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Using artificial intelligence for hiring talents in a moderated mechanism

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Abstract

Globally, artificial intelligence (AI) occupies a burgeoning space among recruiters as it replaces many of the recruitment and selection tasks while hiring the talents. Despite the existence and acceptance of AI being unprecedented among savvy recruiters, the study of it in developing countries' contexts is still at a fancy stage. Particularly, the extant literature documented that very little is known about the intention and actual use (AU) of AI to hire talents with the intervening effects of voluntariness of usage (VU), tenure, and education of the recruiters elsewhere. Hence, using the doctrine of the extended unified theory of acceptance and use of technology (UTAUT), the present study aims to unpack the intention and AU of AI among hiring professionals in the context of Bangladesh, a developing country in the South Asian region. A multi-item questionnaire survey was employed to collect the data of recruiters from talent acquisition departments in both manufacturing and service organizations with a convenience sampling technique. We used partial least square-based structural equation modeling (PLS-SEM) version 4.0.8.9 to analyze the data. Results showed that performance expectancy (PE), facilitating conditions (FC), and hedonic motivation (HM) have a significant influence on the intention to use (IU) AI ($p < 0.05$), and IU also predicts AU of AI significantly ($p < 0.05$). The moderating influence of VU has an insignificant effect on the positive influence of IU on AU. Moreover, the multi-group analysis showed that there is no significant difference between young adults and old adults and highly educated and lowly educated on the association between IU and AU. The findings in this study showed important notations that contributed to advancing the knowledge and filling the gap in the extant literature. Additionally, it also provides fresh insights for developing policy interventions to hire professionals for thriving AI adoption in the context of developing countries effectively.

Keywords Artificial intelligence, Talent hiring, Human resource professionals, UTAUT, Bangladesh

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Introduction

The current and future talent management practices are incessantly transforming into a tech-based work system where artificial intelligence (AI), being a multifaceted tool with the capacity to instigate a profound transformation in the global business arena [1–4], has already received significant research attention across diverse academic domains, including in business [3, 5, 6]. According to Agarwal et al. [7], Chen et al. [8], and Regona et al. [9], the assimilation of AI into business operations and strategic functions is already evident across organizations of varying sizes and types, signifying the widespread adoption of this technology irrespective of geographical boundaries. Given its recent emergence, the incorporation of AI within business sectors remains an ongoing exploration, continually unveiling innovative applications and novel use cases [3, 10]. Nonetheless, according to Chen et al. [8] and Regona et al. [9], the effective integration of AI in organizational contexts necessitates careful consideration of both human elements and competitive dynamics. Considering the role of AI in business and already acknowledged complexities regarding the AI adoption related issues, further research in this area is both reasonable and viable.

Despite the benefits of AI application in business operation, the adoption rate in different Asian countries remained negligible, as suggested by the report published by People_Matters [11]. The report revealed that in countries, namely Indonesia, Thailand, Singapore and Malaysia only 24.6%, 17.1%, 9.9%, and 8.1%, respectively, businesses are utilizing AI in their business operations. Similarly, the study by Pillai, Sivathanu [12] concluded that only 22% organizations in India are using AI in their business activities and processes. These results and the arguments presented by Pillai, Sivathanu [12] are signifying an early stage of adoption for AI technologies in this region. Researchers, such as Chen et al. [8], Hossin et al. [13], Uddin et al. [14] and Uddin et al. [14] have already attempted to explore the reasons of low adoption rate in this region. However, notwithstanding the benefits of AI in human resource (HR) recruits the adoption rate remained negligible [13].

Though a large number of research focused on the impact of AI on business operations and performance [2, 6, 15, 16], the human resistance toward it is visible, which in most cases, if not all, cannot be explained using its stated benefits [17]. Notably, within the realm of human resource management (HRM) activities, AI's most conspicuous application emerges in the employee recruitment process [18, 19], an area of research that exhibits a dearth of diversity and primarily centers its attention on developed countries [20, 21]. Deterioratingly, the factors affecting the adoption of AI in the employee recruitment process remained largely unknown when the perspective of developing countries is considered [22, 23]. AI, in the context of talent acquisition, can be defined as a sophisticated, automated, and computerized tool possessing a high degree of intelligence, which aids in the evaluation of applicants and the identification of suitable employees [24]. According to Tambe et al. [25], it eases the aforementioned process by categorizing applicants based on various metrics, including educational background, work experience, and other demographic factors. The benefits of AI applications, particularly to the process of employee recruitment, are already evidenced in extant literature [17, 26, 27]. Nevertheless, very few scholarly endeavors have attempted to comprehend the perception of organizations and HR professionals toward the efficacy, applicability, and utilization scope of AI-related technologies in the recruitment process, which again underscores a significant research gap [14]. Additionally, studies conducted by, for instance, Pan et al. [28] and Alam et al. [29], banked on the low adoption rate of AI in emerging nations, which cannot be justified by the extant literature, denoting another major research gap Budhwar et al. [30]. The benefits of AI and the mentioned lack of empirical evidence specific to the AI adoption in the employee selection and recruitment process in developing countries motivated the researchers of the present study to ask the following question. "What factors affect the adoption of AI in the employee recruitment process?" This study endeavors to answer this question by employing empirical and quantitative methodologies.

To answer the stated research question, the researchers have examined the factors that can affect this adoption based on the widely accepted unified theory of acceptance and use of technology (UTAUT). The objective of this study includes identifying the determinants of behavioral intentions and actual use (AU) of AI for HR recruitments in the context of developing countries, through the lens of a moderated mechanism. Therefore, the contribution or implication of this research is manifolded. First, it provides empirical evidence for the UTAUT framework in the mentioned multiplicity, which can act as a strong theoretical base for future scholarly works. Second, this research identified the impact of different variables on AI adoption in HR recruitment in Bangladesh. This insight can be beneficial for organizations in this region to formulate HR policies and interventions that will maximize the implementation and usage of AI. Third, the researchers have conducted a necessary condition analysis (NCA), which has not been done before in the given area; hence, it adds another layer of empirical evidence regarding must-have and should-have factors. Finally, this research acknowledged the moderated mechanism by incorporating the roles of age, gender, experience, and voluntariness of usage (VU). Comprehending this mechanism will be beneficial for HR professionals operating in developing countries like Bangladesh to employ the most appropriate individuals.

The structure of this research is as follows. Succeeding this introductory chapter, the second chapter describes the theoretical background and states the study hypotheses. The third chapter transpires the methodology applied for conducting this research. The fourth chapter presents the results of the analysis, which is then discussed in light of existing literature in chapter five. The implication of the research findings has also been discussed in chapter five. Chapter six concludes this paper with a comprehensive summary of the entire research endeavor.

Literature review

Artificial intelligence in recruitment

Artificial intelligence (AI) has emerged as a transformative force in enhancing the recruitment process, addressing longstanding challenges faced by organizations in attracting and selecting the right talent. Recruiting through more conventional means, like online networks like LinkedIn, has not always been successful in finding and hiring top talent [31, 32]. AI provides a transformative solution within this scenario, introducing streamlined and effective processes to attract, retain, and enable proficient personnel; thus, AI establishes a symbiotic situation for employers and candidates [25, 33].

AI in the recruiting process takes the form of smart computers and software that can mimic human behavior without the need for continual human oversight. AI assesses candidates using advanced filtering algorithms, taking into consideration a multitude of criteria including academic credentials and industry-specific expertise. AI can simplify the hiring process, decrease manual labor, and find people with the ability to solve strategic challenges and adapt to new situations. Additionally, AI can streamline the hiring process, reduce costs, and eliminate the challenges associated with manual candidate sorting [25, 34, 35]. The efficacy of artificial intelligence (AI) in talent acquisition is evident through the achievements of notable organizations such as SAT Telecom, L'Oréal, and Unilever [35–37].

Theoretical background and study hypotheses

The complexities associated with quantitative measurement and analysis of psychology-laden phenomena have already been addressed in previous studies [38], which motivated the development of several theories and frameworks, including the Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), UTAUT, Theory of Reasoned Action (TRA) [39, 40]. Multiple studies have shown that by taking a multi-theoretical approach, one can build a more comprehensive model and improve its explanatory ability [41]. However, their empirical findings indicate that the integration of fragmented theories to generate a holistic comprehension of the intention and actual use of a given technology has failed due to the diverse assumptions and beliefs of the fragmented theories [42]. Therefore, Venkatesh et al. [43] created a new approach, UTAUT, to characterize both the intent to use and the actual usage of technology.

UTAUT's strength lies in its ability to explain variance in both intentions to use (70% variance) and actual usage (50% variance) [43]. UTAUT is considered as one of the most used model for studies on technology adoptions including AI adoption different developing countries [22, 44]. Ami-Narh, Williams [45] and Kwateng et al. [46] Hu et al. (2019) further argued that UTAUT has been identified as the best method for predicting technology adoption in LDCs by previous studies.

The components of this model included performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), which combinedly can predict the users' IU any new technology. The application of this particular model for studying different behavioral phenomena in extant literature in areas similar to this present one, also vindicates the generalizability of the findings [47, 48]. Though a more advanced UTAUT2 model has been proposed by Venkatesh et al. [49], the application of UTAUT remained widely popular, with significantly more application in studies related to the early stage of adoption [48, 50–52]. In light of the nascent stage of AI in the context of developing countries, the current study employed the original UTAUT to investigate the intentions and actual utilization of AI.

Moreover, Patil et al. [53] argued that UTAUT still requires some context specific external constructs that can more appropriately capture all possible aspects of AI adoption. Islam et al. [22] suggested to extend original UTAUT model to capture AI adoption more precisely. Therefore, the researchers of the present study extend this particular model. To extend it, the researchers also added Hedonic Motivation (HM) from the UTAUT 2 model and Technology Complexity (TC) from the study conducted by Chin, Lin [54].

Performance expectation and behavioral intention

PE, a core element in technological adoption, reflects users' anticipation of enhancing their functional capabilities. Venkatesh et al. [43] defined it as the belief that technology can solve problems. As a construct of the model, this variable has been repeatedly used, revealing a strong positive influence of it on behavioral intention [48, 55, 56]. Previous researchers from Bangladesh, for example, Alam et al. [55], Dey, Saha [57], Rahman, Rahman [58] have already used this construct within the UTAUT model. In a context similar to the present one, Islam et al. [22] identified a direct relationship between PE and behavioral IU AI technologies. A similar finding has also been revealed in the study conducted by Uddin et al. [14]. Therefore, the researchers of the present study hypothesized that, *H1* Performance expectancy significantly and positively influences behavioral intention to use AI in the employee recruitment process.

Effort expectancy and behavioral intention

As defined by Venkatesh et al. [43], EE indicates the anticipated or perceived degree of ease or difficulty related to the usage of a particular technology. When adopted in a similar context to the present study, it has been defined as the anticipated extent of ease related to the application of AI in the managerial process. In other words, it measures the perceived user-friendliness of an AI system in operations or processes [14, 22]. As an original UTAUT construct, repeated application of this variable can be identified, with strong evidence supporting its efficacy [48, 55, 58, 59]. For Bangladesh, Dey, Saha [57] revealed that this construct positively influences the managers to use information systems. Ikumoro, Jawad [60] and Venkatesh [47] argued that EE can predict the application of AI in organizational settings. In previous studies, the efficacy of EE in determining the IU AI for recruitment and selection by HR in Bangladesh has already been established by Uddin et al. [14], Islam et al. [22], Alam et al. [29]. Hence, the researchers hypothesized that,

H2 Effort expectancy significantly and positively influences behavioral intention to use AI in the employee recruitment process.

Social influence and behavioral intention

As defined by Venkatesh et al. [43], SI encompasses the influence of social norms, expectations, and pressures that can either facilitate or inhibit the adoption of technology. The literature underscores the pivotal role of normative judgments and societal expectations in shaping technology adoption [61, 62]. Research by Shiferaw, Mehari [63] concerning Ethiopian electronic medical recording systems revealed a positive impact of perceived SI among doctors and nurses on the behavioral intention to embrace AI technology. This pattern extends to Bangladesh, where investigations into the recruitment domain have consistently shown that SI holds significant sway over the intention to employ AI for talent acquisition purposes [14, 22, 29]. These findings collectively underscore the substantial impact of SI in molding users' technology adoption decisions. Therefore, the researchers hypothesized that,

H3 Social Influence significantly and positively influences behavioral intention to use AI in the employee recruitment process.

Facilitating condition and behavioral intention

Within the domain of technology adoption, Venkatesh et al. [43]) asserted the pivotal role of FC as a significant determinant of individuals' behavioral intention to embrace technology. These FC encompass the availability of both technical and organizational infrastructures. Scholarly discourse resonates with this perspective, contending that a dearth of technical support, inadequate organizational infrastructure, and deficiencies in knowledge sharing and physical resources can give rise to ambiguity during the technology acquisition and implementation phases [64, 65]. Empirical substantiation emerges from the work of Zahid, Haji Din [66], Mensah [67], which explores e-government adoption in an Indian context, revealing a positive association between FC and the intention to adopt technology. In a context similar to the present research, Alam et al. [29] emphasize the critical role played by FC in predicting recruiters' behavioral intention to employ AI technology. This narrative is further reinforced by research conducted by Uddin et al. [14], Islam et al. [22]. Considering this evidence, the researchers of the present study hypothesized that,

H4 Facilitating condition significantly and positively influences behavioral intention to use AI in the employee recruitment process.

Hedonic motivation and behavioral intention

As an extension to the original UTAUT model, Venkatesh et al. [49] explained HM to be an intrinsic driver. It comprises the enjoyment and pleasure associated with the adoption and application of any particular technology. Despite being a recent addition to the original model, this particular construct has been adopted by scholars around the world repeatedly, mainly due to its ability to predict behavioral intention [59, 68, 69]. Extant literature suggests that HM is deeply associated with the usage of mobile phones [70], FinTech [71], the internet [72], and social media [73], as well as AI [74]. Previous studies in Bangladesh also presented the positive impact of this construct on technology adoption [75]. The study conducted by Alhwaiti [76] revealed that HM can predict AI-related behavioral intention for HR recruitment and selection activities. Therefore, the researchers of the present study hypothesized that,

H5 Hedonic motivation significantly and positively influences behavioral intention to use AI in the employee recruitment process.

Technology complexity and behavioral intention

TC, as defined by Parveen, Sulaiman [77], is the degree to which individuals perceive the intricacy and sophistication of a technological innovation that underpins the consequential impact on individuals' proclivity to embrace and utilize such technology. Previous scholarly works have already established the complex nature of AI, machine learning, blockchain, and big data management, which requires a special set of skills and knowledge from the human counterpart [21, 78, 79]. When considered as an extension of the UTAUT model, its efficacy in determining behavioral intention has already been substantiated [54]. For business organizations, TC also negatively affects the usage of IoT in the supply chain [80]. The study conducted by Pan et al. [28], indicates that the TC, mainly derived from the sophistication associated with AI-related technology, negatively impacts the IU it in employee recruitment process.

H6 Technology complexity significantly and negatively influences behavioral intention to use AI in the employee recruitment process.

Intention to use and actual use

The concept of behavioral IU new technologies, encapsulating users' subjective probability and willingness to embrace them, emerges as a potent predictor of actual utilization [43, 49]. A plethora of studies, approached from diverse perspectives, consistently substantiates the profound influence wielded by behavioral intention on the tangible adoption and utilization of technologies [39, 50]. Notably, the research conducted by Uddin et al. [14], Iqbal et al. [23] within the context of AI adoption among recruiters in Bangladesh firmly establishes a compelling association between the behavioral IU and the subsequent real-world implementation of this technology. Therefore, the researchers of the present study hypothesized that,

H7 Intention to use significantly and positively influences the actual use of AI in the employee recruitment process.

Gender, age, tenure, and voluntariness as moderators

The original UTAUT model comprises the moderating effect of gender, age, tenure, and VU. According to Venkatesh et al. [43], these variables can moderate the effect of different constructs within the model. For instance, [81–83] argued that males are more task-oriented and have a greater interest in innovation and novelty. Hence, the technology adoption rate among males is higher. On the other hand, females, for their emphasis on relationships and stability, have more technology anxiety, which acts as a friction against the adoption of technologies and innovations. In contexts similar to the present research, Alam et al. [55] established that this variable can moderate the impact of PE, EE, and SI on behavioral intention. Again, when proposing the original UTAUT model, Venkatesh et al. [43] already established the impact of age on the relationship between PE, EE, SI, FC, and IU. Several studies have also established that the age of the users can significantly moderate the impact of UTAUT constructs on the behavioral intention related to AI-related technologies [48, 84]. The moderating role of tenure has also been revealed by extant literature [47]. Employees with higher work experience tend to disapprove of novelty and innovation within the organization, which decreases the new technology adoption rate among them [49, 85]. In the case of AI adoption, Andrews et al. (2021) and Venkatesh (2022) evidenced that the moderating effects of tenure on the relationship among EE, SI, FC, and behavioral intention are statistically significant. Lastly, in the original UTAUT model, Venkatesh et al. [43] considered VU as a crucial moderator. Previous studies substantiated that when individuals perceive that their adoption of technology is voluntary, it can positively impact their attitude and willingness to use it. In contrast, if technology adoption is perceived as mandatory or forced, it can lead to resistance [47, 48]. Similar evidence has also been substantiated for AI adoption in HR acquisition [86]. Considering all the discussed moderating effects, the researchers of the present study hypothesized that,

Gender moderates the relationships between performance expectancy and intention to use (H8a), between effort expectancy and intention to use (H8b), and between social influence and intention to use (H8c) AI in the HR acquisition process.

Age moderates the relationships between effort expectancy and intention to use (H9a), between social influence and intention to use (H9b), and between facilitating condition and intention to use (H9c) AI in the HR acquisition process.

Tenure moderates the relationships between effort expectancy and intention to use (H10a), between social

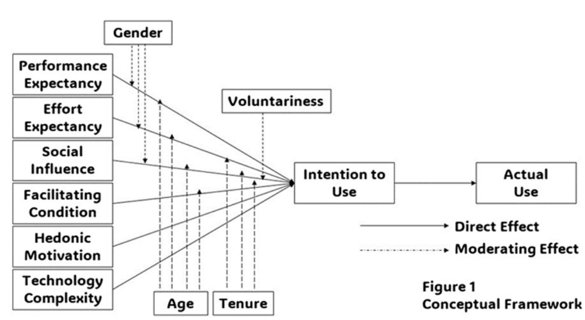

Fig. 1 Theoretical framework

influence and intention to use (H10b), and between facilitating condition and intention to use (H10c) of AI in the HR acquisition process.

Voluntariness moderates the relationship between social influence and intention to use (H11) AI in the HR acquisition process.

Figure 1 illustrates all the mentioned relationships.

Methods

Research design

To study the relationship depicted in Fig. 1, the researchers of the present study employed quantitative techniques following the recommendations and suggestions of Hair Jr et al. [87]. The hypothesized relationships were then tested using deductive reasoning technique. The selection of the quantitative technique along with deductive reasoning is tenable, as argued by Abu-Alhaija [88], for testing theories. Furthermore, the researchers adopted a positivist philosophy, which allows conceptualization and analysis of psychological phenomena in quantitative terms [89]. The philosophical underpinning, deductive reasoning, and quantitative methodology, together, as argued by Urbach, Ahlemann [90] solidified the robustness of the present study.

The researchers designed a cross-sectional data collection strategy with a multi-item questionnaire. As the majority of respondents were non-English speakers, this questionnaire was translated into Bangla following the guidelines of Brislin [91]. To ensure the applicability and face and content validity of the questionnaire, it was sent to academicians and industry experts. Again, a pilot survey was conducted to test whether the questionnaire was free from multicollinearity, and comprehensible to the Native Bangladeshis. After making the required modification as recommended by academicians and industry experts, the refined questionnaire was subsequently sent to collect the data for this study.

Data collection strategy

The researchers of the present study employed the convenience sampling technique, which allowed the identification of the individuals directly associated with the organizational talent-acquiring process. Again, to enhance the generalizability of the findings, organizations from both the manufacturing and service industries located in Dhaka, the capital of Bangladesh and Chattogram, the commercial capital and financial hub of Bangladesh [92], and that have already utilized some form of AI for talent acquisition have been carefully selected. HR professional of each of these organizations, because of their direct involvement in the mentioned process, were subsequently mailed with a cover letter, consent form, questionnaire, and a self-addressed stamped envelope. The researchers sent 390 questionnaires, out of which 283 returned with responses, indicating a 72% response rate. Further, 13 responses were found incomplete, and so were removed from the study. With responses from 270 HR professionals, the sample was deemed sufficient enough to run the PLS path model [87, 88, 93].

Within the cohort of participants, the researchers noted a demographic variability, as well as a difference in organizations' size and type. Both male and female HR professionals participated, but males formed the majority (72.1%). The researchers again identified a large interval or gap in the ages of these individuals. 36.4% of the respondents is above 25 years, 40.7% are above 30 years, 14.1% fall into the above 35 years category, and the smallest group, those above 40 years, make up 8.8% of the participants. In terms of education, 60.6% held bachelor's degrees, 9.1% had Master's degrees, and 30.3% had other educational backgrounds. Regarding positions, 25.3% are in lower-level roles, 58.6% in mid-level positions, and 16.2% in top-level positions. In terms of tenure, 32.3% have worked over 1 year, 32.0% over 5 years, 27.3% over 10 years, and 8.4% over 15 years (see Table 1).

Measures

To maintain the robustness of the research methodology, the researchers utilized measurement tools that have already been tested and validated in previous studies. These five-point Likert scale-based tools were

Table 1 Participants of the study

		Frequency	Percentage (%)
Gender	Male	214	72.1
	Female	83	27.9
Age	Above 25	108	36.4
	Above 30	121	40.7
	Above 35	42	14.1
	Above 40	26	8.8
Education	Bachelor	180	60.6
	Master	27	9.1
	Others	90	30.3
Position	Lower Level	75	25.3
	Mid Level	174	58.6
	Top Level	48	16.2
Tenure	Above 1 Year	96	32.3
	Above 5 Years	95	32.0
	Above 10 Years	81	27.3
	Above 15 Years	25	8.4

Table 2 Constructs' and items' sources

Variable and sources	Example item
PE [74]	AI devices are more accurate than human beings
EE [74]	Working with AI devices is simple to understand and use in services
SI [94]	People who are important to me think that I should use AI for recruiting talents
FC [94]	AI tool is compatible with other systems I use
TC [95]	It was difficult to get the AI to do what I want
HM [43]	Using AI for recruiting talent is very entertaining
IU [43]	I predict I would use AI in the next months
AU) [96]	I am giving a lot of time in AI-based software applications
Voluntariness [97, 98])	My use of AI in recruitment is voluntary

adopted, with 1 representing 'strongly disagree' and 5 'strongly agree'. Nevertheless, the adaption of the measurement tools also allowed modification of the items to ensure face validity and appropriateness to the context of Bangladesh. Table 2 presents all the measurement tools and their respective sources.

Results

Analytical tools

The SEM underwent a rigorous analysis utilizing SmartPLS 4 (version 4.0.9.5). As highlighted by Gudergan et al. [99], PLS-based SEM is a second-generation regression tool ideally tailored for exploring complex causal relationships within management research. This tool is preferred by the researchers over conventional regression methodologies due to its capacity to comprehensively assess the entire model, transcending the limitations of dissecting individual pathways [93, 100–102]. Its adoption stemmed from the advantages in performance and the attainment of superior results [88, 90], making it a preferred choice for elucidating intricate cause-and-effect dynamics in the present research.

Common method bias

The methodological robustness, designed by the researchers with the aim to reduce biases in the study to a negligible state, was meticulously maintained. The participants were made fully aware of the application of their responses, and confidentiality of their identifiable information was strictly maintained. Hence, the researchers conducted Harman's one-factor test. The test indicated that the first factor explained 31.12% of the total variance, which is significantly lower than the recommended maximum of 50%. Again, the collinearity of the variables was tested following the guidelines provided by Kock [103], as this research employed the SEM. According to this author, variance inflation factor (VIF) scores of any SEM should remain lower than 3.3; otherwise, the model is affected by Common method bias (CMB). The analysis conducted for this

Table 3 Measurement model (reliability and convergent validity)

Construct	Items	Loadings	α	CR	AVE
PE	PE1	0.859	0.897	0.928	0.764
	PE2	0.886			
	PE3	0.872			
	PE4	0.879			
EE	EE1	0.961	0.946	0.880	0.713
	EE2	0.690			
	EE3	0.860			
SI	SI1	0.921	0.921	0.950	0.863
	SI2	0.947			
	SI3	0.920			
FC	FC1	0.902	0.896	0.935	0.826
	FC2	0.915			
	FC3	0.910			
HM	HM1	0.925	0.899	0.937	0.833
	HM2	0.930			
	HM3	0.883			
TC	TC1	0.871	0.877	0.923	0.799
	TC2	0.919			
	TC3	0.893			
VU	VU1	0.890	0.883	0.927	0.808
	VU2	0.889			
	VU3	0.918			
IU	IU1	0.923	0.911	0.944	0.849
	IU2	0.936			
	IU3	0.904			
AU	AU1	0.890	0.858	0.914	0.779
	AU2	0.891			
	AU3	0.867			

Table 4 HTMT ratio

	PE	EE	SI	FC	HM	TC	VU	IU	AU
PE									
EE	0.067								
SI	0.304	0.059							
FC	0.154	0.092	0.246						
HM	0.313	0.057	0.402	0.193					
TC	0.058	0.145	0.177	0.077	0.281				
VU	0.295	0.024	0.192	0.159	0.489	0.212			
IU	0.314	0.026	0.294	0.288	0.519	0.145	0.520		
AU	0.276	0.099	0.246	0.249	0.445	0.074	0.444	0.538	

research revealed that all the VIF scores were less than 3.3. Therefore, this research is free from CMB issues.

Measurement issues

Following the guidelines provided by Henseler et al. [104], this research employed both the measurement model and a structural model. The measurement model allowed the researchers to scientifically test the quality criteria, including validity and reliability, of the constructs. Following the steps recommended by Davari, Rezazadeh [100], Hair Jr et al. [101], the researchers evaluated the model with average variance extracted (AVE), composite reliability (CR), and discriminant validity. Tables 3 and 4 present all these scores. First, the AVE scores, quantifying the extent to which a construct encapsulates variance relative to the variance attributed to measurement error, were evaluated. As suggested by Hair Jr et al. [87], Hair Jr et al. [101], this score should be higher than 0.5. All the AVE scores presented in Table 3 exceed this minimum value. Second, the CR scores, indicating internal consistency of the scale items, as suggested by Bacon et al. [105] should be greater than 0.7. Again, the measurement model analysis manifested acceptable values of CR. Similarly, all the Cronbach Alpha values are more than 0.7, which is higher than the acceptable minimum value [106]. With these tests, the researchers of the present study established the convergent validity claim regarding this research.

The measurement model also allowed the researchers to test the discriminant validity. As argued by Ab Hamid et al. [107], the heterotrait-monotrait (HTMT) ratio is more capable and appropriate for testing discriminant validity than Fornell and Larcker's criterion. The researchers, hence, adopted the HTMT ratio to justify this particular validity claim. As recommended by Henseler et al. [104], the HTMT ratio should be less than 0.8. Table 4 shows that all the HTMT ratios are lesser than the acceptable maximum value. Henceforth, this study stands as impervious to concerns regarding discriminant validity.

Evaluation of the structural model

We ran a bootstrapping procedure with a resampling rate of 5000 to test the hypotheses (Hair et al., 2017) particularly to obtain the t values, p values, and bootstrapped confidence intervals. We tested the seven hypotheses, shown in Table 5 and Fig. 2, and most of them were found to be significant. PE has a significant effect on IU ($\beta=0.126$, $t=1.724$, no 0 between LLCI and ULCI) with f^2 of 0.014. Likewise, FC ($\beta=0.172$, $t=2.937$, no 0 between LLCI and ULCI) and HM ($\beta=0.260$, $t=2.989$, no 0 between LLCI and ULCI) have significant influence

Table 5 Structural model

SL No	Path relationship	β	Std. Dev	*T* values	*P* values	LLCI	ULCI	Decision	f^2	R^2
H1	PE—> IU	0.126	0.074	1.724	0.042	0.008	0.249	Supported	0.014	IU (0.384) AU (0.227)
H2	EE—> IU	0.029	0.082	0.224	0.411	−0.158	0.096	Not Supported	0.000	
H3	SI—> IU	0.046	0.068	0.659	0.255	−0.067	0.158	Not Supported	0.002	
H4	FC—> IU	0.172	0.053	2.937	0.002	0.057	0.226	Supported	0.033	
H5	HM—> IU	0.260	0.088	2.989	0.001	0.113	0.404	Supported	0.072	
H6	TC—> IU	−0.015	0.051	0.261	0.397	−0.092	0.070	Not Supported	0.000	
H7	IU—> AU	0.480	0.061	7.850	0.000	0.368	0.569	Supported	0.294	

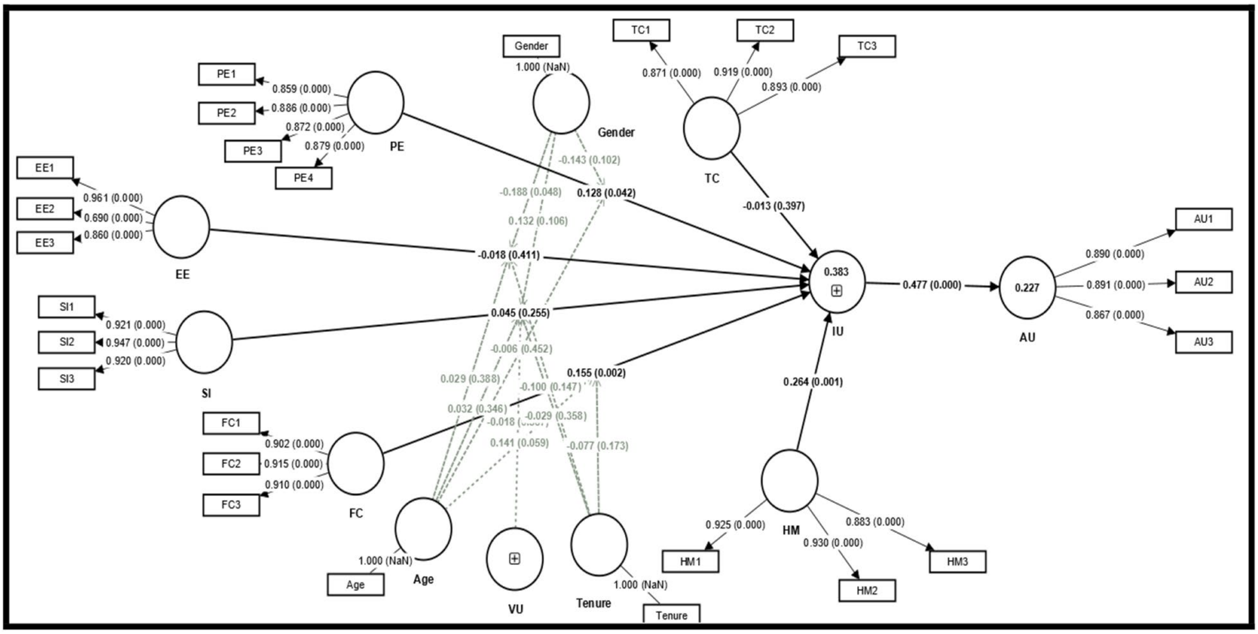

Fig. 2 Structural model

IU with f^2 of 0.033 and 0.072, respectively. In turn, IU significantly influences AU (β=0.480, t=7.850, no 0 between LLCI and ULCI). Thus, H1, H4, H5 and H7 are supported.

Surprisingly, EE (β=0.029, t=2.224, 0 between LLCI and ULCI) and SI (β=0.046, t=0.659, 0 between LLCI and ULCI) are found to have insignificant influence on IU. TC is also found to have an insignificant influence on IU (β=−0.015, t=0.261, 0 between LLCI and ULCI). Therefore, H2, H3, and H6 are not supported.

The R^2 for both IU and AU is 0.384 and 0.227, respectively, which indicates that 38.4% of the variance in IU and 22.7% of the variance in AU can be explained by the exogenous variables.

The researchers also assessed predictive relevance (Q^2) and Ali et al. (2018) suggests that the value of Q^2 should be bigger than zero. As presented in Table 6, the Q^2 values of IU and AU are 0.231 and 0.145, respectively, and the predictive relevance of each construct is substantial. Furthermore, we have conducted a more comprehensive evaluation of predictive significance using tenfold cross-validation and performing seven repetitions with the PLS predict method (Table 6). Only a few of the prediction errors show substantial dispersion. Therefore, we have chosen to use the RMSE value for PLS prediction. In accordance with the suggestion made by Shmueli et al. (2019), it is notable that, for all of the indicators, the RMSE of PLS-SEM is less than that of linear regression model. This indicates that the model possesses a strong level of predictive significance.

Testing of moderating effects

The researchers of the present study analyzed the effect of the mentioned moderating variables within the structural model. The result of this analysis is presented in Table 7. Similar to the direct effect analysis, the researchers reported different metrics in the table. The confidence

Table 6 PLS predict

Endogenous construct	Item	Q^2predict	PLS-SEM RMSE	LM RMSE	Difference
AU (Q^2 = 0.145)	AU1	0.119	0.634	0.644	0.010
	AU2	0.128	0.668	0.678	0.010
	AU3	0.092	0.755	0.768	0.013
IU (Q^2 = 0.231)	IU1	0.220	0.614	0.622	0.008
	IU2	0.200	0.642	0.651	0.009
	IU3	0.165	0.687	0.704	0.017

Table 7 Moderating effect analysis

SL no	Path relationship	*B*	Std. Dev	*T* values	*P* values	LLCI	ULCI	Decision
H8a	Gender x PE—> IU	− 0.143	0.113	1.268	0.102	− 0.321	0.050	Not supported
H8b	Gender x EE—> IU	− 0.188	0.113	1.669	0.048	− 0.403	-0.027	Supported
H8c	Gender x SI—> IU	0.132	0.106	1.247	0.106	− 0.053	0.299	Not supported
H9a	Age x PE—> IU	− 0.006	0.048	0.121	0.452	− 0.080	0.076	Not supported
H9b	Age x EE—> IU	0.029	0.102	0.286	0.388	− 0.110	0.232	Not supported
H9c	Age x SI—> IU	0.032	0.082	0.396	0.346	− 0.111	0.152	Not supported
H9d	Age x FC—> IU	0.141	0.090	1.560	0.059	0.007	0.305	Not supported
H10a	Tenure x EE—> IU	− 0.100	0.095	1.050	0.147	− 0.270	0.042	Not supported
H10b	Tenure x SI—> IU	− 0.029	0.080	0.363	0.358	− 0.146	0.115	Not supported
H10c	Tenure x FC—> IU	− 0.077	0.082	0.941	0.173	− 0.237	0.037	Not supported
H11	VU x SI—> IU	− 0.018	0.062	0.288	0.387	− 0.107	0.100	Not supported

coefficient was again set at 95%, which led to the rejection of all the hypotheses related to the effect of the mentioned moderating variables except for one. Only gender can moderate the relationship between EE and IU. Consequently, hypotheses H8a, H8c, H9a, H9b, H9c, H9d, H10a, H10b, H10c, and H11 were rejected. Only the hypothesis related to the moderating effect of gender on the relationship between EE and IU, or H8b, was accepted.

Necessary conditional analysis

NCA, a comparatively new approach and data analysis technique developed by Dul in 2016 [108], made it possible to classify necessary conditions in data sets. In lieu of analyzing the average relationships between dependent and independent variables, NCA highlights regions in scatter plots of dependent and independent variables that could indicate the presence of a necessary condition [109, 110].

The study aimed to illustrate whether or not PE, EE, SI, TC, FC, and HM are required for intention to use and actual use. We started by conducting a statistical significance test on the effect sizes (d) of the latent variable scores using the suggested random sample size of 10,000 [108, 111, 112]. Dul et al. [112] state that a condition is regarded necessary if it meets all three of the following criteria: (i) theoretical rationale; (ii) effect size $d > 0$; and (iii) a small p-value ($p < 0.05$).

The NCA results (Table 7) reveal that only performance expectancy is meaningful ($d \geq 0$) and statistically significant ($p < 0.05$) prerequisites for intention to use. Particularly, an increase in PE will result in an increase in IU. Likewise, Table 8 reveals that intention to use is the remarkable prerequisite of actual use. Tables 9 and 10 present the complete interpretation of necessary perquisites for both IU and AU, respectively.

Table 9 demonstrates that in terms of intention to use (IU), performance expectancy (PE) emerges as a significant and essential predictor. Conversely, factors such as facilitating conditions (FC) and hedonic motivation (HM) prove to be significant but not crucial predictors of IU. Notably, other predictors, including effort expectancy (EE), social influence (SI), and technology complexity (TC), appear as insignificant and non-essential predictors for intention to use.

Table 10 indicates that regarding actual use (AU), intention to use (IU) stands out as the sole significant and indispensable predictor. Conversely, factors such as effort expectancy (EE), facilitating conditions (FC), and hedonic motivation (HM) are found to be significant but not crucial predictors of AU. Notably, the remaining predictors, including performance expectancy (PE), social influence

Table 8 NCA analysis

	Total effects (PLS-SEM)	CE-FDH effect size (NCA)
Intention to Use		
PE	0.143*	0.063*
EE	− 0.060	0.000
SI	0.056	0.000
FC	0.154*	0.062
HM	0.378*	0.008
TC	− 0.030	0.000
Actual Use		
PE	0.085	0.013
EE	0.102*	0.037
SI	0.018	0.000
FC	0.094*	0.024
HM	0.186*	0.016
TC	0.016	0.000
IU	0.340*	0.221*

Table 9 Endogenous variable intention to use

Exogenous construct	PLS-SEM results	PLS-SEM (Paths; p-value)	NCA results	NCA (d; *p*-value)	Interpretation
PE	Significant	0.143; $p < 0.05$	Necessary condition	0.063; $p < 0.05$	If the PE of AI adoption in hiring talent goes up, the intention to adopt will, on average, go up as well. Also, AI in hiring talents must have a certain minimum level of PE in order to form the intention
EE SI TC	Insignificant	EE: -0.060; $p > 0.05$ SI:0.056; $p > 0.05$ TC: -0.030; $p > 0.05$	Not necessary condition	EE: 0.000; $p > 0.05$ SI:0.000; $p > 0.05$ TC:0.000; $p > 0.05$	EE, SI, and TC are neither must-have nor should-have conditions to form the intention of AI adoption in hiring talents
FC HM	Significant	FC: 0.154; $p < 0.05$ HM: 0.378; $p < 0.05$	Not necessary condition	FC: 0.062; $p > 0.05$ HM: 0.008; $p > 0.05$	On average, an increase in FC and HM adoption of AI for talent acquisition will increase a company's intent to adopt AI. However, there is no minimum requirement for FC and HM to form the intent

Table 10 Endogenous variable actual use

Exogenous construct	PLS-SEM results	PLS-SEM (Paths; *p*-value)	NCA results	NCA (d; *p*-value)	Interpretation
IU	Significant	0.340; $p < 0.05$	Necessary condition	0.221; $p < 0.05$	On average, an increase in the intention of AI adoption in hiring talent will increase its adoption. Also, adoption intention needs to have a certain minimum level to actual adoption
PE SI TC	Insignificant	PE: 0.085; $p > 0.05$ SI:0.018; $p > 0.05$ TC: 0.016; $p > 0.05$	Not necessary condition	PE: 0.013; $p > 0.05$ SI:0.000; $p > 0.05$ TC:0.000; $p > 0.05$	PE, SI, and TC are neither a must-have nor a should-have condition for AI adoption in hiring talents
EE FC HM	Significant	EE: 0.102; $p < 0.05$ FC: 0.094; $p < 0.05$ HM: 0.186; $p < 0.05$	Not necessary condition	EE: 0.037; $p > 0.05$ FC: 0.024; $p > 0.05$ HM: 0.016; $p > 0.05$	On average, an increase in the EE, FC, and HM of AI adoption in hiring talent will increase its adoption. However, no minimum level of EE, FC, and HM is needed for the adoption

(SI), and technology complexity (TC), prove to be insignificant and non-essential predictors for actual use.

Discussion

The present study has undertaken a comprehensive analysis of the pivotal factors crucial for the endorsement of AI-supported technologies in employee recruitment. This analysis was conducted by employing an extended version of the UTAUT model, specifically within the context of a developing country. In order to fortify the originality and rigor of the findings, rigorous testing was conducted to examine the moderation effects of gender, age, work experience, and VU across all hypothesized relationships. The careful design of the methodological approach has enabled the researchers of the present study to conduct a thorough and robust exploration of the nuances within the setting of AI adoption in the context of employee recruitment, particularly within the unique socio-economic landscape of a developing nation.

The findings of the present study indicate that PE, FC, and HM significantly impact IU, which in turn affects actual usage. Furthermore, this research manifests that EE, SI, and technological complexities cannot determine the IU AI to a statistically significant extent. Additionally, an assessment of the moderated mechanism proposed by the designed framework revealed that only gender as a moderator can influence the relationship between EE and IU. The findings of this research exhibit a duality, wherein they buttress and deviate from antecedent evidentiary foundations. Firstly, the impact of behavioral IU on the AU of AI in the described setting supported the previous claim regarding this relation. A significant portion of scholarly works that adopted the UTAUT framework also established the consistency of this relationship between behavioral intention and actual usage [58, 70, 81, 113, 114]. PE, as described by Venkatesh [47], Venkatesh et al. [49] indicates the perceived capabilities of a technology to solve an issue or provide a certain level of performance. In the case of PE related to AI-related technological adoption in the HR acquisition process, this research, being coherent with previous scholarly works conducted in a similar context [14, 22, 55], confirms that it can significantly determine behavioral intention. Whereas investigations showcased a statistically substantial effect of EE on behavioral intention [14, 22], the outcomes of the current study conspicuously display its lack of consequential influence of EE. Similarly, this research contradicts the evidence concerning the direct impact of SI [51, 62, 113] and TC [28] on behavioral intention. This study unequivocally demonstrates that SI, despite its notable impact on behavioral intention as established in prior research, even within the same geographical domain, as documented by Uddin et al. [14], Islam et al. [22], takes on a divergent role within the moderated framework introduced by the current study. The negative relationship between TC and AI adoption already established by previous studies [28] has also been contradicted by this study. However, this research supports the previous evidence regarding the significant impact of FC [14, 22] and HM [76] on the IU AI in the mentioned context.

In the case of the hypotheses related to the moderated roles, this research rejects all except one. Therefore, most of the previous claims regarding the moderated roles made by Andrews et al. [48], Venkatesh et al. [49], Nascimento, Meirelles [84], Tewari et al. [85], Ab Hamid et al. [107], Abu-Shanab [115] have been rejected by the present study. Age, gender, tenure, and VU of usage, as indicated by the analysis, do not moderate the impact of the UTAUT constructs on behavioral intention. Among these moderators, only gender is proven to have a moderating effect on the relationship between EE and IU AI for hiring employees in Bangladesh. The insignificant moderating effect of other mentioned variables in the mentioned relationship dynamics opposes the evidence established by extant literature.

Furthermore, this research, as the first of its kind in the area, employed the NCA, which led to the identification of some necessary conditions for achieving AI adoption-related positive behavioral intention. The outcomes gleaned from the NCA underscore the imperative role played by PE, FC, and HM as indispensable prerequisites for the cultivation of the intention to engage with AI technologies within the domain of employee recruitment. Moreover, when actual usage is considered as an endogenous variable, this research argued that IU, EE, FC, and HM emerge not only as necessary conditions but also as elements imbued with substantive consequence, as affirmed by their robust statistical significance. However, due to the recent development of this particular analysis technique, very few scholarly works have utilized it to present evidence. Therefore, the researchers of the present study failed to justify, compare, and contrast the NCA results for AI adoption in the HR acquisition process.

Implications

Theoretical implications

This research, through a robust design and implementation of methodology, offers several contributions to the area of academia. First, it provides empirical evidence regarding the determinants of AI usage and behavioral intention related to AI application in the HR acquisition process using the lens of the UTAUT model. Whereas previous studies mostly focused on developed nations, this research concentrated on an emerging economy, which enriches the related research field. Second, this research extended the original UTAUT model using the construct TC, which is extremely relevant for sophisticated technologies like AI. Future scholarly endeavors will find ample utility in the adoption of this theoretical framework, rooted in the UTAUT model, as a potent tool for comprehending the intricate determinants that govern the embrace of analogous technologies. Third, the researchers designed and tested a moderated mechanism, evidence related to which should allow future researchers to comprehend the moderating roles of gender, age, work experience, and VU in HR hiring dynamics in developing countries like Bangladesh. Finally, the NCA conducted for this research provided a new type of evidence regarding the determinants of AI technologies in the HR hiring process, which will unfold new research directions and stimulate future researchers to analyze the context similar to the present study from a different perspective and with a different analytical method.

Managerial and practical implications

The present research extends a dedicated focus to the hitherto underexplored scholarly area of developing countries. This emphasis bears the potential to catalyze the adoption of artificial intelligence in businesses, thus auguring heightened levels of efficiency and transparency in the HR acquisition processes. The ramifications of such advancements ripple outward, potentially exerting a consequential impact on the global economy. For instance, Zhang, Jedin [116] revealed that innovation and technical capabilities can enhance the export performance. Both innovation and technical capabilities can be enhanced by utilizing AI technologies in organizational settings [117]. HR professionals in Bangladesh can gain valuable insight regarding the specific impact of PE, FC, HM on behavioral intention, and actual usage of AI in the hiring process. Hence, they will be able to formulate effective HR strategies and interventions that will enhance AI utilization in the mentioned process. Again, this research underscores the significant moderating role of gender in shaping the impact of EE on behavioral intention. Consequently, organizations should consider the necessity of gender-specific training programs to effectively mold EE in the context of AI technologies. Lastly, managers and practitioners, as well as policymakers based on the arguments of Sarangi, Pradhan [118], should acknowledge the necessary conditions identified by the present study to ensure maximum utilization of AI in the hiring process.

Conclusion

This empirical research, utilizing the lens of the UTAUT, endeavored to comprehend the intricate determinants of AI adoption in the HR acquisition process in a developing country. The researchers extended the UTAUT model to study the behavioral intention and usage of sophisticated technologies like AI by adding a new construct, TC. The findings of this research contradict the evidence presented by previous studies regarding the impact of EE, SI, and TC on behavioral intention. However, previous claims regarding the significant impact of PE, FC, and HMs have been reinforced by this study. Again, this research opposes almost all the claims regarding the moderating roles of gender, age, tenure, and VU. Only the claim concerning gender moderating the impact of EE has been proven to be significant in the mentioned research context. Finally, the application of a relatively new statistical tool, NCA, enabled the researchers to identify different necessary conditions or must-have factors.

Limitations and future research directions

The limitation of this research includes the application of only one methodology. Employing only the quantitative lens prohibited the researchers from extracting qualitative psychology-laden factors. Moreover, the researchers of the present study employed convenience sampling, along with the self-reporting survey technique. Hence, the data collection may have been influenced by a non-representative sample and selection bias, leading to a lack of generalizability of the findings. Additionally, ascribing to the application of self-reporting surveys, there is a probability of being affected by, for instance, social desirability bias and interpretation bias. Again, the application of only one framework (i.e., UTAUT) can lead to comprehension bias [119]. Regardless, future scholarly works should utilize a mixed-method approach using both qualitative and quantitative to extract more in-depth psychological expressions. Future studies should also include a more diverse and random sample to increase the generalizability. Besides, by applying data collection tools such as observational methods, the biases associated with self-reporting surveys can be eliminated. Again, the application of other theoretical frameworks, including, UTAUT2, TPB, and TAM, should also be utilized by future research to comprehend the mentioned context from multiple dimensions, which can enrich both theories and practices, as well as the overall effective application of AI.

Abbreviations

AI	Artificial intelligence
AU	Actual use
AVE	Average variance extracted
CMB	Common method bias
CR	Composite reliability
EE	Effort expectancy
FC	Facilitating conditions
HM	Hedonic motivation
HR	Human resources
HRM	Human resource management
IU	Intention to use
NCA	Necessary condition analysis
PE	Performance expectancy
PLS	Partial least squares
PLS-SEM	Partial least square-based structural equation modeling
SEM	Structural equation modeling
SI	Social influence
TAM	Technology acceptance model
TC	Technology complexity
TPB	Theory of planned behavior
TRA	Theory of reasoned action
UTAUT	Unified theory of acceptance and use of technology
UTAUT2	Unified theory of acceptance and use of technology 2
VIF	Variance inflation factors

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MI conceived and designed the experiments; conducted analysis, analyzed and interpreted the data; and wrote the paper, MMR conceived and designed the experiments, and wrote the paper, MAT conceived and designed the experiments and edited the paper, GMAAQ collected data, conceived, and designed the experiments, and MAU collected data, interpreted the findings, and edited the paper.

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