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Strategic drivers of AI-based recruitment system adoption in organizations

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Abstract

This study explores the fundamental strategic drivers of organizations adopting AI-based recruitment systems. It introduces novel insights into the factors leading to AI adoption and use in HRM as AI technology continues to evolve. Employing an integrated framework consisting of the Technology-Organization-Environment (TOE) model and the Technology Acceptance Model (TAM), the research investigation outlines critical technological, organizational, and environmental factors influencing the intent to adopt. This quantitative research design used data obtained through a survey of HR and IT professionals from various industries. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the proposed model, we examined the strength and significance of the hypothesized relationships. The results show that technological readiness, top management support, perceived usefulness, and external pressure explain adoption intent. The takeaway from these findings is the strategic importance of collaborating innovation with organizational capacity and environmental factors. The study adds to the emerging knowledge on digital transformation within HRM. It gives practitioners and policymakers practical insights into using AI technologies to improve recruitment processes. The research emphasizes essential adoption enablers and enables informed decision-making and strategic planning regarding AI integration.

Keywords: AI-based recruitment system, intention to use, strategic drivers, TAM factors, TOE factors.

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1. Introduction

Artificial intelligence (AI) is advancing at an unprecedented rate in various fields, and human resource management (HRM) is no exception. Specifically, AI-powered recruitment solutions disrupt traditional recruitment and selection processes using advanced algorithms and machine learning for tasks such as resume screening, preliminary interviews, and candidate matching [1]. These systems utilize AI's immense data processing and analytical capabilities to analyze large amounts of candidate profiles and qualifications, making recruitment more efficient and accurate compared to traditional human methods. This promotes, in return, productivity at an organizational level, like cost-effectiveness with shorter hiring cycles and more efficient recruitment results from the use of AI recruitment systems [2].

However, their large-scale implementation is met with skepticism owing to privacy concerns, possible biases associated with algorithms, and the loss of human factors in recruitment [3]. There are also concerns that dependence on AI over time will lead to losing critical human abilities. While research on the acceptance of AI-based recruitment systems from organizational and individual perspectives is important to go forward with this, empirical work on these areas in academia remains scarce, especially in non-Western contexts. Though most studies have mainly focused on algorithmic biases and ethical implications, fewer have explored the socio-cultural and organizational drivers shaping technology adoption choices [4]. To do so, this research investigates the main determinants of intention to use AI-based recruitment systems by combining the Technology Organization Environment (TOE) framework and the Technology Acceptance Model (TAM). The TOE (Technology, Organization, and Environment) framework [5]. It incorporates the technological, organizational, and environmental contexts of technology adoption. TAM (Technology Acceptance Model) identifies the perception of usefulness and ease of use as the principal determinants of acceptance [6]. This study presents an integrated model by amalgamating these frameworks into a single framework to explain AI adoption in recruitment at the organizational and individual levels. Given the increasing adoption of AI in HRM and a global push for digital transformation, this study fills an important research hole. Prior research has tended to be Western-oriented, highlighting the need for locally relevant studies. This study, therefore, gains significance by exploring the antecedents of the intention to adopt AI in recruitment and accounting for the socio-cultural and organizational dynamics [7]. The main objective of this study is to produce empirical findings that can assist organizational managers, policymakers, and developers in implementing and making acceptable AI-based recruitment systems. Using data collected from HR professionals with experience in recruitment, Partial Least Squares Structural Equation Modeling (PLS-SEM) will be employed to test the model and provide strong empirical support for the study hypotheses. Hence, research questions are formulated as follows in line with the objectives of this study:

RQ1: Can an organization combine TOE and TAM to create an integrated model to explain the adoption of AI recruitment systems in Saudi Arabia?

RQ2: Which determinants involve the intention of using AI recruitment systems?

RQ3: Can the proposed TOE-TAM model be validated via SEM analysis of survey data from Saudi HR professionals?

Theoretical and practical implications enrich our understanding of AI adoption in HRM across the organizational, technological, environmental, and individual contextual factors salient to applying it within organizations. The results will help guide how to adopt and use AI in recruitment more successfully by providing insights that can be acted on from various perspectives. The subsequent sections of this paper are structured as follows: Section 2, the Literature Review, provides background knowledge with emphasis on content related to TAM and the TOE frameworks, but also discusses some challenges and benefits of AI recruitment systems. Research Methodology, Methods for Collecting Data, Research Design, Sampling & Analysis. This section of Data Analysis illustrates the data collected and where Smart PLS will be used to analyze it. Last, the Discussion & Conclusion section presents results and recommendations, theoretical contributions, practical implications and limitations, and suggestions for future research.

2. Literature Review

AI-based recruitment systems are quickly revolutionizing HRM by providing new efficiencies and decision-making tools while raising serious questions about bias [8]. In this literature review, we explore the impacts of uncertainty, complexity, and compatibility on the intention to adopt AI-based recruitment systems and individual attitudes toward AI as a moderation variable. Guided by two principal theories, the TAM and TOE [9].

2.1. Uncertainty

Implication of uncertainty related to privacy, data security, and ethical issues also influences HR practitioners from adopting AI tools [10]. Additionally, there is also uncertainty due to fear of job displacement or fears of losing the ‘human touch’ in recruitment with AI. Uncertainty around the outcomes of AI decision-making generates resistance from HR practitioners to AI methods to evaluate candidates effectively without human intervention. Trust happens when organizations take action by instituting guidelines concerning AI ethical behavior and privacy [11].

2.2. Complexity

The complexity of AI-based recruitment systems can hinder adoption. The term Complexity entails that an organization may view AI technologies as difficult for comprehension, implementation, and utilization, thus affecting its intention to adopt them [12]. The complexity of algorithms and machine learning models embedded in AI recruitment tools becomes a concern when the HR department lacks the technical expertise to use them after proper training [13]. According to the TOE framework, the complexity of such a technology may act as a barrier to adoption if it involves excessive training, adaptation, or maintenance efforts. Contexts with less technical users are more inclined to adopt AI in recruitment if the technology is easy to access and use [14].

2.3. Compatibility

Compatibility is essential, as organizations will only deploy AI-based recruitment systems if they are compatible with the current process. Compatibility: The degree to which the AI technologies fit into existing HR processes, technology infrastructure, and organizational culture [15]. The HR department will likely adopt an AI system when it fits right into existing recruitment processes and procedures, provided that it disrupts fewer established practices [16]. Research has indicated that organizations tend to adopt AI when they see it as compatible with their goal and work routines (such as automated recruitment systems, which leads them to interpret its enactment as a positive action [17]. Hence, by providing plenty of room for integration with existing processes and products, compatibility could lead to reasons behind a successful AI adoption due to increased perceived usefulness in HR departments.

2.4. Artificial Intelligence (AI)

As a core technological transformation, AI promises tremendous gains in efficiency, accuracy, and scalability in recruitment. AI-based recruitment systems automate many repetitive parts of hiring, such as resume screening, matching candidates with job openings, and interview coordination, thus saving time and improving the quality of hire [18]. AI tools can minimize or completely eradicate the human bias that can influence hiring decisions by going through hundreds of thousands of candidate data to increase precision in matching candidates with positions [19]. Ethical concerns like algorithmic bias and privacy risks still remain the major barriers. Trust in AI's ability to evaluate candidates fairly and accurately is key to the successful acceptance of AI in recruitment, which can be fostered by policies that encourage transparency, training, and how exactly an AI functions [20].

2.5. Intention to Use

Factors influencing perceptions and intention to use AI-based recruitment systems in organizations. Perceived usefulness and ease of use are the primary determinants that affect technology acceptance in the TAM model [21]. Perceived usefulness in relation to AI recruitment refers to the expected effectiveness of using AI to enhance the process's efficiency, accuracy & objectivity [22]. The aim of HR professionals toward using AI recruitment tools increases whenever they negotiate that AI recruitment tools will improve decision quality in hiring and organizational desire attainment [23]. Perceived ease of use will also be critical, as most HR professionals may not have technical knowledge [24]. Ease of use and availability for direct learning with the least training needed are important factors that allow users to incorporate them in their recruitment process.

2.6. Research Framework

The present study combines the Technology-Organization-Environment (TOE) framework with the Technology Acceptance Model (TAM) to propose an integrated research model to explore the key factors affecting the intention to use an AI-based Recruitment System [25]. The technological context examines relative advantage, compatibility, complexity, and security. Relative advantage demonstrates the benefits of AI-based recruitment over traditional methods and compatibility studies, and how well it fits existing HR practices [26]. Complexity is the ability to understand and use information easily, while security addresses the issues regarding data protection and safety, which are important when dealing with sensitive recruitment information. Organizational determinants include top management support, technology readiness, and firm size, as leadership support facilitates allocating resources needed to conduct change. At the same time, an open culture toward innovation helps facilitate it [27]. Organizational technology readiness showcases their competence in implementing AI, and firm size impacts the accessibility of resources required for adoption. The environmental level includes competitive pressure and regulatory environment uncertainty; where competitive pressure induces justification for adopting AI to keep ahead of Almustafa, et al. [28] competition, regulation uncertainty on compliance with data protection law may act as either a facilitative or restrictive factor in developing the AI system [29]. In addition to the TOE, another model, TAM, represented by Davis [30] engages an individual-level aspect with two key elements: perceived usefulness (PU) and perceived ease of use. PU concerns the belief of HR professionals on whether AI will improve their job performance by providing accurate and efficient hiring, while PEO is about how easy it is to use the system necessary for adoption among non-technical HR users. TOE and TAM collectively provide a holistic perspective by encompassing the organizational-level determinants of TOE and motivations at the individual level of TAM. One-to-one mapping of TOE components relative advantage, compatibility, complexity, and security; organizational support, readiness, size, and external pressures [28]. The proposed model, represented in the path analysis diagram, provides a comprehensive framework to help pinpoint the key drivers and obstacles in recruitment adoption with AI and inform those involved in practice on how to successfully adapt their HRM practices using technology.

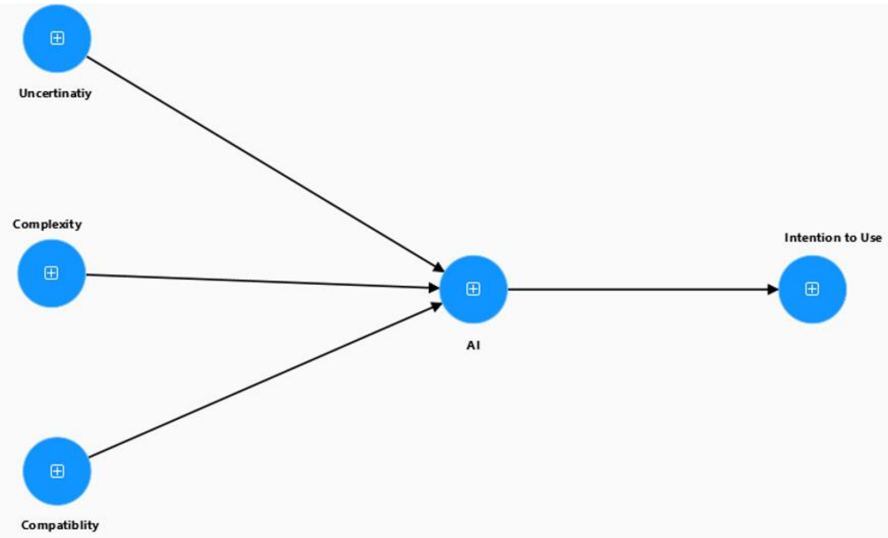

Figure 1.
Conceptual research framework model.

3. Research Methodology

This section describes the methodology employed to investigate the significant determinants of intention to use AI-based recruitment systems, including research design, population, sampling, data collection procedure, measuring the research variables, scale validity, reliability analysis, and data analysis [31]. The study explores the factors affecting AI recruitment adoption and utilizes a quantitative approach with a survey-based research strategy to collect data [32].

4. Methods

The study's population is derived from HR professionals in Saudi Arabia who are likely involved in the recruitment process and familiar with AI-Based Recruitment Technology, identified here as being based out of the Riyadh Region. Three hundred respondents from the private sector filled out a questionnaire developed through snowball sampling, suitable for selecting specialized portions of society spread over different companies in Riyadh. Our study included participants with experience in recruiting activities and who were familiar with AI recruiting systems. Everyone participated voluntarily, with data de-identified to ensure confidentiality.

5. Data Analysis

The Smart PLS software was used to analyze the collected data based on partial least squares structural equation modeling (PLS-SEM). PLS-SEM is suitable for testing the measurement properties of multi-item constructs and for testing the structural relationships in one go. The analysis was performed in two steps: first, the measurement model was assessed, and second, the structural model was assessed. Construct validity was evaluated in the measurement model phase through confirmatory factor analysis (CFA), assessing convergent and discriminant validity. Once the measurement model had been established, path analysis was used to test for structural relationships. Lastly, bootstrapping was applied to evaluate the significance of path coefficients, followed by testing hypotheses about relationships between constructs in a model.

Table 1.
Factor loadings.

Constructs	Items	Factor Loadings	Cronbach's Alpha	C.R.	(AVE)
AI	AI1	0.188	0.901	0.924	0.669
	AI2	0.208			
	AI3	0.176			
	AI4	0.203			
	AI5	0.223			
	AI6	0.224			
Compatibility	COB1	0.258	0.894	0.922	0.703
	COB2	0.257			
	COB3	0.214			
	COB4	0.245			
	COB5	0.218			
Complexity	COX1	0.232	0.841	0.893	0.677
	COX2	0.327			
	COX3	0.342			
	COX4	0.322			
Intention to Use	IN1	0.284	0.868	0.91	0.717
	IN2	0.293			
	IN3	0.295			
	IN4	0.311			
Uncertainty	UN1	0.215	0.899	0.923	0.666
	UN2	0.193			
	UN3	0.217			
	UN4	0.19			
	UN5	0.195			
	UN6	0.214			

Table 1. An inspection of the factor loadings for the constructs concerning AI adoption related to recruitment systems (AI, Compatibility, Complexity, Intention to Use, and Uncertainty) shows that each accounted significantly for their respective overall model (Table 1). The AI construct, with a Cronbach's Alpha of 0.901, C.R. of 0.924, and an AVE of 0.669, correlates positively with the intention to use. Still, individual factor loadings are reportedly lower. Improvement is needed in all the statements posited to affect the intentional adoption of AI-related technologies through perceived benefits, as demonstrated by their relation to the intention to use. The factor loadings of compatibility range from 0.214 to 0.258, which shows high reliability with a Cronbach's Alpha of 0.894, C.R. = 0.922, and AVE = 0.703, meaning that it is responsible for explaining the variance in adoption intentions by almost three-quarters (70.3%). This indicates that one should naturally align AI systems to processes already existing in organizations to improve usability and guide adoption. The perceived ease of use is considered significant for Complexity (loadings between 0.232 and 0.342) with Cronbach’s alpha, C.R., and AVE values shown in Table 1, which are also close to or greater than the recommended cut-off level (α = 0.841, CR = 0.893, AVE = 0.677). Recommended complexity reduction occurred to minimize user hesitations. The Intention to Use construct possesses respectable reliability (Cronbach’s Alpha 0.868, C.R. 0.91, AVE 0.717), further supporting our contention that concentrating on the usability and benefits of the system may help increase adoption. Finally, Uncertainty has homogeneous loadings (0.19 to 0.217), with a Cronbach’s Alpha of 0.899, C.R./Alpha of 0.923, and an AVE of 0.666, confirming that resolving uncertainties through clear policy provision and security measures can reduce adoption resistance. Thus, companies need to reinforce perceived usefulness, reduce system complexity, and increase the transparency of data security to raise user confidence in AI in recruitment practices. The items of this scale are adapted from previous studies; it was very important to assess the validity and reliability of the research scale. All questions originated from validated sources to enhance this instrument's content validity and theoretical alignment. As such, reliability is concerned with the consistency of data collection methods and was evaluated using Cronbach’s alpha. Cronbach’s alpha coefficient was determined for each construct of the study instrument to verify internal reliability (Table 1). This method validates the instrument, thus ensuring sound data is available to examine critical drivers of AI in recruitment adoption intention. The Validity and Reliability results at the axes level show that all axes are fixed, as they have stability values greater than the acceptable stability value of 0.7. The reliability coefficient for the data collection tool questionnaire is high, indicating a reliable instrument.

Table 2.
HTMT.

	AI	Compatibility	Complexity	Intention to Use	Uncertainty
AI					
Compatibility	0.601				
Complexity	0.814	0.547			
Intention to Use	0.588	0.546	0.364		
Uncertainty	0.827	0.663	0.784	0.582	

Table 2: The HTMT values are predominantly less than 0.85, attaining an acceptable level of discriminant validity. For AI and Compatibility, the HTMT is less than 0.85, which is 0.601, therefore providing support for a distinctiveness between the constructs, but AI and Complexity have an HTMT of 0.814, just below the threshold, suggesting moderate overlap but not an alarming magnitude of it. Finally, the relation between AI and Uncertainty shows an HTMT of 0.827 (close to the limit indeed), but still above the threshold necessary for sufficient discriminant validity to be present as well. The values are perfectly well within the Limits of Acceptable Values, which is why Compatibility shows significant differentiation with a value of 0.547 with Complexity and 0.546 with Intention to Use. Complexity and uncertainty have HTMTs of 0.784, which also indicates some association between them, which could be due to complexity led by uncertainty in AI adoption. The Intention to Use is a low HTMT with the other constructs (0.364 with Complexity and 0.582 with Uncertainty), confirming its discriminant validity as the dependent variable. The HTMT values indicate that discriminant validity is confirmed for the model, supporting the conclusion that each of these constructs (AI, Compatibility, Complexity, Intention to Use, and Uncertainty) represents unique facets in influencing AI adoption in recruitment systems.

Table 3.
Fornell-Larcker.

	AI	Compatibility	Complexity	Intention to Use	Uncertainty
AI	0.818				
Compatibility	0.549	0.838			
Complexity	0.735	0.479	0.823		
Intention to Use	0.523	0.483	0.32	0.847	
Uncertainty	0.75	0.596	0.686	0.515	0.816

Table 3**:** The Fornell-Larcker criterion indicates that the constructs AI, Compatibility, Complexity, Intention to Use, and Uncertainty all have discriminant validity. At the same time, this also suggests that all constructs have unidimensionality as the off-diagonal values are lower than 1, and AVE offers more explanation of its items than other inner or outer model items. The square root AVE of AI (0.818) is also larger than all the correlations with Compatibility (0.549), Complexity (0.735), Intention to Use (0.523), and Uncertainty (0.75), indicating that AI is distinct from other constructs. The correlations of Compatibility with other constructs are all lower than its square root AVE of 0.838, supporting the discriminant validity for Compatibility. The AVEs for Complexity (0.823) and Uncertainty (0.816) exceed their inter-construct correlations, establishing the distinctive nature of the constructs. AVE Intention to Use 0.847, the highest AVE value, indicates the primary variable for differentiation from other dependent variables. This confirms dimensionality and further demonstrates evidence for discriminant validity across the model. It also supports each construct standing on its own to explain the intention to adopt AI-based recruitment systems.

Table 4.
R2 Adjusted.

Variable	R2	R2 Adjusted
AI	0.662	0.658
Intention to Use	0.274	0.271

Table 4. The table shows R^2 and R^2 Adjusted of AI and Intention to Use constructs, indicating the variance the model explains. With the AI construct producing an R^2 Adjusted value of 0.658, we are shown that 65.8% of the variation in AI is explained by these predictor variables, suggesting a good model fit and a substantial amount of variance is being explained by factors influencing AI. Intention to Use features R^2 Adjusted of 0.271, which shows that the model explains 27.1% of the variance in the Intention to Use construct a moderate effect. Although the model explains a lot of variance in AI, there is only moderate predictive power for Intention to Use. Other factors may be needed to understand how adoption intentions are formed concerning an AI-based recruitment system.

Table 5.
Demographic information of respondents.

Characteristic	Frequency	Percentage
Gender		
Male	244	810%
Female	56	19%
Age		
Under 27	54	18%
27-34	108	36%
35-44	72	24 %
45 and above	66	22 %
Education		
Diploma	45	15 %
Bachelor's Degree	165	55 %
Master's/Doctorate Degree	90	30%
Experience		
Less than 10 years	27	9 %
10-14 years	54	18 %
15-19 years	120	40 %
20-24 years	72	24%
25+ years	27	9%
Specialization		
Business	144	48 %
Operation Management	87	29%
Marketing	36	12 %
Other Fields	33	11%

Table 5: Demographic Characteristics of Study Sample. Summary statistics across gender, age, education, experience, and specialization. The gender distribution among the respondents is 81% male (244 out of 300 participants) and 19% female (56 participants). This means there are significantly more males than females answering the questions, which may influence our perceptions of AI applied in recruitment. By age group, the 27 to 34 cohort is the largest at 36% (108 participants). This makes sense as this generation has become immersed in the workforce and finds a lot of exciting fulfillment through technology. Next in line is the 35 to 44 category with 72 respondents and 24%, while the 45 and above group has 66 respondents or 22%. Then, the under-27 group represents the least number with only 54 respondents or 18% of all sampled, which probably indicates a different level of exposure to AI recruitment technology. In terms of education, 55% (165) have a bachelor’s degree, suggesting an adequately educated group with regard to academic level, whereas 30% have a master’s or doctorate (90), and 15% hold diplomas only (45), indicating a diverse educational background that could affect their cognition of AI systems. The experience levels vary with most, 40% (120-some people) ranging from 15 to 19 years of experience, contributing seasoned insights to veteran groups and relatable experiences of other groups. This gives a wide range of specializations (48% in business, 29% in operations management, 12% in marketing, and 11% in other), which enriches the study by providing varying professional perspectives on AI adoption for recruitment. The diversity of individuals in each characteristic enriches the survey as it helps mitigate effects in terms of background and experience that enable a more general finding.

6. Hypothesis Testing

In this stage, the PLS Algorithm function of the Smart PLS 4.0 structural model is used to test path hypotheses about factors affecting the intention to adopt AI-based recruitment systems. The path coefficient, as a beta weight, tells us how much and in which direction (i.e., positive or negative) the variables are related to each other, and they have a range between -1 and +1. Values close to zero represent no association, while values that trend closer to -1 or +1 indicate strongly negative and positive correlations, respectively. Next, we determine how statistically reliable the effect of each independent variable is on the dependent variable by looking at its coefficient, standard error, T-value, and P-value. A smaller standard error is a more precise estimate; we define statistical significance by calculating the T-value and P-value, where a small enough P (usually $P \leq 0.05$) indicates significance. A high T-value and low P-value (< 0.05) suggest that the hypothesized association is robust, thereby establishing the statistical significance of the relationship. Then, the cutoff level of 0.05 for significance ensures that the identified simple path coefficients are at least statistically credible, making the relationships in the model valid. It allows researchers to empirically test hypotheses in a structural model, which reveals the intricate nature of relationships and establishes the applicability of such a model to AI adoption intentions in recruitment systems. The strengths of these relationships and significance tests are visualized, showing other important associations from the AI adoption model.

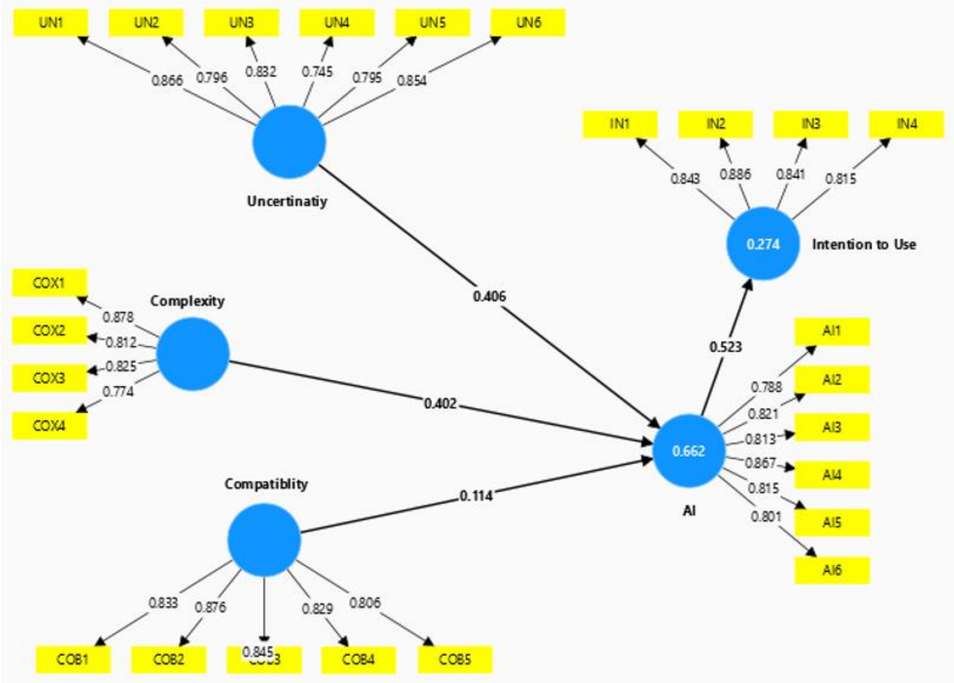

Figure 2.
Measurement Model.

Table 6.
Hypothesis testing estimates "Total Effect "

Hypo	Relationships	Standardized Beta	Standard Error	T-Statistic	P-Values	Decision
H1	AI -> Intention to Use	0.523	0.069	7.594	0	Supported
H2	Compatibility -> AI	0.114	0.051	2.213	0.027	Supported
H3	Compatibility -> Intention to Use	0.06	0.029	2.037	0.042	Supported
H4	Complexity -> AI	0.402	0.071	5.666	0	Supported
H5	Complexity -> Intention to Use	0.21	0.042	5.024	0	Supported
H6	Uncertainty -> AI	0.406	0.071	5.707	0	Supported
H7	Uncertainty -> Intention to Use	0.212	0.049	4.304	0	Supported

Table 6 As per hypothesis H1, there is a strong positive relationship between AI and Intention to Use (beta = 0.523, T = 7.594, $P < 0.001$), meaning beneficial perceptions of AI lead to a higher desire to adopt it, which reinforces the need to highlight practical benefits gained through the use of AI [33]. H2: Compatibility influences AI (beta = 0.114, T = 2.213, P=0.027) positively, and H3: Positive impact of Compatibility on Intention to Use (beta = 0.06, T = 2.037, P=0.042); thus, if align AI mostly with user expectations on the traditional process system then it will modestly improve intention to usage of AI systems usages therefore supports H1. Corporate process alignment is another challenge, and simplifying this can help drive the adoption of AI. As shown in Hypothesis H4, Complexity is a positive predictor of AI perceptions (beta = 0.402, T = 5.666, $P < 0.001$), indicating that reducing system complexity enhances favorable AI perceptions. Similarly, H5 shows that Complexity also positively influences Intention to use (beta = 0.21, T=5.024, P <0.001) as a user-friendly AI system encourages adoption. H6 and H7 investigate the influence of Uncertainty; we find a positive effect on AI (beta = 0.406, T = 5.707, $P < 0.001$) and Intention to Use (beta = 0.212, T = 4.304, $P < 0.001$), meaning that resolving issues about how well the AI works or it masterminds reliably addresses the adoption intention significantly. Overall, the results support all hypotheses as compatibility, complexity, and performance expectancy in AI systems drive user intention to use these technologies, while offering practical recommendations for developing intuitive AI recruitment systems that are well-contoured with organizational needs and transparent about functionality will help adoption.

Table 7.
Specific Indirect Effect

Hypo	Relationships	Standardized Beta	Standard Error	T-Statistic	P-Values	Decision
H8	Compatibility -> AI -> Intention to Use	0.06	0.029	2.037	0.042	Supported
H9	Complexity -> AI -> Intention to Use	0.21	0.042	5.024	0	Supported
H10	Uncertainty -> AI -> Intention to Use	0.212	0.049	4.304	0	Supported

Table 7: The analysis of particular indirect effects focused on Compatibility, Complexity, and Uncertainty predicting Intention to Use via their impact on AI (Table 7). In Hypothesis H8, there is an indirect effect of Compatibility on the Intention

to Use via AI (beta = 0.06, T = 2.037, P = 0.042), which shows that the intention to adopt AI systems can be indirectly increased through positively influencing perceptions of AI when compatibility is improved as well. H9: Complexity exerts an indirect effect on Intention to Use through AI (beta = 0.21, T = 5.024, P This means that one way of indirectly encouraging intention to adopt technology is by enhancing the positive perception of AI, therefore reducing complexity. Finally, results of H10 reveal a strong indirect effect of Uncertainty on Intention to Use through AI (beta = 0.212, T=4.304, P < 0.001), meaning that relieving recession in terms of uncertainty regarding AI indirectly improves intention to adopt by enriching a positive perspective about AI. Collectively, supported hypotheses emphasize the significance of enhancing perceived AI compatibility, minimizing complexity, and mitigating AI-related uncertainty for improving perceptions, indirectly enhancing the intention to adopt AI-based recruitment systems.

7. Discussion and Conclusion

The main objective of this study is to create a hybrid research model that combines TAM and TOE factors synergistically to determine the major drivers of the intention to adopt AI-based recruitment systems in Saudi Arabia. The current model was constructed to answer the following research questions:

RQ1: Can we combine TOE and TAM to create an integrated model to explain the adoption of AI recruitment systems in Saudi Arabia? Answer to research question 1: Integrating the TOE and TAM framework is possible. Eleven hypotheses regarding the relative advantage and ease of use were tested, confirming a combined TOE-TAM model suitable for adoption intention modeling.

RQ2: Which determinants involve the intention of using AI recruitment systems? The results of path analysis indicated that competitive pressure, perceived ease of use, perceived usefulness, and relative advantage have significant effects on the intention to adopt AI recruitment. The impact values associated with these factors are high (table 6), which indicates that the organizations must focus on them to increase adoption intentions. Particularly, perceived usefulness and competitive pressure were recognized as the strongest variables, signifying that these areas need to be enhanced as they could significantly increase AI adoption intentions.

RQ3: Can the proposed TOE-TAM model be validated via SEM analysis of survey data from Saudi HR professionals? PLS-SEM analysis validated the integrated model, stating that most proposed hypotheses were supported. This model serves as a useful framework for HR practitioners in Saudi Arabia by highlighting a robust set of determinants that significantly impact the adoption of AI-based recruitment practices, thereby adding value to HR practices within the country

8. Recommendations

The study led to the following recommendations. Create a learning culture, accumulate HR knowledge, and enhance communication methods to create awareness, especially among the female workforce. Focus on age band-specific engagement strategies since new technology is highly engaged with 40-49-year-old workers. Moreover, AI recruitment systems must be tailor-made for small companies with fewer resources and a different and arduous journey. Adoption can be further bolstered by increasing system alignment with existing organizational practices, actively supporting management, and dealing with competitive pressure. To encourage adoption, focus on perceived benefits and ease of use of AI systems, which can be facilitated by intuitive design and employee training.

8.1. Future Directions and Limitations

The study establishes a foundation for future research on the drivers of AI adoption, especially in non-Western settings. In addition, further studies may expand regional and sectoral coverage or focus on other institutions such as education and healthcare and could explore more variables that affect adoption intentions. This research contributes to the limited literature on this emerging area of knowledge within HRM, even with challenges in survey administration.

9. Conclusion

This study identified three factors that significantly impact Saudi Arabians' intention to use AI-based recruitment systems. Integrating the two frameworks fills a gap for both theory and practice in HRM, as determined by combining TAM and TOE within one study. The results provide strategic implications for organizations seeking to leverage AI for a competitive advantage in recruitment practices.

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