and the Confidentiality, Integrity and Availability (CIA) framework, the proposed model examines the impact of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivations (HM) and habit (HAB), perceived confidentiality (PC), perceived integrity (PI) and perceived availability (PA) on candidates' BI towards AI for TA. The proposed model contributes to existing knowledge by integrating security and privacy as a new perspective to the original model that can impact candidate behavior towards AI in TA.

Keywords: *Artificial Intelligence, Talent Acquisition, UTAUT, CIA Framework, Candidate Behavior, Behavioral Intention*

Introduction

With the global economy shifting, there is increasing demand for skilled professionals in all different sectors. A global survey by Manpower Group reveals that 40% of businesses worldwide are facing a shortage of skilled workers, as reported in HR.com's 2019 report 'The Advancing HR Function' (Hr.research institute, 2019a). Organizations currently face intense global competition to attract, develop and retain the most talented and skilled employees. TA has evolved to become an essential component of strategic HRM. Its role in attracting, selecting and integrating talent has a direct impact on the long-term performance and success of the organization (Guthridge et al., 2008; Marrybeth et al., 2019).

The shift towards remote working and the emergence of a globalized talent pool have removed the geographical boundaries of labor markets. Today's highly skilled workers have more opportunities to move between companies, cities and countries.

Attracting candidates from a global pool has increased the complexity of TA. Traditional methods, which rely on manual selection of CVs and prolonged interviews, require considerable resources and do not allow the best candidates to be identified quickly. These methods are not efficient in benefiting from the diversity of talent available in global talent pool (Black & van Esch, 2021). To meet new TA and the borderless talent market challenges, companies are increasingly relying on AI-driven solutions to improve the efficiency of TA (Albert, 2019; Black & van Esch, 2021).

AI for TA refers to the use of AI and machine learning technologies to automate and optimize various tasks of the recruitment process (Pan et al., 2022). AI has revolutionized TA by offering advanced tools and technologies that streamline the hiring process. Through AI, organizations can automate repetitive tasks such as resume screening and candidate sourcing, significantly reducing the time and effort spent on initial candidate evaluation. AI-powered algorithms can analyze large volumes of data to identify top candidates more accurately, using predictive analytics to match skills and experience with job requirements. This technology also helps mitigate biases in hiring decisions, promoting a more diverse and inclusive workforce.(Albert, 2019; Upadhyay & Khandelwal, 2018).

Artificial Intelligence (AI) in recruitment processes is transforming the way organizations attract, assess and hire talents. Despite the transformative potential provided by AI, a number of challenges remain. The biggest challenge may be how candidates perceive AI in the

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recruitment process. This, in turn, could influence their intention to apply for or accept job offers.

Talents are at the heart of the TA process. They are considered as the important stakeholder. Their experiences and satisfaction levels must be carefully addressed as they have a significant impact on the overall success and effectiveness of recruitment (Miles & McCamey, 2018). The use of AI solutions for TA significantly influences the candidate experience. It is therefore essential to understand the factors impacting acceptance of using this technology to ensure a positive candidate experience.

The research question addressed in this study is therefore as follows: **What are the key determinants influencing the adoption of AI for TA among Moroccan talent?**

The nature of our research object leads us to adopt a post-positivism as an epistemological foundation. Results generated through studies based on hypothesis testing and establishment of empirical relationships through the collection and analysis of quantitative data, do not represent absolute reality. They are rather approximations that help us to understand the underlying trends and patterns in the data. For example, candidates' perceptions of AI-driven recruitment tools may be influenced by factors such as previous experience, technological knowledge and cultural context, introducing a level of subjectivity into their responses. Post-positivism allows us to recognize these subjective influences while striving to ensure the objectivity and rigor of the research process.

The objective of this study is to conceptualize a model allowing the understanding of candidates' perception of AI technology for TA and the identification of factors affecting their acceptance of using this technology. Through this study, we also attempt to fill the UTAUT main model's gap related to the lack of factors investigating the perception of security and confidentiality of new technologies, by integrating UTAUT into the CIA framework.

This conceptual study is organized in four sections. The first section provides a literature review outlining previous AI research in the area of HRM in general and technology adoption specifically. The second section presents theories used to build our research model. The third section presents the hypothesis formulation and the proposed research model. The final section presents the conclusion, highlighting the implications and potential directions for future research.

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1. LITTERATURE REVIEW

1.1. TA in a Connected World: Recruiting best talent fit in a Borderless Job Market

Technological advances and new working patterns, such as teleworking, have profoundly reshaped the TA landscape. Identifying key skills is no longer limited by geographical borders. Organizations today benefit from a global talent pool, creating an international labor market with no boundaries. This evolution brings both interesting opportunities and significant challenges for TA professionals. Globalization of the talent market promotes cultural and experiential diversity. Which leads in turn to more creativity, innovation within an organization, in contrast this stronger the war of talent. Organizations are therefore called upon to rethink their TA strategies to enhance their global competitiveness.

TA rise as a critical function of HR management to help achieving strategic objectives. To overcome all the above challenges, technology 4.0 is playing an increasingly important role in transforming TA processes, boosting efficiency and improving the candidate experience. To automate repetitive tasks and analyze the huge data available in the global labor market, AI solutions have been developed.

1.2. AI for TA

Responding to the TA challenges associated with an increasingly global labor market, innovations are increasingly emerging to ensure the efficiency of the various phases of the TA process. AI is transforming TA by automating tasks, providing data-driven insights and improving the candidate experience. The following table presents the available AI solutions for each stage of the TA process as well as the AI method employed to develop these solutions.

Table 1: AI Tools for TA: Summary from Literature Review

Stage of TA process	Tool Function	AI Method Used
Sourcing	Identifies potential candidates from various sources	NLP, ML
	Automates candidate search and engagement	Predictive Analytics, NLP
	Provides candidate sourcing and diversity hiring	ML, NLP

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Screening	Assesses candidates' cognitive and emotional traits	Neuroscience-based algorithms, ML
	Enhances candidate search and talent mapping	Deep Learning, NLP
	Automates initial candidate screening via chatbots	Chatbots, NLP
Interviewing	Conducts and analyzes video interviews	Video Analysis, ML
	Facilitates video interviews with AI analysis	Video Analysis, ML
	Integrates AI-driven assessments with interviewing	AI-driven Assessments, ML
Assessment	Evaluates candidates using neuroscience games	Cognitive Neuroscience, ML
	Tests candidates' coding skills through simulations	Coding Simulation, ML
	Offers pre-employment assessments	Pre-employment Assessment, ML
Onboarding	Streamlines onboarding processes and engagement	Workflow Automation, NLP
	Enhances onboarding experience with personalized content	Chatbots, ML
	Automates onboarding workflows and document management	Workflow Automation, NLP

Source: (Albert, 2019; Hr.research institute, 2019b; Upadhyay & Khandelwal, 2018)

1.3. Previous studies

AI solutions offer the potential to make significant advances in all fields, including areas which traditionally rely on human intelligence and unique skills. To stay at the forefront of this technological revolution, scientific researches pertaining with AI has begun to be issued in the various sectors where AI could make a contribution.

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From existing literature dealing with AI, three distinct categories can be identified. The first concerns engineering researches aimed at developing and implementing technological solutions for different industries. The second focuses on ethical and social researches, exploring the wider impacts of AI adoption on the economy and society, such as concerns about job loss. Finally, managerial researches which involve in-depth analyses of AI's contribution within specific sectors, from the adoption issues to the evaluation of user experiences. In the area of HR management, AI researches are increasingly numerous, although a great deal of researches in the management category are descriptive and lacks empirical exploration.

(Upadhyay & Khandelwal, 2018) discuss the implications of AI in the hiring process and its impact on the recruitment industry. Similarly, (Albert, 2019) explores the current applications of AI in the recruitment and selection of candidates. (Fritts & Cabrera, 2021) address the dehumanization problem associated with AI recruitment algorithms, raising concerns about the potential loss of human touch in the hiring process. (Ore & Sposato, 2022) delve into the opportunities and risks of AI in recruitment and selection, providing insights from recruitment professionals in a multicultural multinational organization. (Chen, 2022) explores the collaboration between recruiters and AI in removing human prejudices in employment. They discuss how AI technology has improved recruitment efficiency and the various stages of the recruitment process where AI is utilized. (Johnson, Stone, et Lukaszewski 2020) discussed the benefits of electronic human resource management (eHRM) and AI for TA in the hospitality and tourism industry, they highlighted how e-recruiting, e-selection, and AI tools can improve recruiting and selection outcomes in these sectors. (Nyathani, 2022) delved into the evolution of HR digital transformation and the pivotal role of AI-powered recruitment solutions in redefining traditional recruitment practices. (França et al., 2023) provided insights into the relationship between AI and Human Resource Management (HRM), synthesizing studies on AI applied to potential assessment and talent identification in an organizational context. Finally, (Popo–Olaniyan et al., 2022) reviewed the current state of AI adoption in HR practices in the United States, focusing on how AI and analytics are transforming HR decision-making in American organizations.

The adoption of AI for TA is a topic that has gained significant attention in recent years. (Pillai & Sivathanu, 2020) conducted a study that empirically validated a model revealing the predictors of adoption and actual usage of AI technology for TA. The study utilized the Technology-Organization-Environment (TOE) and Task-Technology-Fit (TTF) framework to explore the adoption of AI technology for TA. Similarly (Shakeel & Siddiqui, 2021) studied

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the impact of technological, organizational, environmental, and task technology fit on the adoption and usage of AI for TA in the Pakistani banking sector. (Van Esch & Black, 2019) found that attitudes towards organizations using AI in recruitment significantly influence potential candidates' likelihood to complete the application process. They suggest that organizations should not hide their use of AI but rather promote it to attract candidates with positive views of both the organization and AI. (Laurim et al., 2021) focus on the acceptance criteria for AI-based technologies in the recruitment process. They highlight transparency, complementary features of AI tools, and a sense of control as key factors influencing the acceptance of AI in recruiting.

Most studies investigating the AI for TA drivers have focused on the organizational level, whilst very few studies have explored the factors influencing end-user adoption. In the following sections, we will highlight the most relevant research models for investigating AI adoption drivers for TA among end-users.

2. Theoretical framework

2.1. Technology acceptance models

Technology acceptance models (TAMs) are theoretical frameworks used to understand and predict how users accept and use a technology. These models identify which factors influence users' decisions to adopt and integrate new technologies into their daily routines or work processes. The following table presents the principal models of technology acceptance:

Table 2: Overview of Technology Acceptance Models

Model	Definition	Author(s)
Technology Acceptance Model (TAM)	Explains user acceptance of technology based on perceived usefulness and perceived ease of use.	(Davis, 1989)
Innovation Diffusion Theory (IDT)	Explains how, over time, an innovation is adopted and spread across a population.	(Rogers et al., 2014)
Unified Theory of Acceptance and Use of Technology (UTAUT)	Explains user acceptance based on performance expectancy, effort expectancy, social influence, facilitating conditions, and moderating variables.	(Venkatesh et al., 2003)

Model of PC Adoption and Use (MPCU)	Focuses on factors influencing individual adoption and use of personal computers.	(Thompson et al., 1991)
Task-Technology Fit (TTF)	Examines the fit between a task and a technology to determine user acceptance.	(Goodhue & Thompson, 1995)
Technology-Organization-Environment (TOE) Framework	Examines how technology, organizational factors, and environmental factors influence technology adoption.	(Tornatzky et al., 1990)

Source: (Davis, 1989; Goodhue & Thompson, 1995; Rogers et al., 2014; Thompson et al., 1991; Tornatzky et al., 1990; Venkatesh et al., 2003)

UTAUT appears as the most relevant framework for investigating user acceptance of technologies.

TAM focuses mainly on perceived usefulness and ease of use, which limits its explanatory power for complex technologies or when other factors are significant. IDT Focuses mainly on the diffusion of innovations within a social system and offers only limited insight into technology adoption decisions at the individual level. MPCU Specifically designed for PC adoption, the MPCU is not generalizable to other technologies and neglects broader contextual factors. TTF considers the importance of alignment between technology and tasks, but ignores other crucial factors influencing user acceptance, hence it cannot be used on its own. The TOE is one of the most widely used models because it frames Technological, organizational and environmental factors on technology adoption, but it does not address the individual user behavior.

Finally, UTAUT's ability to explain technology acceptance in a variety of contexts, combined with its empirical support, makes it the framework of choice for researchers.

2.1.1. UTAUT

UTAUT provides an in-depth analysis of explanatory factors affecting user acceptance and future use of technologies. The UTAUT model has undergone a number of modifications since its introduction in 2003. Iterations such as UTAUT2 (2008) (Venkatesh et al., 2008) and the UTAUT2 Model (2012) (Venkatesh et al., 2012), have extended its explanatory coverage by introducing additional concepts. These concepts address factors such as HM (enjoyment from

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technology use), perceived value (cost-benefit analysis), and HAB (habit formation), , all reflecting a more nuanced understanding of user behavior in the context of technology adoption.

For understanding which factors explain candidates' acceptance and use of AI for TA, UTAUT2 will be used. This model was chosen for its comprehensive and integrative approach, which incorporates a large variety of explanatory variables from the main theoretical models developed to explain technology acceptance and use; The UTAUT identifies the main determinants with a direct impact on technology adoption: PE, EE, SI, FC, HM and HAB. Compared to other models, UTAUT is specifically designed to explain how individuals adopt and use technologies; this focus on user perception and motivation makes it relevant for our specific research. Moreover, UTAUT is designed to go beyond user perceptions by including moderators that take into account contextual factors such as age, experience and culture, which is crucial in TA, where individual and organizational differences can influence AI adoption. This broad applicability suggests its ability to provide valuable insights into AI adoption in TA.

Ultimately, UTAUT provides a powerful framework for understanding candidates' BI towards AI for TA. Nevertheless, this model overlooks users' perceptions of technology security and data privacy. For a broader investigation, it is important to consider candidates' perceptions of the privacy and data security of AI for TA and how these factors may impact their BI towards the technology. To overcome this gap, it is necessary to integrate UTAUT into a complementary model.

To overcome this shortcoming, (Hartono et al., 2013) used the CIA framework to examine how security factors, regarded as a second-order concept, impacted the actual use of e-commerce in Seoul, South Korea. (Yigitbasioglu, 2014) highlighted the identification of security factors as crucial to the adoption of cloud computing, as it involves providers who may act opportunistically with user information. (Salam & Ali, 2020) incorporated the three security elements into the UTAUT model to investigate the determinants of cloud computing adoption in local government in Indonesia.

2.1.2. CIA Framework

The CIA framework is a fundamental framework for information security. It defines three key principles that frame the security of technology:

Confidentiality: This principle guarantees that only authorized users have access to sensitive information. It includes measures to prevent the unauthorized disclosure, interception or modification of data.

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Integrity: This principle ensures the accuracy and completeness of information. It involves protecting data from unauthorized modification or destruction, so that it remains reliable and trustworthy.

Availability: This principle ensures that authorized users can access information and systems when they need them. This involves preventing breakdowns, interruptions or cyber-attacks that could hinder access.

3. HYPOTHESES DEVELOPMENT AND PROPOSED RESEARCH MODEL

Drawing from the UTAUT framework (Venkatesh et al., 2003) and the CIA security concept (Hartono et al., 2013; Tsiakis & Sthephanides, 2005), this study identifies ten constructs that directly influence BI to use AI based TA.

3.1. Variables Of The UTAUT Model

3.1.1. Performance Expectancy

The degree to which an individual believes that using a system will enhance job performance (Venkatesh et al., 2003). Previous research consistently demonstrates a strong positive relationship between PE and BI (Alomari & Soh, 2023; Kim et al., 2024; Nordhoff et al., 2020; Tanantong & Wongras, 2024). Individuals are more likely to adopt a technology, including AI-enabled systems, if they believe it will enhance their job performance or provide a competitive advantage. In the context of AI for TA, candidates are more likely to use AI tools if they believe it will improve their chances of finding suitable jobs. Hence

H1: PE of AI for TA will positively influence candidates' intention to use AI-enabled recruitment systems.

3.1.2. Effort Expectancy

The degree of ease associated with using the system (Venkatesh et al., 2003). In the realm of AI adoption, EE – the perceived ease of use – emerges as a crucial factor influencing user behavior. Studies across education, e-commerce, and human-computer interaction highlight that user-friendly interfaces, clear instructions, and readily available support all contribute to positive EE (Alomari & Soh, 2023; Nordhoff et al., 2020; Tanantong & Wongras, 2024). This, in turn, translates to higher adoption rates for AI tools, as users find them easier to learn and integrate into their workflows. Candidates are more likely to use AI-based TA if they perceive it as easy to use and navigate, therefore.

H2: EE of using AI for TA will positively influence candidates' intention to use AI-enabled recruitment systems.

3.1.3. Social Influence

The degree to which an individual perceives that important others believe he or she should use the system. Research suggests SI plays a significant role in AI adoption. Studies show that individuals are more likely to embrace AI tools if others they trust (colleagues, industry leaders) have positive experiences or express confidence in the technology (Alomari & Soh, 2023; Nordhoff et al., 2020, p. 2). This highlights the importance of social proof and testimonials in promoting AI acceptance and influencing user behavior. Candidates are more likely to use AI-based TA if their peers or influencers recommend it. Thus we hypothesize that:

H3: SI has a positive effect on BI to use behavioral intentions of using AI for Job Application

3.1.4. Facilitating conditions

The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). In AI adoption, FC – the perceived availability of resources and infrastructure – influence user behavior. Studies indicate that individuals are more likely to adopt AI if they believe their organizations provide the necessary technical support, training, and hardware/software resources for successful implementation (Alomari & Soh, 2023; Kim et al., 2024, p. 2; Nordhoff et al., 2020, p. 2). This emphasizes the importance of organizational readiness and infrastructure investment to create a supportive environment for AI adoption. Candidates are more likely to use AI-based TA if they have access to necessary devices, internet connectivity, and technical support. Consequently, the hypothesis put forward is as follows:

H4: FC will positively affect the adoption of AI for Job application

3.1.5. Hedonic Motivation

The degree to which an individual believes that using the system is enjoyable (Venkatesh et al., 2003). Research suggests HM, the desire for enjoyment and positive experiences can influence AI adoption. Studies show users are more likely to embrace AI tools if they perceive them as engaging, fun to use, or offering a more efficient and streamlined experience (Alomari & Soh, 2023; Nikolopoulou et al., 2021; Nordhoff et al., 2020). This highlights the potential of gamified features or user-friendly interfaces to motivate AI adoption and drive positive BI

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towards the technology. Candidates are more likely to use AI-based TA if they find the process engaging and fun. We hypothesize: (Tsiakis & Sthephanides, 2005)

H5: HM will have a positive effect on the BI to use AI for Job application.

3.1.6. The price value

The degree to which an individual believes that the perceived benefits of using the system outweigh the perceived costs. While price is often a major factor in traditional technology adoption, research on AI suggests a more nuanced relationship with BI. Studies haven't found a clear correlation between cost and AI adoption (Alomari & Soh, 2023; Nordhoff et al., 2020). Instead, the focus seems to be on perceived value. Users are more likely to adopt AI if they believe the benefits (performance improvements, efficiency gains) outweigh the costs (financial or time investment). Candidates are more likely to use AI-based TA if they perceive the benefits (e.g., time savings, job opportunities) as greater than the perceived costs (e.g., data privacy concerns). Hence we hypothesize

H6: Price value will positively impact the BI to use AI for Job application.

3.1.7. Habit

According to Venkatesh et al HAB can be defined as the degree to which an individual automatically or repeatedly uses the system. Research on HAB and AI adoption is emerging, but some studies suggest a potential moderating effect. Existing user habits with similar technologies might influence their openness to AI(Alomari & Soh, 2023; Nikolopoulou et al., 2021; Nordhoff et al., 2020). For instance, individuals accustomed to using recommendation algorithms might be more likely to adopt AI-powered recruitment tools. However, further research is needed to fully understand the interplay between HAB and BI in the context of AI adoption. Candidates who have a habit of using AI-based tools in other areas of life may be more likely to use AI-based TA. Thus we hypothesize that:

H7: HAB will have a positive impact on the BI to use AI for Job application.

3.1.8. Behavioral intention

BI to adopt technology, often abbreviated as BI, is a crucial dependent variable in research on user acceptance of new technologies. Studies by (Venkatesh et al., 2003) and (Taylor & Todd, 1995) demonstrate its importance in the UTAUT and the Technology Acceptance Model (TAM), respectively. These influential models highlight BI as a key indicator of users' willingness to adopt and integrate new technology into their habits. By measuring BI,

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researchers can assess the potential success of a new technology in a specific context, informing development and implementation strategies.

3.2. Variables of the CIA framework:

While the CIA Triad outlines the objective security goals, these terms, when prefixed with "perceived," focus on individuals' subjective evaluations of these security properties. In essence, by using "perceived" confidentiality, integrity, and availability, the researchers emphasize the importance of understanding users' subjective evaluations of system security, which ultimately impacts their technology adoption decisions.

This approach aligns with the focus on user perceptions and attitudes in technology acceptance models like UTAUT.

3.2.1. Perceived Confidentiality (PC)

Within CIA framework, Confidentiality refers to the ability of the technology to Protect information from unauthorized access (Tsiakis & Sthephanides, 2005). In the context of AI for TA, Preventing unauthorized disclosure of candidate data (e.g., personal information, resumes, and test results). PC has not previously been tested in AI for recruitment, however a previous study by (Salam & Ali, 2020) has confirmed the lack of a positive impact of PC on AI adoption. We consider in our context that when users are uncertain about data confidentiality and how their information will be handled by AI systems, users are in turn less likely to trust and adopt the technology. Hence,

H8: PC will negatively impact the BI to use AI for Job application

3.2.2. Perceived Integrity

Integrity Ensuring information is accurate and complete Protecting candidate data from modification or corruption (e.g., preventing tampering with application data, test scores) (Tsiakis & Sthephanides, 2005) in the context of AI for recruitment, refers to the perceived fairness and trustworthiness of the technology. (Salam & Ali, 2020) 's study has shown a non-relation between PI and behavioral intention to adopt AI, in contrast(Van Deventer et al., 2017) revealed that PI had a notable positive effect on an individual's trust in a system. When candidates believe AI recruitment tools operate ethically, without bias or manipulation, they are more likely to trust them and accept their adoption.

Accordingly, the hypothesis introduced is:

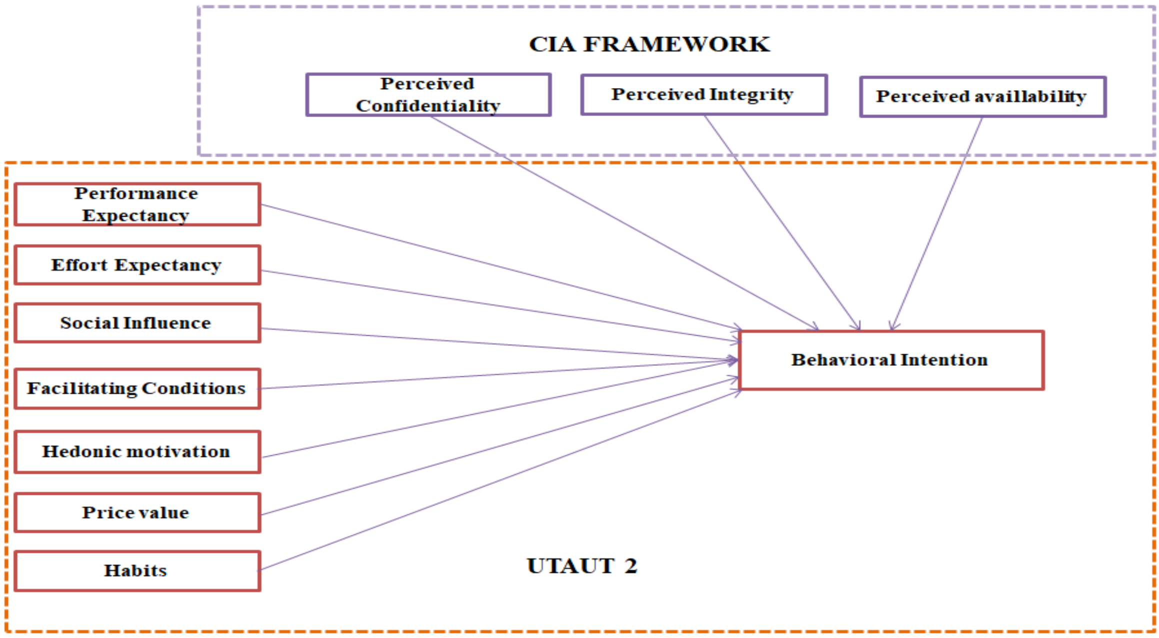
H9: PI will positively affect candidates' BI to use AI for TA.

3.2.3. Perceived Availability

Availability pertains to the perceived ease of access and implementation of the technology (Tsiakis & Sthephanides, 2005), (Salam & Ali, 2020) study confirmed a positive correlation between PA and BI to adopt AI. In the context of AI for recruitment, when candidates believe that AI recruitment tools are readily available, with clear pricing models and accessible integration options, they are more likely to consider adopting them. Thus,

H10: PA has a positive impact on the intention to use AI for job applications.

Figure 1: Research Model



Source: Author

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4. Conclusion

This conceptual study aims to develop a model that explains factors impacting candidates' BI towards AI for TA. The proposed research model provides a comprehensive framework for analyzing talent's acceptance to be involved in a recruitment process that deploys AI.

This framework suggests that factors such as PE, EE, SI, FC, HM, HAB, PC, PI and PA all have a significant impact in determining candidates' BI towards the technology of interest. The integration of the UTAUT model and the CIA framework can enable us to address privacy and security issues.

This study serves as a reference for future research. This model could also be used to investigate recruiters' BI towards this technology. It is essential to empirically test the proposed framework with real data to validate its effectiveness in predicting candidates' BI towards AI in TA.

An empirical validation of this model can have implications that extend to both organizations and technology developers in the field of AI- based TA. For organizations, understanding how the targeted talent market perceives the use of AI can help them in their decision-making on adopting and communicating the use of this new technology.

For technology developers, understanding the factors that influence candidate behavior can help in designing AI-powered recruitment tools that prioritize a positive candidate experience. This includes features that mitigate potential bias in algorithms, promote trust and transparency, and ultimately encourage candidates to engage with AI throughout the hiring process.

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