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Artificial Intelligence (AI) for Talent Acquisition:

Human Resource Professionals' Perspective

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ABSTRACT

The present study's aim is to investigate the intention to use and actual use of a artificial intelligence (AI) for talent acquisition in Bangladesh. The authors used deductive reasoning approach in a positive paradigm. The study finally collected 243 responses through self-administered questionnaire and used the PLS-based structural equation modeling to analyze the data. The findings of this study revealed that each of the predictors is significantly associated with the intention to use and actual use of AI for recruiting talents, excepting the influence of facilitation conditions on actual use of AI. The influence of age demonstrated that there is no moderating effect of the influence of users' intention to use on actual use of AI for talent acquisition. This study also advances knowledge in AI adoption for recruiting talents, and enhances literature in the fields of AI adoption for recruiting talents by providing insights for the policy makers in a developing country's context. Furthermore, the study also provides insightful directions for future researchers.

KEYWORDS

Artificial Intelligence, Bangladesh, HR Professionals, Recruitment, Talent Acquisition, UTAUT

INTRODUCTION

Talent acquisition has undergone massive change due to the revolution in information technology, robotics, and social media that necessistates sustainable acquisition model for the future (Chetna, Sreejesh, & Rajneesh Ranjan, 2019; Dhanya & S. Vijayakumar, 2016; Mamta & Priyanka, 2018; Marcial & Albert, 2021). Accordingly, the emerging technological tool, for example artificial intelligence (AI), reflects capacities that resemble an intelligent human (Kaplan & Haenlein, 2019; Wogu et al., 2021) and redefines administration and organizational practices impacting organizational decision-making (Jarrahi, 2018; Wogu et al., 2020) and reclassifying administration models (Assibong

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et al., 2020; Kolbjørnsrud, Amico, & Thomas, 2016). AI's perceivable impacts can be observed in core competency and business processes such as information administration (Liebowitz, 2001), and service quality and customer satisfaction (Brynjolfsson & Mcafee, 2017). The impact of AI is proclaimed as an effective human resource management instrument to replicate activities in human resources (Tambe, Cappelli, & Yakubovich, 2019; Upadhyay & Khandelwal, 2018).

The utilization of AI apparatus has developed in nearly every step of recruitment, such as selecting the applicants from an endless pool of applicants (Ore & Sposato, 2021), making bias-free wording in the advertisement for candidate selection (Rąb-Kettler & Lehnervp, 2019; Sharma, 2018; Van Esch & Black, 2019), and processing voluminous human resource related data surpassing human capacity (Dijkkamp, 2019; Van Esch & Black, 2019)[REMOVED HYPERLINK FIELD]. Bhalgat (2019) highlighted that AI saves recruitment time and moneyof the firms. Wisskirchen et al. (2017) recommended the utilization of AI in recruitment because it evacuates all inclinations that intensify feelings and sensitivities. Savola and Troqe (2019) said that the utilization of AI not only alters the organization inside, but also it affects the recruitment canvass.

AI makes a difference to recognize candidates' abilities, competencies and characteristics that coordinates the work connected. Van Esch and Black (2019) bolstered the claim that AI supports a firm to target and select suitable candidates cost-effectively. Bersin (2017) reported that 96 percent recruiters feel that AI helps them recruit and retain their talents and 13 percent of them predict that AI is going to be a mainstream of human resource (HR) activities. Another study of HRPA (2017) referred that around 84 percent firms acknowledged that AI is an important device and, however, 33 percent of those firms attested that they are not prepared at all for applying AI at their HR activities.

Despite the growth of AI-based technology is unleashed, academic research and scholarly works are meager for the adoption of AI in the contexts of organizations (Alam, Khan, Dhar, & Munira, 2020; Pillai & Sivathanu, 2020). However, the adoption of AI at recruiting talents assists HR professionals to ensure the functional and technical efficiencies of the overall HR division by reducing the repetitive tasks from both candidates and employers' sides (Pillai & Sivathanu, 2020). Surprisingly, having all these inclusive benefits of AI-based recruitment, the adoption of former is still at fancy both in Bangladesh and other developing countries (Albert, 2019). In Indian context, many foreign organizations are using AI and the adoption among local organization is at the earliest stage of acceptance (Pillai & Sivathanu, 2020), but in the context of Bangladesh, many of the local organizations are still far away from thinking of tech-based workplace (Alam et al., 2020). Hence, the present study will not only fill the gap in the literature in the context of a developing country, Bangladesh, but also provide a policy interventions to the recruiters for effective utilization of AI elsewhere. Thus, the following research questions are developed:

RQ1: What predicts AI adoption and implementation for HR activities in Bangladesh?
RQ2: Are there any indirect effects of age and intention to use (IU) of AI on actual use (AU) of AI in Bangladesh?

Following the guidelines mentioned in (Misra, 2021), the rest of the paper is structured as follows: the next section includes theories and hypotheses development on direct, mediating, and moderating effects. The research methodology includes research design, data collection procedure, measurement tools, analytical tools, and bias concern. Results section reports on descriptive statitistics, measurement issues, and test-estimate on direct and indirect (mediating and moderating) effects. Finally discussion and conclusion sections shed light on implications and directions for future research.

THEORETICAL BACKGROUND

The public's acknowledgment or dismissal of ideas, and technology posits overbearing significance on the accomplishment of endeavors to convince behavior modification (Jahanshahi, Tabibi, &

Van Wee, 2020). Adoption of a technology by the user has been verified by a few theories over the decades, for example,the theory of reasoned action (Ajzen & Fishbein, 1977), the theory of planned behavior (Ajzen, 1985), and the technology acceptance model (Davis, 1989). Critics showed a pessimistic endorsement of these fragmented theories that fizzles to mirror a comprehensive view of a new technology adoption and implementation (Uddin, Alam, Mamun, Khan, & Akter, 2020). Venkatesh, Morris, Davis, and Davis (2003) designed a new research model called the unified theory of acceptance and use of technology (UTAUT) to describe the IU and AU of a technology.

The objective of the UTAUT is to model IU and AU of a technology. The UTAUT model includes performance expectancy (PE), effort expectancy (EE), facilitating (FC), and social influence (SI) as direct predictors of users' IU that finally predicts AU behavior (Patil, Tamilmani, Rana, & Raghavan, 2020; Venkatesh et al., 2003).Whereas previous theoretical underpinning failed to clarify the variance of IU, the UTAUT of Venkatesh et al. (2003) explains around 70% variance in IU and also explains 50% variance in AU. The robustness of the proposed UTAUT model was validated by numerous previous studies in diverse fields (Alam et al., 2020; Jahanshahi et al., 2020; Patil et al., 2020). Moreover, a study by Oshlyansky, Cairns, and Thimbleby (2007) using data from 11 countries suggested that the UTAUT model yields better estimates than other models. Therefore, the authors took variables from the original UTAUT model to interpret the behavioral IU of AI alongside mediating effect of FC with the moderated effect of age of users.

HYPOTHESES DEVELOPMENT

Direct Effects

PE is an influential predictor of IU for both voluntary and compulsory settings (Venkatesh et al., 2003). PE refers to the extent to which a user aspires and expects to complete a job using a given technology (Venkatesh et al., 2003). Venkatesh et al. (2003) explored that PE significantly explains users' IU of a technology. Studies witnessed that PE has a significant influence onIU, such as ERP, mobile banking (Alalwan, Dwivedi, & Rana, 2017), E-HR adoption (Obeidat, 2016), Human Resource Information Systems (Hmoud & Várallyai, 2020). Recruiting professionals' perceived benefits in AI for recruiting talents through AI inspire them to apply it in different activities involved in recruitment and selection. It also influences an individual's behavioral IU of AI in recruiting talents by Bangladeshi firms (Alam et al., 2020). The researchers suggested the following hypothesis from the above discussion:

Hypothesis 1: PE positively predicts the IU of AI.

EE refers that individuals feel ease associated to use a particular technology (Venkatesh, Thong, & Xu, 2012). During the initial period of technology adoption, the perceived cognitive and/or behavioral efforts required to learn and utilize a new technology impacts behavioral intention (Gefen, 2003). Previous studies found a comprehensive and positive association between EE and IU (Alam et al., 2020; Alam & Uddin, 2019), such as adoption of cashless payment in tourism (Wulandari, 2017), smartphone for mobile learning (Onaolapo & Oyewole, 2018), bicycle sharing (Liu & Yang, 2018), and mobile payment services (Aslam, Ham, & Arif, 2017), etc. The existing literature linking EE and IU posits that users will not endorse a given technology if they found them complicated and tedious to handle and operate (Uddin et al., 2020). The following hypothesis can be derived from the above literature:

Hypothesis 2: EE positively influences the IU of AI.

SIrefers to the magnitude to which the technology used by an individual is affected by others' opinions surrounding them(Baishya & Samalia, 2020; Venkatesh et al., 2003). An individual who undergoes social pressure control the intention to model in a specific way that reckons from their surrounding environments. In both UTAUT and UTAUT2, SI emerged as a noteworthy predictor of behavioral intentions. Studies found that there is an important and positive association between these two variables (Chatterjee & Bhattacharjee, 2020; Rather, 2018). Likewise, individuals decide to model a behavior by keeping social groups' culture, values, and norms in mind (Jeon, Lee, & Jeong, 2018). In this article, it is predicted that employees will use AI if they are encouraged by people in the company or peers, and perceived identity or prestige for using AI (Alam et al., 2020). Based on literature, theauthors formulated the following hypothesis:

Hypothesis 3: SI positively predicts the IU of AI.

FC refers to the extent to which an individual warrants that the necessary supports (e.g. maintenances and technical infrastructures) will be accessible when using atechnology (Venkatesh et al., 2003). In order to embrace new technology, the existence of organizational and technical expertise, such as technical expert people, knowledge to use technology, post-sales supports, or supportive institutions for maintenance and repairs, etc., must be available for the proliferation of technology adoption (Kavandi & Jaana, 2020; Uddin et al., 2020). FC through the confirmations of required resources, knowledge, and support can augment the possibility of adoption and implementation of AI (Alam et al., 2020). Studies reported findings on the influence of FC on the IU technology (Jahanshahi et al., 2020; Sivathanu, 2019). Notably, by providing essential support and technical advice on how to use that particular service, an organization can make the users ready to use proposed technology (Nysveen & Pedersen, 2016). Kamal, Shafiq, and Kakria (2020) reported the importance of sufficient technical infrastructure and its successive impact on IU and AU of technology. The following hypotheses are developed from the above discussion:

Hypothesis 4: FC positively influences the IU of AI.
Hypothesis 5: FC has a direct impacton the AU of AI.

IU explains the extent of an individual's eagerness and attempt to perform the intrinsic behavior and the AU refers to the exhibition of a discernible reaction in an unsurprising setting concerning a given target (Ajzen, 1991). IU and AU both are extremely correlated, which means the IU is the most important predictor of the AU of technology (Jahanshahi et al., 2020). In previous studies, AI is explored as the proximal determinant of actual technology use, such as mobile banking (Patil et al., 2020), the bicycle sharing system (Jahanshahi et al., 2020), service delivery (Gursoy, Chi, Lu, & Nunkoo, 2019), AI-based medical diagnosis support system (Fan, Liu, Zhu, & Pardalos, 2020), enterprise resource planning (Uddin et al., 2020), AI in recruiting talents (Alam et al., 2020), etc. Researchers observed no discrepancies between these two constructs of accepting AI in the organization. From the literatures,the researchers developed the following hypothesis:

Hypothesis 6: IU has a positive influence on the AU of AI.

Mediating Effect of IU on FC and AU

In the previous studies,a small difference of opinion reported the influence of FC of IU and AU of a particular technology. Admiring the theorem of UTAUT, the authors can connect and announce FC works as both direct and indirect predictorof the AU of a technology (Venkatesh et al., 2012). In line with the documented findings of Dwivedi, Rana, Jeyaraj, Clement, and Williams (2019), Uddin et al. (2020)[REMOVED HYPERLINK FIELD], Raza, Shah, and Ali (2019), and Alam et al. (2020), the evidence shows that FC influences IU which, in consequence, predicts AU. Moreover, the logical connection of hypothesis 4 and hypothesis 6 justifies the mediating influence of IU on the association between FC and AU. From the above discussion, the following hypothesis is developed:

Hypothesis 7: IU mediates the impact of FC on AU.

Moderating Effect of Age

Users' IU a particular technology can be directly and indirectly affected by user demographics (Hamner, 2009; Lee, Lim, Jolly, & Lee, 2009; Tarcan & Varol, 2010). Demographics such as age can be a moderator which can influence the association between IU and AU of technology. Generally, the authors observe that younger generations are enthusiastic and willingly accept any technological change. Studies showed that young adults are more open to change or adopt technology than old adults because old adults are afraid of change or adopting new technology (Kwateng, Atiemo, & Appiah, 2019; Soliman, Karia, Moeinzadeh, Islam, & Mahmud, 2019). Moreover, younger employees will also positively accept any sorts of technological changes such as the adoption of AI. Basing on the previous studies, the authors postulated that age dividend, such as young and old, moderates the influence of IU on AU for recruiting talents. Therefore, the following hypothesis is developed:

Hypothesis 8: Young users tend to have a powerful impact on the positive influence of IU on AU than adult users of AI.

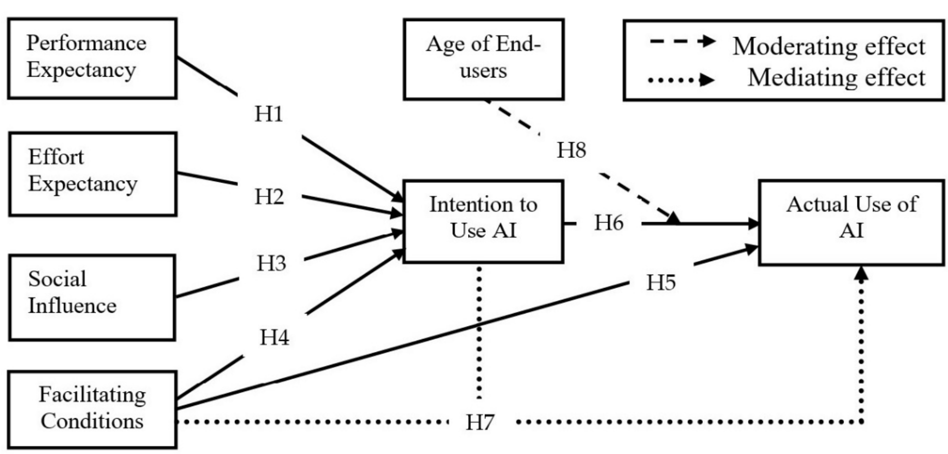
Thus, using the lens of UTAUT and previous studies, the following hypothesized model, Figure 1, is developed that shows how PE, EE, SI, FC connects, which, in consequence predicts AU of AI. Additionally, the figure displays the moderating effect of age on the influence of IU on AU of AI to recruit talents.

RESEARCH METHODOLOGY

Research Design

This study employed deductive reasoning to investigate proposed relationships in the hypothesized model. From the previous researches, the authors collected a multi-item scale for measuring constructs after that the researchers collected data from all the AI users in the firms during the interval from

Figure 1. Hypothesized model



August 2020 to January 2021. A survey questionnaire has been sent to organizations addressing higher authority where employees are regularly using it. For the ease and comfort of responding to our questionnaire, the authors posted a self-addressed envelope to the respondents at the time of delivering it (Azim, Fan, Uddin, Jilani, & Begum, 2019). Partial Least Square based structural equation modeling (PLS-SEM) is applied to examine the data, which is widely used now in the business deciplines. A good number of researchers approved PLS-SEM on the top of simple regression because of its soundness of the results through examining the model entirely rather than assessing each path alone (Hair Jr, Hult, Ringle, & Sarstedt, 2016; Uddin, Mahmood, & Fan, 2019).

Data Collection Procedure

This study was conducted in various manufacturing firms, where AI is used. The authors distributed the survey questionnaires among the respondents. It promises the soundness of the results from the basic depiction of samples across firms. Finally,243 responses were collected from the targeted respondents viaa self-administered survey from 400 assigned survey-questionnaires from both national and multinational firms with a 60 percent response rate, that sounds enough to use the PLS-path model (Fan, Mahmood, & Uddin, 2019) as well as higher than related researches in various contexts (Elgohary, 2019; Tajasom, Hung, Nikbin, & Hyun, 2015; Wanko, Kamdjoug, & Wamba, 2019).

Measurement Tools

Items were collected from the prior studies which were used in several contexts given in Table 6 in the Appendix. To ensure the face validity of the constructs, the authors brought some changes in these items aiming to elicit correct understanding of the scales among the respondents. PE, EE, SI, FC, and IU are examined using the constructs which were proposed by Venkatesh et al. (2012), and AU is examined using the items filtered by Rajan and Baral (2015).

Analytical Tools

In this study, the suggested hypotheses were examined through the PLS-SEM version 3. The distinctiveness of PLS-SEM is its holistic measurement of the measurements via reliabilities, validities and cross-loading, and structural model via beta-coefficient, R^2, and path-significance (Hair Jr et al., 2016).The study used PLS-SEM because our study's aim is to predict IU and AUby the use of AI among HR professionals to recruit their talents (Hair Jr., Hult, Ringle, & Sarstedt, 2017). Moreover, PLS-SEM is less sensitive to sample size and more flexible than covariates based SEM (Astrachan, Patel, & Wanzenried, 2014; Dash & Paul, 2021; Rigdon, Sarstedt, & Ringle, 2017). 5000 bootstrapping sample cases were examined to generate the results.

Bias Concern

The authenticity of any research outcomes is very essential for any study and two kinds of bias such as method and response bias canprevent the authenticity (Podsakoff, MacKenzie, & Podsakoff, 2012; Spector, Rosen, Richardson, Williams, & Johnson, 2019). Henceforth,to remove bias issues the researchers took preventive measures in advance (Uddin, Priyankara, & Mahmood, 2020). Primarily, the authors assured anonymity of their responses which leads them to respond in more accurately without any fear of being identified (Fan et al., 2019; Howladar, Rahman, & Uddin, 2018). Furthermore, the study assessed Harman's one-factor test to examine whether any individual factor describing above 50 percent of the overall variance (Uddin et al., 2019) and the result shows that a single factor does not explain more than 50 percent of the variance. Finally, to know whether there is any relationship above 90 percent between two variables were observed, the correlation matrix is also tested (Pavlou, 2003; Spector & Brannick, 2010). Remarkably, the study found that the largest correlation score between any two variables is only 0.622. Thus, no response bias is observed (Bagozzi, Yi, & Phillips, 1991).

RESULTS

Sample Characteristics

Table 1 demonstrated the chosen individual employees' age, gender, degrees, experience, designation, and the size of the firms. The majority of the respondents was males (male=80 percent and female=20 percent) with the employees' mean age is 33.28 years, had 1 to 5 years (63 percent) working experience, worked in large firms (54 percent), and completed master degrees (64 percent).

Measurement Issues

In PLS-SEM, the measurement issues are examined through convergent validity via reliability and average variance extracted (AVE) scores, and discriminat validity via checking confirmatory factor analysis (cross-loading) and correlation matrix through the Fornell and Larcker (1981) method. The minimum reliability score of each construct, in Table 2,is more than the cut-off limit of 0.70 (Mahmood, Uddin, & Luo, 2019; Yi, Uddin, Das, Mahmood, & Sohel, 2019). Moreover, AVE estimates showed that the minimum score of any particular variable's AVE is 0.640 (>0.500). Hence, the threshold limit of convergent is maintained (Hair Jr. et al., 2017). Estimates on confirmatory factor analysis showed that items were highly loaded to their own construct than other constructs. With regard to discriminant validity, Table 2 exhibited that the AVE's square root of a variable is larger its correlation estimates with other variables. Thus, no issue is observed in the discriminant validity (Hair Jr. et al., 2017).

Structural Model Evaluation

β, p-value, and R^2 are the widely used criteria to assess the strength of the structural model. The Figure 2 exhibited that except the path of FC to the AU of AI, all other path estimates are found significant. Moreover, the coefficient of determination (R^2) stated that the scores are above the threshold limit set by Cohen (1988) since the minimum R^2 is 0.367. Moreover, standardized root mean square residual (SRMR) for model fitness, multi-collinearity for the detection of error in regression weight, and predictive relevance were examined (Hair Jr. et al., 2017). The calculated SRMR was 0.045, which is less than the threshold limit (<0.08) (Henseler et al., 2014). The multi-collinearity effect is measured with variance inflation factor where any score higher than 10.00 is problematic (Field, 2018). Accordingly, none of the variance inflation factors exceeds 2.00 (EE=1.378). Finally, the predictive relevance was estimated to 0.359 for IU and 0.317 for AU which ranges from medium to large (Hair Jr. et al., 2017). Thus, there is no issue with the structural model.

Table 1. Demographic information (n=243)

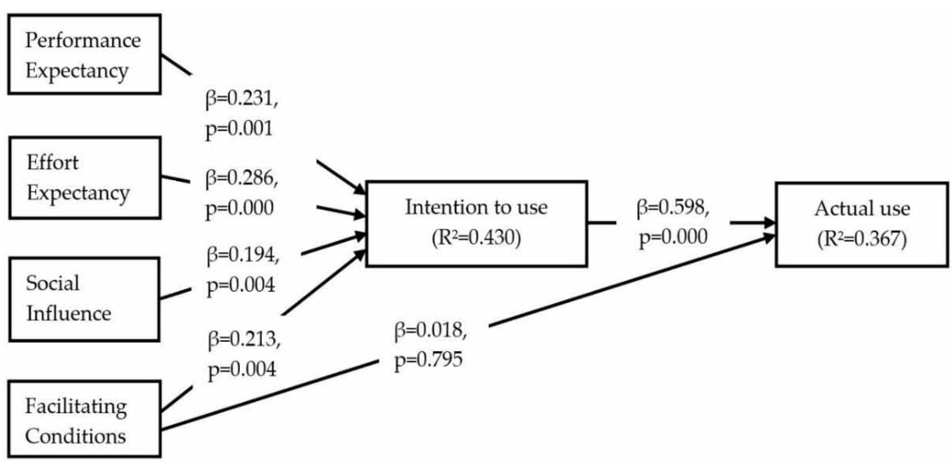
Characteristics	Classifications	Frequencies	Percentage
Gender	Male Female	195 48	80 20
Age **Mean=33.28 years**	20 to 29 years 30 to 39 years 41 and above	61 145 39	25 60 15
Experience **Mean=5.99 years**	1 to 5 years 6 to 10 years More than 10 years	152 61 30	63 25 12
Degree Completed	Undergraduate Master	87 156	36 64
Size of the firm	Small Medium Large	21 91 131	9 37 54

Table 2. Estimates on measurement issues

Variables	1	2	3	4	5	6	7	8	9	10	11
Control variables											
1. Age	1										
2. Experience	.804**	1									
3. Degree	.106	.028	1								
4. Size	.043	.065	.243**	1							
5. Gender	.081	.048	-.012	.002	1						
Latent variables											
6. IU	.051	.021	.119	-.006	.038	0.934					
7. EE	-.068	-.083	.042	-.039	-.060	0.522	0.874				
8. FC	-.038	.002	-.013	.091	.058	0.418	0.344	0.906			
9. PE	-.113	-.067	-.073	.000	-.120	0.473	0.446	0.213	0.800		
10. SI	.005	-.036	-.023	-.039	.042	0.427	0.307	0.296	0.355	0.900	
11. AU	-.108	-.048	-.019	.001	-.018	0.606	0.294	0.268	0.338	0.287	0.939
Cronbach's alpha	-	-	-	-	-	0.926	0.897	0.927	0.814	0.921	0.932
Composite reliability	-	-	-	-	-	0.953	0.928	0.948	0.877	0.944	0.957
AVE	-	-	-	-	-	0.872	0.763	0.820	0.640	0.809	0.881

IU = Intention to use; EE = Effort expectancy; FC = Facilitating conditions; PE = Performance expectancy; SI = Social influence; AU = Actual use; AVE = Average variance extracted

Figure 2. Path of FC to the AU of AI



Testing Direct Effects

Estimates in Table 3 showed that all of the proposed hypotheses (**H1**: β=0.231; p=0.001, **H2**: β=0.286; p=0.000; **H3**: β=0.194; p=0.004, **H4**: β=0.213; p=0.003, and **H6**: β=0.598; p=0.000) are found significant, excepting H5 (β=0.018; p=0.795). Thus, all of the hypotheses (H1, H2, H3, H4 and H6) are supported excepting hypothesis 5 (β=0.018; p=0.795).

Table 3. The test statistics of direct effects

Hypotheses	Path relations	β	SE	t-statistics	p-value	Decision
Hypothesis 1	PE → IU	0.231	0.072	3.214	0.001	Supported
Hypothesis 2	EE → IU	0.286	0.071	4.028	0.000	Supported
Hypothesis 3	SI → IU	0.194	0.067	2.887	0.004	Supported
Hypothesis 4	FC → IU	0.213	0.070	3.024	0.003	Supported
Hypothesis 5	FC → AU	0.018	0.068	0.260	0.795	Not supported
Hypothesis 6	IU → AU	0.598	0.060	9.958	0.000	Supported

IU = Intention to use; EE = Effort expectancy; FC = Facilitating conditions; PE = Performance expectancy; SI = Social influence; AU = Actual use; SE = Standard error

Testing the Mediating Effect

Two preconditions must be satisfied to deal with the mediation. First, the study examined whether the direct effect (c) of exogenous variable on endogenous variable without mediating variable is significant or not (Chou & Yeh, 2013; Hayes, 2013). Second, the study assessed the change in direct effect ($c^{/}$), for example significantly reduced (partial mediation) or disappear (full mediation) after using mediating variable (Azim et al., 2019; Fan et al., 2019). The Table 4 demonstrates a significant direct effect (β_c=0.272, p=0.000) before estimating mediator variable, and indirect effects ($\beta_{a(FC\rightarrow IU)}$=0.213, p=0.003 and $\beta_{b(IU\rightarrow AU)}$)=0.598, p=0.000) and the insignificant direct effect after employing mediating variable ($\beta^{/}_{c\,(FC\rightarrow AU)}$)=0.018, p=0.795). Thus, the study can delineate the result is significant, and H7 is supported.

Testing the Moderating Effect

We considered the age of AI users as moderating variable and its effect was tested using multi-group analysis. In Hypothesis 8 (Table 5), the authors examined the moderating effect of age to find out whether there is any meaningful difference of path estimates between young and old adults between

Table 4. Result of mediation (IU as a mediator variable)

Path relations	B	Indirect Effect	Total Effect**	t-statistic	p-Value	Decision
FC → AU (c)	0.272			3.763	0.000	
FC → IU (a)	0.213	0.127*	0.145	3.024	0.003	Supported
IU → AU (b)	0.598			9.958	0.000	
FC → AU ($c^{/}$)	0.018			0.260^{ns}	0.795	

FC = Facilitating conditions; AU = Actual use; IU = Intention to use; ns = Not significant, *Indirect effect = FC→ IU times IU → AU; **. Total effect = Direct effect ($c^{/}$) + Indirect effect

Table 5. Moderating effect using Multi-group analysis

Hypothesis	Path relations	Old adults			Young adults			Difference in β	p-Value	Decision
		B	SE	p-Value	β	SE	p-Value			
Hypothesis 8	IU → AU	0.611	0.087	0.000	0.592	7.012	0.000	0.014	0.903	NS

AU = Actual use; IU = Intention to use; SE = Standard error; NS = Not significant

IU and AU. The result shows that there is no significant difference of the influence of IU on AU between young and old adults (β=0.014; p=0.903). Therefore, H8 is not supported.

DISCUSSION AND CONCLUSION

Basing on the UTAUT model, the current study investigated the IU and AU of AI in a developing country's context. Additionally, an extended UTAUT model has been put forward in this research along with the test of mediation and moderation to unearth IU and AU of AI. The findings of the study are demonstrated in Tables3, Table 4, and Figure 3.The findings of this study revealed that each of the variables in the original model has found strong predictor of the adoption of AI, but there is no significant influence found in between facilitation conditions and AU because of the full mediation effect of IU.

Furthermore, our study has revealed very similar results with prior research in the field of adoption of technology in different environments (Alam et al., 2020; Awa, Uko, & Ukoha, 2017; Dwivedi et al., 2019; Rajan & Baral, 2015). The findings of this research illustrated that when users feel that PE, EE, SI, and FCexist, they tend to bemotivated to use AI more than before, and vice versa (Asamoah & Andoh-Baidoo, 2018). The direct effect of FC to AU was found insignificant, which is similar to the findings (Dwivedi et al., 2019; Salloum & Shaalan, 2018). The dominant mediating influence of IU on the association between FC to AU makes the previously significant direct path (without mediation in Table 4) insignificant. Moreover, the full mediation effect of IU on the influence of FC on AU postulated that influences AU indirectly through IU than directly.

The influence of age as the moderating variable, who is associated with the IU and AU of AI, exposed that there is no moderating effect influences users' IU and AU of AI. The main reason of this insignificant multi-group analytics' result is the small difference between old adults and young adults because the majority of the employees are very young. Finally, whether the users being older or younger does not influence their IU and the AU of adopting AI by the professionals responsible for talent acquisition.

Managerial Implications of the Study

This research bestows an enthralling observation thatembeds in AI adoption for recruiting talents from HR professionals. The study disclosed that vendors, marketers of AI, professionals, and practitioners will be benefited by studying our research findings. The outcome of this research will also encourage entrepreneurs and enterprises to understand the adoption behavior of users and areas to invest to become successful in the field of AI adoption. Moreover, our findings will help AI developers to develop need-based AI programs and customizing that program with human resource activities especially for talent acquisition professionals. Additionally, as the study observed no significant difference between the older and younger generation of AI adoption and AU of it, AI program developers need not think it seriously while developing and applying AI technology and its applications. The main reason behind it is the little age gap among young and old adults using AI technology. Thus, the policy makers might think of bringing quick breakthrough to reap the benefits of younger HR professionals. This study suggests that AU is encouraged by the indirect influence of IU rather than the direct effect of FC and this result found similar with the studies of Dwivedi et al. (2019) and Chao (2019). Henceforth, the relevant policy-makers and AI marketers must focus on FC feeding to reviving IU of AI. The outcome of this research will facilitate the policy-makers to formulate need-based strategies and policy interventions by understanding the influences of the factors in accepting AI.

Limitations of the Study and Future Research Directions

Despite the significant novelties and contributions, the present study has few limitations that might work as important notes for future researchers. First, responses were collected just from the HR professionals working at various manufacturing and service organizations with limited scope. Thus, sample from other professionals who are associated with HR professionals needed because the adoption of AI technology is not merely the decision of the former. Second, the respondents were very young (33.28 years) with a very limited experience (between 1 to 5 years) that prevents to understand the breadth and rigor of the adoption and actual use of AI in recruiting talents. Henceforth, scholars need to collect responses from a variety of demographic characterisctics such as more aged and experienced employees for getting an essential insight on AI adoption in Bangladesh and abroad. Third, the comprehensiveness and causality of the outcomes are averted by the sample size and cross-sectional data. Therefore, researchers suggest to use a large sample size in a longitudinal survey with a mixed-method design. Finally, the study of adoption of AI by professionals for recruitment and selection is very relatively new. It will not be able to provide a clear picture of the broad canvass if the researchers base it only on Bangladesh perspective. Therefore, the study suggests to the scholars to expand research scope in cross-cultural settings to make findings more generalizable and comprehensive.

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APPENDIX

Table 6. Measurement tools

Measures	Items
Performance expectancy	In talent acquisition process – (PE1) Use of AI improves my productivity (PE2) I would find AI useful in my job (PE3) Using AI saves my time (PE4) If I use AI, I will increase my chances of getting a raie
Effort expectancy	(EE1) Learning to operate AI is also easy for me (EE2) I would find AI easy to use (EE3) Becoming skillful at using AI will be easy for me (EE4) My job related activities with AI-technology are clear and understandable
Social influence	(SI1) People who are important to me think that I should use AI-based software (SI2) People who affect/influence my behavior think that I should use AI-based software (SI3) People whose opinions that I value prefer that I must use AI-based software (SI4) In general, the organization has supported the use of AI-based software
Facilitating conditions	(FC1) I have the resources necessary to use AI-based software (FC2) I have the knowledge necessary to use AI-software (FC3) AI technology is not compatible with other available software/technologies I use (FC3) I can get help from others if I have difficulties using AI software
Behavioral intention	(BI1) I intend to continue using AI-based software in future (BI2) I will always try to use AI technology in my dAIly life (BI3) I plan to continue to use the AI technology frequently
Use behavior	(UB1) I have been using AI-based software for last few weeks (UB2) I am using this regularly now (UB3) I am giving a lot of time in AI-based software applications

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