Adoption of AI in Talent Acquisition: A Quantitative Study on HRM Practitioners Using the Technology Acceptance Model (TAM)

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Abstract

Using the Technology Acceptance Model (TAM) this study analyzed the adoption of Artificial Intelligence (AI) technologies for talent acquisition processes among Egyptian startups. The research deployed quantitative methods to gather data from 320 HR professionals throughout Egyptian startups. The study evaluated how respondents' perceived usefulness of AI (PU) and perceived ease of use (PEOU) led to attitudes towards the use (ATU) of AI tools which then shaped behavioral intention to use AI (BIU) in recruitment processes. The research analyzed how Perceived Risk functioned as a moderator in the relationship between Perceived Usefulness and Attitude Towards Use while studying how Organizational Culture moderates the link between Perceived Ease of Use and Attitude Towards Use. The research applied Structural Equation Modeling (SEM) using Partial Least Squares (PLS) to carry out data analysis. Studying the relationships indicated that PEOU shows strong impacts on both ATU and PU with PU exerting no direct influence on ATU. Results showed that PR reduced the PU-ATU relationship through a negative moderation while OC enhanced the connection between PEOU and ATU through positive moderation. ATU strongly predicted BIU. Research outcomes advance the comprehension of AI adoption patterns in emerging markets while offering tactical information for startups that want to execute AI solutions for talent acquisition workflows. The study emphasizes three key components to improve talent acquisition with AI by enhancing user interface systems and building innovative company cultures with varied HR feedback mechanisms to reduce risks during implementation.

Keywords: *Artificial Intelligence (AI) Talent Acquisition, Egypt Startup Ecosystem, Technology Acceptance Model (TAM), Perceived Risk (PR), Organizational Culture (OC).*

1. Introduction

The development of AI at such a pace has accelerated the pace at which the technological implementation is taking place at such a rapid pace in different sectors, such as Human Resource Management. Perhaps one of the most affected of all the sub-areas of HRM in light of AI-powered tools and systems, there is some potential for the application of AI to talent acquisition for further efficiency, reduced bias, and strengthened candidate job fit (Vardarlier and Zafer, 2020; van Esch et al., 2019). Although these benefits exist, the rate of adoption is extremely variable across organizational and geographic contexts about the adoption of AI technologies. Considering its emergent startup ecosystem, which is very much emergent, Egypt represents one of the best contexts in which to study the adoption of AI in HRM, particularly in talent acquisition. Although quite young, with a relatively tech-savvy population, Egypt has become one of the most active startup ecosystems in the MENA region, accompanied by growing governmental and private sector support for entrepreneurship (Startup Blink, 2023). In Africa, Egypt led the top three countries (more than 500 startups, 176% investment growth in 2022) in both the number of startups and total amount of venture capital funding (Disrupt Africa, 2022). It was home to notable startups such as Swvl, Fawry, and MaxAB, which have raised high investments, and others such as Vezeeta, which innovated in the health tech, fintech, and e-commerce domains. In an industry where startups are widely acclaimed for their agility and innovation, they are usually the first movers in the adoption of evolving technologies such as AI (Ghobakhloo & Tang, 2013). Nonetheless, the Egyptian context might be different, considering its own distinctive cultural, economic, and technological environment, which, in turn, might affect the way AI will be adopted and routed in the framework of human resource management practices, particularly in talent acquisition (ElKassas et al. 2021). The Technology Acceptance Model (TAM) proposed by Davis (1989) was adapted to this study to investigate AI adoption by Egyptian start-up companies. The current study seeks to explore the level of AI diffusion in talent acquisition, the determinants that drive the acceptance and use of AI by HRM practitioners, and the moderating roles of perceived risk and organizational culture. Nevertheless, it suggests, based on evidence, ways in which AI can be effectively embedded within HRM practices in Egypt's flourishing startup industry.

1.1 Research Objectives

1. Evaluate the reality of AI adoption in talent acquisition by the Egyptian startup community.
2. Investigate the main determinants of acceptance and usage of AI in talent acquisition by HRM practitioners in Egyptian start-ups.
3. Examine the moderating role of perceived risk and organizational culture on AI adoption in talent acquisition.
4. Provide data-driven recommendations on how AI can be better integrated into HRM practices with specific implications for Egypt's startup ecosystem.

As a result, this researcher presents empirical evidence of how best AI can be adopted in Egypt's unique dynamic startup landscape when it comes to talent acquisition.

1.2 Research Gap

Although evidence on AI adoption in HRM is growing slowly, particularly in developed economies, very limited research has dealt with the use of AI in talent acquisition for startups in emerging markets (Black & van Esch, 2020; Tambe et al., 2019). Most of the literature is available on the possibility of the application of AI in the recruitment life cycle, especially regarding efficiency, less bias, and better decision-making (Upadhyay & Khandelwal, 2018; van Esch et al., 2019). Although the technological framework for adopting AI and its cultural readiness are high, most research has been conducted in developed countries. However, there is a noticeable understanding of how AI diffusion takes place within the talent acquisition process of startups in emerging economies, particularly in the MENA region. Hence, Egypt provides an interesting and underexplored background for the investigation of AI adoption, given that it is one of the largest economies in MENA and its start-up community is growing rapidly (Ismail, 2016). In general, Egyptian startups are agile and innovative (Ghobakhloo and Tang, 2013). However, their socioeconomic context is surprisingly different from that of the socioeconomic context studied in the AI adoption domain. Organizational culture, economic constraints, and the regulatory environment in Egypt determine the extent to which AI is used in HRM practices (El-Kassas et al., 2021).

Businesses across different sectors accept the TAM model as a common method to explore technology adoption patterns while HRM research into AI implementation experiences limited use of this approach. Studies using Technology Acceptance Model (TAM) for HR technologies generally focus on traditional HRIS systems and e-HRM solutions (Voermans & van Veldhoven 2007; Yoon & Kim 2007; Poba-Nzaou et al. 2016). AI recruitment technology analysis using TAM models shows limited presence with research concentrating on startups from developing markets including Egypt lacking visibility.

Existing studies demonstrate barriers to AI use and organizational culture as vital adoption factors yet show that they continue to receive inadequate attention in modern theoretical frameworks (Venkatesh & 2008). Despite the Egyptian cultural and economic environment impacting AI implementation by startups these factors require deeper examination from academic studies.

This study creates an improved TAM framework for studying AI deployment in Egyptian startup talent acquisition procedures while filling gaps identified in existing research. Through examining both unusual conditions and organizational culture along with perceived risk factors researchers want to advance their knowledge about delegating HRM AI deployment functions in emerging markets. The research extends the technology acceptance theory and supplies practical recommendations to help Egyptian entrepreneurs integrate AI technologies in their developing ecosystems. This study expands the theory of technology acceptance and provides practical insights on how to facilitate AI integration within Egyptian startups in their growing ecosystem.

The research gap is articulated by:

1. Identifying the geographical and contextual gap (the scarcity of studies in Egypt and the MENA region).
2. Demonstrating the unclear applicability of TAM in AI in HRM, more specifically within startups.
3. Highlighting the important need to explore moderating factors such as perceived risk and organizational culture.
4. The study positions itself as a contribution to theoretical knowledge and to practical application in emerging economies. Positioning the study as a contribution to both theoretical knowledge and practical application in emerging economies.

2. Literature Review

2.1 AI in Talent Acquisition

AI as a force for transformation in the field of HRM is showing up more and more especially in talent acquisition. The use of AI applications within the recruitment processes can solve several traditional challenges and promises to increase efficiency, decrease bias, and fit candidates better (van Esch and Ireland, 2019; Vardarlier and Zafer, 2020). The mechanisms by which AI is used include screening of curricula vitae, matching, and chatbots that could take preliminary interviews and predictive analytics to gauge candidate fit (Upadhyay & Khandelwal, 2018).

The advantages of adopting AI in recruitment are overwhelming: AI is said to decrease the time to hire an employee, improve the quality of hired employees, and reduce human biases in conducting the selection procedure (Van Esch et al., 2019) An example is the report by Ideal in 2018; a report that shows that AI can bring down the cost per screen by 75 percent, the time to hire by 71 percent, as well as the increase in recruiter productivity by 3.7x. This is also beside the fact that AI-based recruitment tools can process large volumes of data at speed and would offer one the ability to dynamically provide better decisions throughout the hiring process (Tambe et al., 2019).

However, not all challenges are bereft of AI's adoption for talent acquisition. While practitioners were quick to raise their concerns about data privacy, and algorithmic bias (Tambe et al., 2019; Black & van Esch, 2020) it took researchers longer to express similar concerns. As some AI algorithms turn out to be a black box, there is increasing concern about whether those hiring decisions can be explained to applicants; however, applying such explanations could open legal and ethical questions about fairness and accountability (Raub, 2018).

2.2 Adoption of AI in Emerging Economies and Start-ups

Although significant research on AI use in HRM has been conducted in developed economies, there is a big gap in research on AI adoption in EMs, particularly in the MENA region. Another special case in studying AI adoption in HMR practice is Egypt which is one of the biggest economies in the MENA region with one of the fastest-growing startup domains (Ismail et al., 2018). By nature, startups are innovation-driven and agile and have often been the early adopters of new technologies, like AI or any other thing that could increase productivity, as Ghobakhloo & Tang (2013) point out.

However, they have distinct challenges in technology adoption with limited resources, a scarcity of domain expertise, and the tightrope walk between innovation and system stability (Nambisan, 2017). Numerous studies have been conducted in Egypt and other notions to study the adoption of technology in various industries (for example, Kamel & Hussein, (2002), Akinfieva & Oppong, R. 2018). However, research greatly lacks focus on Egyptian startups which utilize AI technologies for the recruitment of new employees. In Egyptian startups utilization of AI for HRM depends heavily on one distinct cultural-economic-technology setting (El-Kassas et al., 2021).

2.3 Technology Acceptance Model (TAM) in the HRM Context

One of the most used models to explain and predict user acceptance of new technologies has been the Technology Acceptance Model (TAM) proposed by Davis (1989). Application of this theory in the HRM context into studies dealing with the issues of technology adoption has been undertaken in various cases. Yoon and Kim (2007) in their study of computer-based HRIS adoption in Korean organizations, used TAM.

Likewise, Voermans and van Veldhoven (2007) adopted the TAM to examine the e-HRM adoption in a large global company and found that the user-friendliness of e-HRM and its perceived use had an important role in the users' attitude towards using the e-HRM system. In their recent study, Poba-Nzaou et al. (2016) studied the adoption of e-HRM in SMEs, using an extended version of TAM. Another factor, viz., management commitment and organizational culture was introduced as these contextual factors beget technology adoption.

Nevertheless, no previous TAM has been specifically applied to analyze the adoption of AI for talent acquisition, and even more specifically to startups in nations characterized by their development. The existence of this literature gap offers an opportunity for this proposed study's contribution to the evolving knowledge regarding the theoretical basis of AI acceptance and especially the diffusion of AI into HRM practices in emerging economies.

3. Theoretical Background and Hypotheses Development

3.1 Technology Acceptance Model (TAM)

One of the most widely used frameworks to date in understanding user acceptance of new technologies is the Technology Acceptance Model by Davis (1989). According to TAM, technology acceptance is driven principally by two key factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). The two constructs form the basis for predicting technology adoption in workplace settings (Venkatesh & Davis, 2000).

Perceived Usefulness (PU): known as the extent to which a person believes that using an application system will increase his/her job performance (Davis, 1989). The nature of this construct involves how HR professionals view AI as a tool to improve recruitment processes, e.g., speed up applicant screening, enhance decision-making, and increase the matching of applicants to jobs (Tambe et al., 2019). van Esch et al. (2019) point out that AI's ability to reduce time-to-hire and improve the quality of hires makes PU a key driver of adoption. Perceived usefulness was found to be strongly positively related to attitude toward use. Contemporary research, however, found that perceived usefulness has 50 percent more impact than ease of use in its effect on usage and is therefore an important determinant of user attitudes and behavior (Davis 1993). Park et al. (2012) also found in similar settings that perceived usefulness had a stronger impact on attitude than perceived ease of use. The fact is most studies have shown that there exists a strong positive relationship between perceived usefulness and attitude toward use. In the TAM, the relationship between perceived usefulness and attitudes towards use is central, and there has always been evidence that perceived usefulness has a strong effect on users' attitudes to using the technology. The form and strength of this relationship, however, will depend on the technology and context of analysis that lead to the selection of technology. Based on these theoretical arguments and empirical evidence, the following hypothesis is proposed.

H1: Perceived Usefulness (PU) positively influences the Attitude Towards Use (ATU) of AI in talent acquisition.

Perceived Ease of Use (PEOU): This refers to the degree to which a person believes that using a system will be free from effort (Davis, 1989). This factor is crucial for AI adoption because if HR professionals find AI systems complicated or difficult to integrate into their existing workflows, they are less likely to adopt them (Vardarlier & Zafer, 2020). For instance, if HR practitioners in Egyptian startups perceive AI tools as too technical or requiring extensive training, their PEOU would be low, potentially hindering adoption. Consequently, perceived ease of use has always been positively related to attitude toward use across different technology acceptance contexts. There is a correlation between several studies. For in-vehicle GPS products, perceived ease of use has a positive, significant effect on attitude toward usage according to Chen and Chen (2010). Likewise, Kanchanatanee et al. (2014) found that perceived ease of use was one of the factors influencing attitudes toward the use of E-Marketing by small and medium business owners. Perceived ease of use had a significant influence on attitude within the context of e-learning, and this relationship was significant (Ratna and

Mehra, 2015). However, the strength of this relationship between speed and appearing live can be quite a bit dependent on technology and context. For example, Renny, et al., (2013) claimed that in the case of airline ticket reservations, perceived ease of use had a higher influence on attitudes towards usability than perceived usefulness. It is suggested that the relationship is normally positive, but its relative contribution is likely to vary across applications. Based on this background, the following hypothesis is proposed.

H2: Perceived Ease of Use (PEOU) positively influences attitude Towards Use (ATU) of AI in talent acquisition.

The perceived ease of use and perceived usefulness have been widely studied as subaspects of the Technology Acceptance Model (TAM) in multiple contexts. Several studies have reported a positive relationship between PEOU and PU. According to Karahanna and Straub (1999), the ease-of-use perceptions of a medium impact usefulness perceptions. Second, Ohk et al. (2015) further strengthened this relationship, since they found that PEOU and PU were positively related to consumer satisfaction with mobile applications. A meta-analysis of 26 empirical studies by Ma and Liu (2004) found that usefulness correlated somewhat strongly with ease of use. Some studies have found that PEOU is a more indirect technology acceptance factor because it affects PU. Ratna and Mehra (2015) found that perceived ease of use had a strong positive influence on perceived usefulness that in turn significantly mediated the relationship between perceived ease of use and attitude toward e-learning. Based on these arguments, the following hypothesis was structured:

H3: Perceived Ease of Use (PEOU) positively influences the Perceived Usefulness (PU) of AI in talent acquisition.

Attitude Towards Use (ATU) and Behavioral Intention to Use (BIU)

Central to technology acceptance research, attitude toward use has been conceptualized as a mediator of the effects of perceived usefulness, perceived ease of use, and behavioral intentions (Marikyan et al., 2023; Wixom & Todd, 2005). According to the Technology Acceptance Model (TAM), an individual's intention to use a technology is largely determined by their attitude toward using the technology (Sek et al., 2010). It has been consistently supported in virtually all contexts (mobile commerce; Chhonker et al., 2017; Chhonker et al., 2018; social networking sites, Weerasinghe & Hindagolla, 2018; emerging technologies, Wang et al., 2023; metaverse, Dhingra & Abhishek, 2024). Interestingly, attitude towards use, although very important for the adoption of technology, may not be of equal importance for different technologies and in different contexts. For example, in the fintech adoption case, trust, financial literacy, and safety are noteworthy determinants, in addition to conventional TAM constructs (Firmansyah et al., 2022). Moreover, integrating the user satisfaction literature in technology acceptance research has shown the difference between object attitude (towards the system) and behavioral attitude (towards using the system) in clarifying the impact of attitude on technology adoption (Wixom & Todd, 2005). However, they are evolving and adapting existing models to accommodate the intricacies of user attitudes and behaviors as technology continues to grow, and new applications appear. The theoretical refinement occurring through the ongoing application of advanced analytical techniques such as computational literature reviews (Mortenson & Vidgen, 2016) will continue to reveal new insights into the position of attitudes toward technology acceptance across different areas and user groups. Thus, the following hypothesis is developed:

H4: Attitude Towards Use (ATU) positively influences Behavioral Intention to Use (BIU) of AI in talent acquisition.

3.2 Perceived Risk in AI Adoption (Moderator)

Although TAM provides a sound foundation for many studies, with the increasing adoption of AI and related key concerns of users regarding privacy, algorithmic bias, and job displacement, there is a crucial need to examine the role of Perceived Risk (PR) in moderating AI system adoption (Tambe et al., 2019; Raub 2018). Thus, PR may mean potential loss or negative outcomes resulting from using a particular technology (Featherman & Pavlou, 2003). Practitioners using AI for human resource recruitment may worry that algorithms will make biased or nontransparent decisions with consequential ethical and legal risks. These risks can attenuate the potentially positive effects of Perceived Usefulness (PU) on Attitude Towards Use (ATU). Even when AI is perceived to be useful, high levels of perceived risk obscure enthusiasm for its adoption. Thus, the following hypothesis is proposed:

H5: Perceived Risk (PR) moderates the relationship between Perceived Usefulness (PU) and Attitude Towards Use (ATU) of AI in talent acquisition.

3.3 Organizational Culture in Startup Context (Moderator)

Technology adoption in startups is influenced by the organizational culture (OC). Most startups consist of a culture of innovation, flexibility, and risk-taking (Ghobakhloo & Tang, 2013). Employees will perceive AI positively because of such cultural traits and develop a more open attitude toward adopting them. Faster adoption of new technologies by organizations comes from innovative cultures, whereby employees in such environments allow themselves to be receptive to experiments and change (Dasgupta & Gupta, 2019). Therefore, organizational culture may moderate the relationship between Perceived Ease of Use (PEOU) and attitudes Towards Use (ATU). Thus, the following hypothesis is proposed:

H6: Organizational Culture (OC) moderates the relationship between Perceived Ease of Use (PEOU) and Attitude Towards Use (ATU) of AI in talent acquisition.

Figure 1: Proposed TAM-based model (Davis, 1989) with the moderation effects of Perceived Risk (PR), and Organizational Culture (OC)

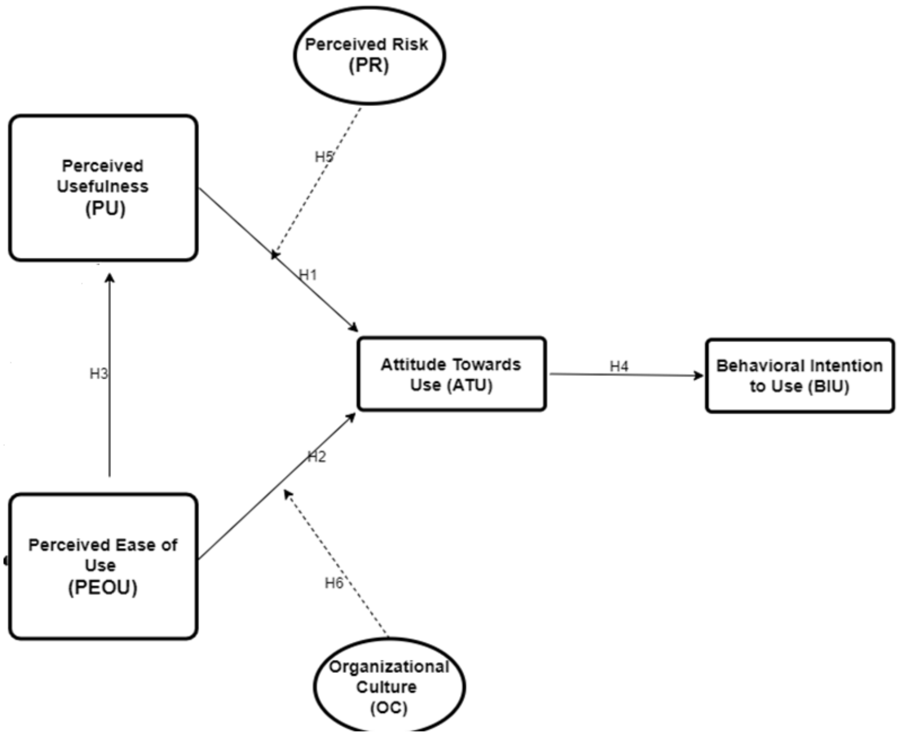

Figure 1. The Hypothesized Model

4. Methodology

4.1 Research Design

This study used a quantitative research design that explores the factors prompting the adoption of AI in talent acquisition in Egypt's startup ecosystem. The research is grounded in the Technology Acceptance Model (TAM) (Davis, 1989), which proposes that two main determinant factors, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), determine users' acceptance of the technology. To better understand AI adoption in Talent Acquisition, additional constructs–Perceived Risk (PR) and Organizational Culture (OC)–are integrated. The data collection for this cross-sectional study was conducted at a particular point in time, and its methodology was a survey.

4.2. Population and Sample

The research focused on HR employees and talent acquisition staff at Egyptian startups that currently use or intend to implement AI recruiting processes. A total of 320 participants entered the study sample after selection by a basic random sampling approach. Researchers selected this sample size so it would accurately reflect HR professionals from startups while meeting the minimum sample size of 200 for structural equation modeling (SEM) analysis as needed for robust statistical outcomes (Hair et al., 2010).

4.3 Measures

The data collection instrument was a structured questionnaire consisting of 5-point Likert scale items. The scale ranged from Strongly Disagree (1) to Strongly Agree (5). The survey items were adapted from established instruments to ensure the content validity. A pilot test was conducted with 30 participants to refine the questions before they were fully deployed. The constructs measured included the following:

Perceived Usefulness (PU) was based on a 3-item scale developed byDavis (1989). An example item for this construct included "Using AI in talent acquisition would improve my job performance"

Perceived Ease of Use (PEOU) was based on a 3-item scale developed by (Davis, 1989), An Example item is "Learning to use AI for talent acquisition would be easy for me"

Attitude Towards Use (ATU) was based on a 3-item scale adopted by (Taylor and Todd (1995). An Example item is "Learning to use AI for talent acquisition would be easy for me."

Behavioral Intention to Use (BIU) was based on a 3-item scale developed by (Venkatesh et al., 2003), An Example item is “I predict I would use AI in recruitment processes in the next 6 months”.

Perceived Risk (PR) was based on a 3-item scale adopted from Featherman and Pavlou (2003); An Example item is “Using AI in talent acquisition would involve more risk than traditional methods.”

Organizational Culture (OC) was based on a 4-item scale adopted from (Dasgupta & Gupta, 2019; Cameron & Quinn, 2011), An Example item is “My organization values innovation and new ideas”.

4.4 Data Collection

Through Google Forms all HR employees from Egyptian startups received the survey during the distribution process. The research ensured confidentiality and anonymity throughout while acquiring informed consent from every respondent. The study measured responses for nine weeks and used participant reminders to obtain as many responses as possible.

5. Data Analysis

Data analysis was implemented through Structural Equation Modeling (SEM) which used Partial Least Squares (PLS). Because SEM can analyze hidden connections between variables and simultaneously estimate both measurement and structural models it stands as the ideal method. This analysis utilized Smart-PLS software because it works well with datasets of moderate size while evaluating both moderation and mediation effects.

The analytical data examination proceeded through these specific actions.

- Reliability analysis: The internal consistency among the constructs achieved measurement through Cronbach's alpha statistical method (Cronbach, 1951). The required threshold for an alpha level acceptable in internal consistency analysis was 0.50.
- Confirmatory Factor Analysis (CFA): The research tested the validity structure by evaluating convergent and discriminant aspects. Convergent validity assessment employed the Average Variance Extracted (AVE) method and applied a cut-off point of 0.50 according to Fornell and Larcker (1981).
- Structural Model Testing: Research determined the strength of correlation between factors by calculating path coefficients and analyzing t values. Our path significance testing applied the bootstrap method by generating 5000 subsamples (Chin, 1998).

5.1 Confirmatory Factor Analysis (CFA) (Measurement Model)

Two types of validity are used for assessing the model's measurements: convergent validity (CV) and discriminant validity (DV).

5.1.1 Convergent Validity

The convergent validity of the measurements model was evaluated by analyzing three criterions; (1) factors loadings, (2) average variance extracted (AVE), and (3) composite reliability (CR) Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Tehseen, Sajilan, Gadar, & Thurasamy, 2017) Three criteria are found in the literature for acceptable loadings of >0.5, 0.6, or 0.7. However, methodologists currently recommend the last criterion (> 0.7) (Hair, Hult, Ringle, & Sarstedt, 2017) Hence, the item loadings for this model were above 0.7, except for one item related to IWE with a measure of 0.69. In addition, the composite reliability (CR) for every dimension was more than the threshold of 0.7, and the AVE for each variable was greater than 0.5, as suggested in the literature (Table 5.1).

Table 5.1: Assessment of Construct Convergent Validity

No	Items	Factor Loadings > 0.60	Cronbach's Alpha > 0.5	VIF > 3	Composite Reliability (CR) > 0.7	Average Variance Extracted (AVE) > 0.5
1	ATU1	0.765	0.60	1.206	0.773	0.532
2	ATU2	0.743		1.168		
3	ATU3	0.677		1.123		
4	BIU1	0.732	0.60	1.187	0.787	0.553
5	BIU2	0.773		1.213		
6	BIU3	0.724		1.187		
7	OC1	0.688	0.66	1.257	0.799	0.50
8	OC2	0.75		1.304		
9	OC3	0.671		1.18		
10	OC4	0.712		1.298		
11	PEOU1	0.787	0.64	1.29	0.805	0.58
12	PEOU2	0.806		1.346		
13	PEOU3	0.686		1.178		
14	PR1	0.731	0.56	1.158	0.771	0.528
15	PR2	0.746		1.146		
16	PR3	0.703		1.157		
17	PU1	0.725	0.57	1.139	0.775	0.534
18	PU2	0.694		1.163		
19	PU3	0.773		1.204		

Table (5.1) shows the first part of CFA, which is an assessment of convergent validity by measuring factor loadings (outer loading), Cronbach's alpha, variance inflation factor (VIF), composite reliability (CR), and average variance extracted (AVE). Furthermore, all items met the criteria for factor loading > 0.60, Cronbach's alpha > 0.50, VIF < 3, CR > 0.70, and AVE > 0.5.

5.1.2 Discriminant Validity

Next, there are three criteria for assessing the discriminant validity (DV), namely by examining cross-loadings and the Fornell-Larcker criterion: First, to evaluate the items' cross-loadings scores, which can be described as the score of outer loadings for items of latent variable in one construct should be greater than the respective items' cross-loading of latent variable's cross-loading for another latent variable (Hair et al., 2017; Tehseen et al., 2017).

Table5.2: Cross Loadings

Items	ATU	BIU	OC	PEOU	PR	PU
ATU1	**0.765**	0.444	0.519	0.422	0.369	0.402
ATU2	**0.743**	0.417	0.488	0.394	0.442	0.43
ATU3	**0.677**	0.396	0.353	0.453	0.377	0.353
BIU1	0.417	**0.732**	0.534	0.452	0.479	0.436
BIU2	0.457	**0.773**	0.447	0.454	0.358	0.437
BIU3	0.406	**0.724**	0.461	0.422	0.472	0.448
OC1	0.407	0.434	**0.688**	0.417	0.515	0.456
OC2	0.493	0.426	**0.75**	0.49	0.477	0.433
OC3	0.45	0.473	**0.671**	0.46	0.459	0.519
OC4	0.407	0.494	**0.712**	0.453	0.504	0.497
PEOU1	0.472	0.418	0.446	**0.787**	0.456	0.441
PEOU2	0.502	0.53	0.527	**0.806**	0.434	0.451
PEOU3	0.331	0.411	0.513	**0.686**	0.377	0.409
PR1	0.397	0.402	0.5	0.424	**0.731**	0.489
PR2	0.422	0.438	0.514	0.429	**0.746**	0.443
PR3	0.362	0.432	0.489	0.357	**0.703**	0.388
PU1	0.402	0.351	0.434	0.459	0.441	**0.725**
PU2	0.376	0.467	0.483	0.362	0.468	**0.694**
PU3	0.411	0.484	0.558	0.424	0.429	**0.773**

Table 5.2 reflects that the outer loading of each indicator is greater than its respective latent variable than its cross-loading on another latent variable. Therefore, all the items met the rules set by scholars.

Table 5.3: Fornell and Larcker Criterion

Items	ATU	BIU	OC	PEOU	PR	PU
ATU	0.729					
BIU	0.575	0.743				
OC	0.626	0.645	0.706			
PEOU	0.578	0.596	0.646	0.762		
PR	0.543	0.583	0.69	0.557	0.727	
PU	0.543	0.592	0.673	0.57	0.607	0.731

Finally, to examine the DV, the Fornell-Larcker criterion was applied, wherein the square root of AVE for each latent variable was ranked higher than its correlation with another latent variable. In line with the stated criteria, we found that the square root of AVE for each latent variable was greater than its correlation with another latent variable. The results are presented in Table 5.3.

6. Hypotheses Testing

6.1 Structural Model Assessment

To get an appropriate result from the path modeling technique, bootstrapping for the path coefficient was run Specifically, to analyze the path coefficient (Hair et al., 2017), R^2 (Cohen, 1989) (Ramayah, Cheah, Chuah, Ting, & Memon, 2018), and Q^2 (Hair et al., 2017) (see table 6.1 and figure 2). The hypotheses of this study were tested. Table 6.1 shows that all hypotheses were supported because of the t-value > 1.96 and P<0.01.

Table 6.1: Results stemmed from Structural Modeling

Hypothesis	Relationship	Std. Beta	Std. Error	T-value	P-value	Decision
H1	PU -> ATU	0.116	0.079	1.475	0.07	Not Supported
H2	PEOU -> ATU	0.277	0.082	3.389	***	Supported
H3	PEOU -> PU	0.197	0.065	3.021	0.001	Supported
H4	ATU -> BIU	0.575	0.04	14.213	***	Supported
H5	Moderating Effect (1) PR on PU -> ATU	0.096	0.056	1.723	0.042	Supported
H6	Moderating Effect (2) OC on PEOU -> ATU	0.169	0.063	2.67	0.004	Supported

Note: ***p<0.005, **p<0.01, *P<0.05. Perceived Risk (PR), Perceived Usefulness (PU), PEOU (Perceived Ease of Use (PEOU), Organizational Culture (OC), ATU (attitude Towards Use), (Behavioral Intention to Use).

For this model, Table 6.1, and based on the above-mentioned evidence, the researcher found that all the hypotheses were supported except for hypothesis one was not supported. In more detail;

H1: PU positively influences ATU (β = 0.116, SE = 0.079, t = 1.475, p < 0.07), which is not supported because the t-value was less than the expected criterion and the p-value was less than 0.05. However, the following hypothesis is supported:

H2: PEOU positively influences ATU (β = 0.277, SE = 0.082, t = 3.389, p < 0.000); H3: PEOU positively influences PU (β = 0.197, SE = 0.065 t = 3.021, p < 0.001); H4: ATU positively influences BIU (β = 0.575, SE = 0.04 t = 14.213, p < 0.000); H5: PR negatively moderates the relationship between PU and ATU (β = 0.096, SE = 0.056 t = 1.723, p < 0.042); H6: OC) positively moderates the relationship between PEOU and ATU (β = 0.169, SE = 0.063 t = 2.67, p < 0.004).

6.2 Statistical Model

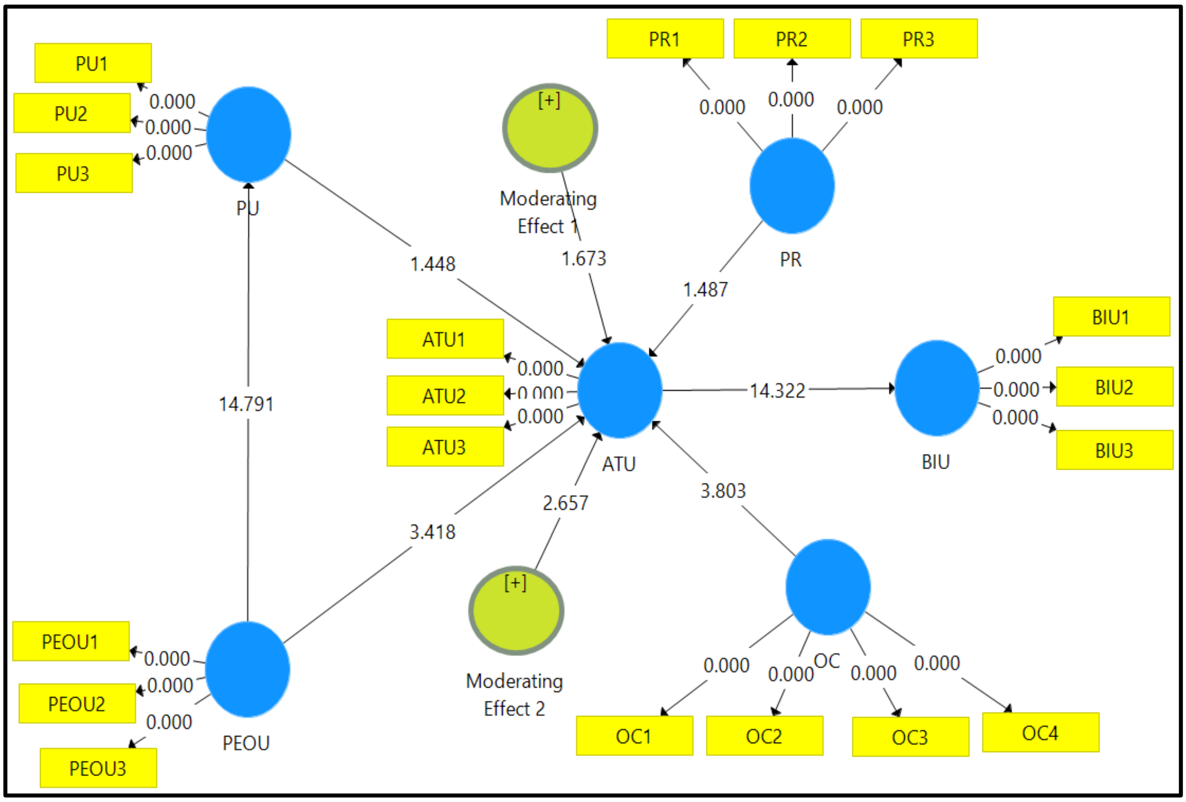

Figure 2: The Statistical Model of Study (Smart-PLS 3.2.9)

Figure 2 shows the statistical model that reveals all the results of this study, which includes eight direct relationship hypotheses and two moderating hypotheses. All hypotheses were accepted except hypothesis number one due to achieving fewer results that are below the criterion of t-value and p-value; for more details, see (Table 6.1).

7. Discussion and conclusion

This investigation into AI recruitment methods at Egyptian startups provides broader knowledge about digital solutions acceptance together with artificial intelligence applications in emerging market economies. Researchers simultaneously validate parts of existing technology acceptance frameworks while identifying fresh distinctions through their analysis which thereby augments understanding of AI implementation by startups in Egypt. When studying talent acquisition systems AI shows that Perceived Ease of Use (PEOU) acts as an essential predictor for Attitude Towards Use (ATU) while Perceived Usefulness (PU) demonstrates no significant statistical influence on ATU. According to Davis's Technology Acceptance Model from 1989 user attitudes depend upon Perceived Ease of Use and Perceived Usefulness but these findings diverge from traditional TAM framework requirements. The lack of a significant relationship between PU and ATU in this context may be attributed to several factors specific to the Egyptian startup ecosystem: 1. Limited exposure and understanding: Egyptian start-up HR professionals show inadequate interaction with sophisticated AI recruitment tools which leads them to question their usefulness. In their specific professional areas' organizations discount AI usefulness because setbacks exist without clear empirical proof of its benefits. 2. Resource constraints: Most startup enterprises operating in developing economies face operational challenges because resources remain scarce. Building confidence in AI tools becomes difficult when users examine their budgetary implications and needed resource allocation. 3. Cultural factors: Egyptian organizations continue to base their recruitment success criteria on personal connections and established hiring practices causing them to underestimate the merit of AI-prescribed recruitment platforms.

Research results show that Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) maintain a strong connection during AI incorporation into human resource practices at Egyptian budding businesses. Several factors: 1. Positive correlation: Data shows that better Perceived Ease of Use generates higher Perceived Usefulness in the eyes of HR professionals according to

Venkatesh and Bala (2008). The study demonstrates why organizations need to implement user-friendly AI interfaces alongside complete training regimens to both strengthen staff perceptions of usability and boost functional appreciation of AI recruitment tools. Examination outcomes demonstrate that the relationship between ATU and BIU follows strongly positive interactions validly supported through classical technology acceptance frameworks as presented by Ajzen in 1991. HR professionals need positive attitudes about AI in their work because these perspectives determine successful AI integration within talent acquisition systems.

Start-up data research from Egypt reveals the essential factors driving AI adoption for staffing decisions. The research confirms that when users perceive higher risk it weakens the connection between their assessment of AI usefulness and positive attitude formation. Organizational Culture strongly benefits the relationship between users' perceived ease of use and their resulting attitude Towards use. To determine their influence, Operational Culture served as a variable in the analyses relevant to Perceived Risk which measured a value of 1. Negative moderation: High Perceived Risk (PR) disrupts how AI tools function by weakening the relationship between Perceived Usefulness (PU) and Attitude Towards Use (ATU). 2. Specific impacts on AI adoption: When AI systems hold personal information they present significant threats against user privacy security. Algorithmic bias: Machine learning recruitment systems repeatedly embody previous employment prejudices and establish consistent patterns which shape human resources results. Job displacement fears: The rise in AI poses potential threats to HR jobs. 3. Contextual factors: Egypt needs improved assessment mechanisms to deal with emerging market conditions because of its weak regulatory systems. - Startup environment: Scarce resources generate concerns in companies that plan to make investments in artificial intelligence technology. Organizations hoping to implement AI for hiring must solve data privacy protection problems together with concerns about algorithmic discrimination and workflow disruptions (Raub, 2018; Tambe et al., 2019). Despite recognizing AI instruments deliver positive outcomes companies block implementation processes due to perceived risk factors. For enterprises to overcome potential doubts they need to cultivate transparent AI systems while communicating their protective strategies.

Organizational Culture: 1. Positive moderation: Automated Task Units show increased robustness in User-friendly Systems when they function in Organization Cultures that emphasize innovation. 2. Specific impacts on AI adoption: Entrepreneurial organizations which incorporate technological advancements within their operational structures gain enhanced acceptance as they implement artificial intelligence. Risk tolerance: Together with innovative organizational changes pioneer enterprises consciously decide to proceed with riskier AI system implementation. Learning orientation: The integration process of artificial intelligence systems achieves higher efficiency when organizations maintain knowledge acquisition as their top priority. 3. Contextual factors: By embodying entrepreneurial principles startups build organizational environments that improve their AI implementation processes. Generational factors: Younger generation HR professionals demonstrate better acceptance of practices related to artificial intelligence deployment. Startups achieve higher acceptance levels in recruiting artificial intelligence systems through their innovative cultural frameworks combined with technological transparency according to Cameron & Quinn 2011). These research results demonstrate the critical elements for successful AI technology implementation by startups through establishing innovative organizational cultures.

The research identified modulation factors for AI integration by expanding the TAM framework to examine the effects of organizational culture and perceived risk. The outcomes indicate necessary user issue corrections along with technological advancement and learning emphasis in organizations while managing privacy concerns and biased restrictions during resource limitations.

7.1 Theoretical and Practical Implications

This study expands the Technology Acceptance Model (TAM) by introducing perceived risk and organizational culture as moderating variables in the adoption of AI in the talent acquisition process. This study expands the existing knowledge on technology acceptance by introducing TAM to the context of an emerging market and provides a foundation for future TAM research in this context. Moving further practically, the results suggest actionable recommendations for startups interested in implementing AI in their recruitment processes: they should allow for a smoothly user–friendly system that demonstrates value, provides risk mitigation solutions, and supports the development of an innovation-friendly culture within their organization.

7.2 Recommendations

Considering boosting AI implementation in talent acquisition within Egypt's startup landscape, some practical suggestions are proposed: 1. Focus on user-friendly AI systems: Research suggests HR professionals show a preference for AI systems that feature clean navigation because they understand that their ease of system understanding (PEOU) powers their decision to use these systems (ATU). PEOU developers must construct intuitive user interfaces first before launching comprehensive training programs to assist users. 2. Demonstrate tangible benefits: Perceived Usefulness impacts system adoption through its influence on Perceived Ease of Use not direct control over Attitude Towards Use. Departments of Human Resources need to demonstrate AI recruitment benefits by evidencing faster hiring timelines and improved candidate matches which also eliminate racial and gender biases during job selection. 3. Address perceived risks: Executive responses target threats demonstrated by the negative moderating presence of Perceived Risk (PR) triggered by data privacy concerns as well as algorithmic biases and workforce displacement issues. IT systems must operate transparently while clear communications must come from well-defined risk mitigation actions to stakeholders. 4. Foster an innovation-friendly culture: The positive moderating influence of Organizational Culture explains why workplaces need to transform into settings where technological innovation takes center stage. The leadership at any organization needs to create an organizational culture that embraces both continuous learning and acceptance of technological changes. 5. Provide ongoing support: The success of HR implementations requires professionals to receive continuous technical help along with troubleshooting support to overcome obstacles. Through this practice, organizations maintain a positive approach when adopting artificial intelligence procedures. 6. Measure and communicate AI performance: Organizations need to develop assessment standards that examine both the economic value generated and the performance quality of AI recruiting systems. The performance results of AI tools provide measurable data that reveals their value creation. 7. Tailor implementation strategies: Successful implementation of AI adoption requires customizable strategies to fit Egyptian startup ecosystems. Creating your implementation plan requires addressing local cultural elements and existing resource constraints together with regulatory restrictions. 8. Encourage knowledge sharing: HR professionals across startups should connect for mutual knowledge exchange while grasping successful AI adoption methods and beneficial best practices.9. Gradual implementation: By launching an AI recruitment system for initial functions companies can establish user trust before using AI in advanced organizational tasks. The provided structured recommendations allow Egyptian startups to advance their talent acquisition by adopting AI functional advantages together with reducing implementation barriers.

7.3 Limitations and Directions for Future Studies

The results of this research on AI adoption in talent acquisition for startups in the Egyptian ecosystem are important, although it comes with several constraints. Owing to cultural, economic, and technological differences, it is unclear whether the results of this study apply to other emerging markets or more developed economies. Cross-sectional research provides data at a snapshot in time and does not allow the observation of changes in attitudes and behaviors over time, which is useful for explaining technology acceptance trajectories. The scope of this study is limited to AI in talent acquisition, thereby limiting the learning of the broader implications of the integration of AI on other HR functions, such as performance management or employee engagement. Without demographic data (such as age, gender, or level of education), this potential for deeper insight into AI adoption attitudes across different groups is lacking. Other factors such as organizational readiness, technological infrastructure, and market competition were not examined as potential moderators, but PR and OC were included as moderating variables.

Although beyond the scope of this study, future research might investigate contextual factors that influence the relationship between perceived usefulness (PU) and attitude toward use (ATU), such as the interaction of perceived risk, organizational culture, and the amount of practical exposure to AI. A deep understanding of why perceived usefulness is undervalued compared to other factors could be achieved using qualitative methods. Additionally, human resource management AI adoption in emerging markets can be informed by comparative studies across emerging markets where cultures and economic factors are considered.

References

- Ajzen, I. (1991). Theory of planned behavior. *Organizational Behavior and Human Decision Processes*.
- Akinfieva, Y. V., & Oppong, R. (2018). E-Commerce in Modern World-Electronic Transactions and Some Challenges and Perspectives: Comparative Analysis of the UK, Egypt, and South African Legislation.".
- Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is this and how should a manager use it? *Business Horizons, 63*(2), 215-226.
- Cameron, K. S., & Quinn, R. E. (2011). *Diagnosing and changing organizational culture: Based on the competing values framework*. John Wiley & Sons.
- Chen, C.-F., & Chen, P.-C. (2010). Applying the TAM to travelers' usage intentions of GPS devices. *Expert Systems with Applications*, *38*(5), 6217–6221.
- Chhonker, M. S., Verma, D., & Kar, A. K. (2017). Review of Technology Adoption frameworks in Mobile Commerce. *Procedia Computer Science*, *122*, 888–895.
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research*, 295(2), 295-336.
- Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297-334.
- Dasgupta, P., & Gupta, R. K. (2019). Organizational culture and technology adoption: Understanding contextual influences on technology adoption in emerging economies. *Technology in Society, 59*, 101197.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.
- Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies*, *38*(3), 475–487.
- Dhingra, S., & Abhishek, A. (2024). Metaverse adoption: a systematic literature review and roadmap for future research. *Global Knowledge, Memory and Communication*.
- *Disrupt Africa*. (2022). Startup funding report.

- El-Kassas, S., Aly, A. M., & Masoud, R. (2021). Artificial intelligence applications in Egypt: An emerging economy's perspective. *Journal of Innovation Management in Small & Medium Enterprises, 2021*, 1-14.
- El-Kassas, S., Al-Zawawy, A., & Osman, H. (2021). AI-powered recruitment in emerging markets: Challenges and opportunities in Egypt. *Journal of Organizational Studies and Innovation*, 8(1), 45-57.
- El-Kassas, S., Ismail, M., & El-Gharbawy, N. (2021). AI in recruitment: The Egyptian startup context. *Journal of HRM in Emerging Economies*, *7*(2), 99-117.
- F. Hair Jr, J., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM) An emerging tool in business research. *European business review*, *26*(2), 106-121.
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451-474.
- Firmansyah, E. A., Anshari, M., Masri, M., & Besar, M. H. A. (2022). Factors Affecting Fintech Adoption: A Systematic Literature Review. *FinTech*, *2*(1), 21–33.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.
- Ghobakhloo, M., & Tang, S. H. (2013). IT adoption in Malaysian SMEs: An application of the TOE framework. *Journal of Enterprise Information Management*, *26*(3), 45-59.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson Prentice Hall.
- Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, 26(2), 106-121.
- Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2011). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*(3), 414-433.

- Ismail, K. (2016). 9. the Egyptian Revolution: An Entrepreneurial Act? A personal Account. *Entrepreneurship and Innovation in Egypt*, 187.
- Ismail, M., El-Kassas, S., & Abdalla, M. (2018). AI adoption in Egyptian startups: A case study. *International Journal of Emerging Markets*, *14*(2), 300-315.
- Ismail, M., Tolba, A., & Abdou, M. (2018). Entrepreneurship and innovation in Egypt: Overview and the role of educational institutions. *Journal of Entrepreneurship Education, 21*(2), 1-12.
- Kamel, S., & Hussein, M. (2002). The status of e-commerce in Egypt. *Global E-commerce: Impacts of National Environment and Policy*, 31-57.
- Kanchanatanee, K., Jarernvongrayab, A., & Suwanno, N. (2014). Effects of Attitude toward Using, Perceived Usefulness, Perceived Ease of Use and Perceived Compatibility on Intention to Use E-Marketing. *Journal of Management Research*, *6*(3), 1. https://doi.org/10.5296/jmr.v6i3.5573
- Karahanna, E., & Straub, D. W. (1999). The psychological origins of perceived usefulness and ease-of-use. *Information & Management*, *35*(4), 237–250. https://doi.org/10.1016/s0378-7206(98)00096-2
- Ma, Q., & Liu, L. (2004). The Technology Acceptance Model. *Journal of Organizational and End User Computing*, *16*(1), 59–72.
- Machdar, N. M. (2019). The effect of information quality on perceived usefulness and perceived ease to use, *Business and Entrepreneurial Review*, *15*(2), 131–146.
- Marikyan, D., Stewart, G., & Papagiannidis, S. (2023). Technology acceptance research: Meta-analysis. *Journal of Information Science*.
- Mortenson, M. J., & Vidgen, R. (2016). A computational literature review of the technology acceptance model. *International Journal of Information Management*, *36*(6), 1248–1259.
- Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship theory and practice*, *41*(6), 1029-1055.
- Ohk, K., Park, S.-B., & Hong, J.-W. (2015, April 18). *The Influence of Perceived Usefulness, Perceived Ease of Use, Interactivity, and Ease of Navigation on Satisfaction in Mobile Application*.
- Park, E., Kim, K. J., Del Pobil, A. P., & Jin, D. (2012). *Towards a Successful Mobile Map Service: An Empirical Examination of*

Technology Acceptance Model (pp. 420–428). springer berlin heidelberg. https://doi.org/10.1007/978-3-642-30507-8_36

- Poba-Nzaou, P., Lemieux, N., Beaupré, D., & Uwizeyemungu, S. (2016). Critical success factors for e-HRM adoption in SMEs. *Personnel Review*, *45*(6), 1274-1301.
- Poba-Nzaou, P., Uwizeyemungu, S., & Raymond, L. (2016). Toward an integrative model of e-HRM adoption in SMEs: A multiple case study. *Information Systems Frontiers, 18*(5), 1031-1049.
- Quinn, R. E. (2011). *Diagnosing and changing organizational culture: Based on the competing values framework*. Jossey-Bass.
- Ratna, P. A., & Mehra, S. (2015). Exploring the acceptance for e-learning using technology acceptance model among university students in India. *International Journal of Process Management and Benchmarking*, *5*(2), 194.
- Raub, M. (2018). Bots, bias, and big data: Artificial intelligence, algorithmic bias and disparate impact liability in hiring practices. *Arkansas Law Review, 71*, 529-570.
- Renny, R., Guritno, S., & Siringoringo, H. (2013). Perceived Usefulness, Ease of Use, and Attitude Towards Online Shopping Usefulness Towards Online Airlines Ticket Purchase. *Procedia - Social and Behavioral Sciences*, *81*, 212–216.
- Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Cham: Springer International Publishing.
- Sek, Y.-W., Teoh, K.-K., Parumo, S. B., Lau, S.-H., & Law, C.-Y. (2010). Prediction of User Acceptance and Adoption of Smart Phone for Learning with Technology Acceptance Model. *Journal of Applied Sciences*, *10*(20), 2395–2402.
- StartupBlink. (2023). *Startup Ecosystem Rankings 2023: Measuring startup ecosystems in 100 countries and 1,000 cities worldwide*. StartupBlink. Retrieved from https://www.startupblink.com
- Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15-42.
- Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144-176.

- Tehseen, S., Sajilan, S., Gadar, K., & Ramayah, T. (2017). Assessing cultural orientation as a reflective-formative second order construct-a recent PLS-SEM approach. *Review of Integrative Business and Economics Research*, *6*(2), 38.
- Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. *Strategic HR Review, 17*(5), 255-258.
- van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. *Computers in Human Behavior*, 90, 215-222.
- Vardarlier, P., & Zafer, A. (2020). The impact of AI-based technologies on HR processes: A review. *Procedia Computer Science*, *171*, 2142-2149.
- Vardarlier, P., & Zafer, C. (2020). Artificial intelligence in HR processes: The case of talent acquisition. *Procedia Computer Science*, 158, 452-457.
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273-315.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.
- Voermans, M., & van Veldhoven, M. (2007). Attitude towards e-HRM: An empirical study at Philips. *Personnel Review, 36*(6), 887-902.
- Wang, N., Mutzner, N., & Blanchet, K. (2023). Societal acceptance of urban drones: A scoping literature review. *Technology in Society*, *75*, 102377.
- Wixom, B. H., & Todd, P. A. (2005). A Theoretical Integration of User Satisfaction and Technology Acceptance. *Information Systems Research*, *16*(1), 85–102. https://doi.org/10.1287/isre.1050.0042
- Yoon, C., & Kim, S. (2007). Convenience and TAM in a ubiquitous computing environment: The case of wireless LAN. *Electronic Commerce Research and Applications, 6*(1), 102-112.

اعتماد تقنيات الذكاء الاصطناعي في عمليات اكتساب المواهب: دراسة كمية على ممارسي إدارة الموارد البشرية بإستخدام نموذج قبول التكنولوجيا (TAM)

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المستخلص

هدفت الدراسة الحالية إلى تحليل مدى اعتماد تقنيات الذكاء الاصطناعي (AI) في عمليات اكتساب المواهب بين الشركات الناشئة في مصر، حيث استخدمت الأساليب الكمية لجمع البيانات من ٣٢٠ من ممارسى إدارة الموارد البشرية بالشركات الناشئة بمصر. قامت الدراسة بتقييم كيفية تأثير الفائدة المدركة (PU) وسهولة الإستخدام المدركة (PEOU) على المواقف تجاه استخدام أدوات الذكاء الاصطناعي(ATU) ، والتي شكلت بدورها النية السلوكية لاستخدام الذكاء الاصطناعي (BIU) في عمليات التوظيف. كما قامت الدراسة بتحليل دور المخاطر المدركة (PR) كمعدل في العلاقة بين الفائدة المدركة (PU) والمواقف تجاه الاستخدام(ATU) ، بالإضافة إلى دراسة كيفية تأثير الثقافة التنظيمية (OC)كمعدل في العلاقة بين سهولة الاستخدام المدركة (PEOU) والمواقف تجاه الاستخدام (ATU)، وقد تم تطبيق النمذجة بالمعادلات الهيكلية (SEM) بإستخدام المربعات الجزئية (PLS) لتحليل البيانات. أشارت نتائج الدراسة إلى أن سهولة الاستخدام المدركة (PEOU) أظهرت تأثيرات قوية على كل من الفائدة المدركة (PU) والمواقف تجاه الاستخدام(ATU) ، بينما لم تُظهر الفائدة المدركة تأثيرًا مباشرًا على المواقف تجاه الاستخدام(ATU) . كما أظهرت النتائج أن المخاطر المدركة تقلل العلاقة بين الفائدة المدركة والمواقف تجاه الاستخدام عبر تأثير معدل سلبي، في حين أن الثقافة التنظيمية عززت العلاقة بين سهولة الاستخدام المدركة والمواقف تجاه الاستخدام عبر تأثير معدل إيجابي. وأوضحت النتائج أن المواقف تجاه الاستخدام (ATU) تعد مؤشرًا قويًا للنية السلوكية لاستخدام الذكاء الاصطناعي.(BIU) .ساهمت نتائج الدراسة في فهم أنماط اعتماد الذكاء الاصطناعي في الأسواق الناشئة بمصر، مع تقديم مقترحات عملية للشركات الناشئة التي تسعى إلى تنفيذ حلول الذكاء الاصطناعي في سير عمل اكتساب المواهب. كما أكدت الدراسة على ثلاثة مكونات رئيسية لتحسين عمليات اكتساب المواهب باستخدام الذكاء الاصطناعي، وهي: تحسين أنظمة واجهات المستخدم، وبناء ثقافات تنظيمية مبتكرة، وإنشاء آليات متنوعة لتلقي ملاحظات الموارد البشرية لتقليل المخاطر أثناء التنفيذ.

الكلمات المفتاحية: الذكاء الإصطناعى (AI)، اكتساب المواهب، الشركات الناشئة في مصر، نموذج قبول التكنولوجيا(TAM) ، المخاطر المتصورة(PR) ، الثقافة التنظيمية.(OC)