Will you choose me, Dear Computer? An exploratory study utilizing the UTAUT framework on job candidates' perceptions of AI-powered hiring

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Abstract: *This study investigated candidates' perceptionsof accepting an AI-driven recruitment and selection process by using the "unified theory of acceptance and use of technology (UTAUT)"model. For this study,The UTAUT model is enhanced by incorporating two additional components, namely Trust In AI, and perceived value, as constructs.A total of 260 candidates(applicants)participated in a web-based surveyfor data collection purposes. The reliability and validity of the data were assessed using Cronbach's alpha coefficient test and Principal Component Analysis. The hypothesized relationships were analysed using multiple linear regression analysis. The ifindingsindicate that the primary components of the UTAUT model, such asiperformanceexpectancyi, effortexpectancy, social influence, and facilitating conditions, strongly impact the intention of using AI-based technologies in the recruitment and selection process whereas the two newly added constructs have negligible impact on behavioral intention of the job applicant. The study provides a theoretical addition by confirming the effectiveness of AI-based technologies in the recruitment and selection process in this specific setting by using UTAUT model.The construct developed in the research has consequences for managerial decision-making and suggests an impact on the effectiveness of its processes.*

Keywords: *AI-empowered recruitment process, Candidates' perception, UTAUTmodelBehavioural intention, Trust in AI, Multiple linear Regression analysis.*

Introduction

Human resource management functions have evolved from being primarily administrative to becoming a strategic partner in organizational decision-making, focusing on talent management, talent recruitment, development, and retention. The integration of technology has also led to the extensive adoption of digital tools for recruitment, performance management, employee engagement, and data analytics. HRM functions are more becoming data-driven, using analytics to predict candidates' recruitment to exit interviews [9].Especially after 2000, organizations have startedconsidering "People as a source of competitive advantage with a multidimensional contribution towards the success of the organization"[27].They are now the strategic partners of business from an RBV perspective and so also their contribution has significant strategic importance [37].The recruitment and selection functions play a vital role in HRM, spanning the process of identifying, assessing, and choosing individuals for positions inside a company. The implementation of AI in the recruitment process has facilitated a rapid and effortless experience for both candidates and firms. "Recruiters in various industries are widely utilizing artificial intelligence (AI), which has emerged as a prominent trend in the recruiting sector" as researched by[2]. AI functions as a supplement to humans rather than a replacement, assisting with challenging, repetitive, and time-consuming tasks compared to the traditional recruitment process.It enhances human cognitive abilities, embodies human icapabilities, and expands iphysical capabilities [30].The inception of idigital recruiting 1.0 occurred in the mid to late 1990s, immediately after analog recruiting. Analog recruiting was distinguished by the use of actual job iboards, newspapersi, and other forms of print media [4].The emergence of digital recruiting 2.0 was marked by the consolidation of job listings from several job boards and the creation of specialized platforms for both professional and social networking. Soon after the integration of AI led to the evolution of digital recruitment 3.0. AI is not a readily deployable technology that produces flawless and instantaneous outcomes, as demonstrated by Amazon's experience (2018) with a recruiting algorithm, which faced challenges related to fairness, ethics, and legal considerations.

While recruiters may find it easier, candidates often have uncertainties. The efficacy of AI-enabled recruitment processes is attributed to their capacity to carry out faster screening and selection operations. Nevertheless, apprehensions of equity and prejudice have been expressed. Transparency and trust are crucial for fostering confidence among candidates. Artificial intelligence can customize the recruitment process by providing employment suggestions and feedback that are specifically tailored to individuals. However, candidates usually express concerns over the accuracy of job fit and the level of human engagement,[36]. This research aims to assess the perceptions of job applicants to adopt the AI-enabled recruitment process through UTAUT model.

Literature Review

Digital Era and Artificial Intelligence in Recruitment

From 2010 to 2015, Digital Recruiting 2.0 evolved and became more advanced. During this time, Digital Recruiting 3.0 moved beyond discussions at conferences and started being used in commercial applications. The primary novel component of Digital Recruiting 3.0 refers to the implementation of artificial intelligence, as stated by [22]. In the ongoing battle between job-finding people and people finding a job digital recruitment has significantly expanded its reach. Walmart received a staggering 23,000 applications for just 600 positions,[23].While Johnson and Johnson shattered records with over one million applications for their 28,000 available positions. In 2018, it was quite challenging to secure a job at Google due to the overwhelming ratio of 2 million applicants to just 14,500 available positions. s [38].Undoubtedly, the level of friction between job seekers and employers has considerably diminished. However, this has resulted in the emergence of a conspicuous issue: a substantial collection of unqualified candidates, akin to a waste pool. Effectively discerning both proactive and reactive job prospects is crucial for firms to have the most optimal candidate pool. No doubt the friction between applicants and employers has significantly reduced but this led to another visible problem of having a large igarbage pool of unqualified icandidates. Intelligently identifying iboth active and passiveiijob candidates is critical for companies to create the best possible candidate pool [16].The iarrival and acceptance of AI is predicted to greatly boost recruiters' productivity and free them up for more strategic and human-centric activities.[41] AI integration in recruitment processes provides benefits, but it also creates difficulties. One of the most significant concerns in AI-powered recruitment is algorithmic bias. Data privacy and security are critical for AI in recruiting since it handle vast volumes of sensitive candidate information. AI can make the recruitment process easier, but overreliance on automated tools may lead to a lack of human supervision. Using AI in recruitment creates moral dilemmas that are deep and multifaceted in most organizations. Transparency, accountability, employment displacement, and unfairness are among the most pressing ethical concerns regarding algorithmic decision-making [6].These problems also generate the same amount of concern for a job applicant such as Perceived Fairness and Transparency, Trust in AI, Personalization and Candidate Experience, Perceptions of Dehumanization, and Impact on Job Search Strategies [17].The aforementioned issues, namely Perceived Fairness and Transparency, Trust in AI, Personalization and Candidate Experience, Perceptions of Dehumanization, and Impact on Job Search Strategies, also elicit equal levels of anxiety for job applicants [18].

Objectives

1. Identify the influencing elements for the adoption of AI in the recruitment and selection process
2. To investigate the components of the UTAUT model that elucidate the variability in candidates' Behavioral Intention to utilize the AI-enabled recruitment process
3. To Identify the key variables that are essential in adopting an AI-powered recruitment process according to the UTAUT model.

Conceptual Framework

Artificial intelligence can automate repetitive operations, analyze vast amounts of data, and produce significant insights to assist HR professionals in making strategic decisions. In the recruitment field, AI algorithms are specifically used for resume screening, candidate matching, and predictive analytics to efficiently discover highly skilled individuals Marle,H & Boudreau,J (2017)Job applicants' perceptions of AI-powered recruitment processes are shaped by factors such as fairness, transparency, trust, personalization, and dehumanization. Organizations must prioritize transparency, mitigate algorithmic biases, and strike a balance between AI automation and human interaction to foster positive perceptions among job seekers [21]. To address the perception of technology adoption, various theories have been proposed like "Theory of iReasoned Action" (TRA; Fishbein, 1975), "The Technology Acceptance Model" (TAM; Davis, 1989), the "Motivational Model" (MM; Davis et al., 1989), the "Theory of iPlanned Behavior" (TPB; Ajzen, 2011), However, for this research effort, the ATAUT itheory has been selected iand deemed convincing as per[2].The UTAUT is ipredominantly used in research because iit is a unified model that combines a variety of variables from eight prominent theories,[43].Itprovides a framework for understandingi technology adoption among iemployees, iemployers, and managers. The UTAUT model has been widely used in many technology adoption istudies. It forecasts the ibehavioral intention to use new technologies. iThe UTAUT model explains why users iadopt information systems and their usage ipatterns. The model outlines ifour essential factors(PE)Performance Expectancy (faith in the system's ability to improve job performance), (EE)effort expectancy (ease of use), (SI)Social Influence (others' importance), and (FC) FacilitatingConditions (belief in organizational support). These ifactors influence (BI) Behavioral Intention (intended to use) and usagei behavior while adopting new technologies. The model takes into account gender, age, prior experience, ivoluntariness, and other characteristics also [8].The Unified iTheory for Acceptance and Use of Technology (UTAUT) model guarantees 70% accuracyi when assessing behavior connected to information technology use. The model is regarded as reliable, with an average explanatory capability ofi 40% to 50%[39].This study adopts the UTAUT as a conceptual framework. Two additional constructs, Trust in AI and Perceived Value, are introduced to assess the perception of applicants on the adoption of the AI-powered recruitment process. The original UTAUT model is illustrated below.

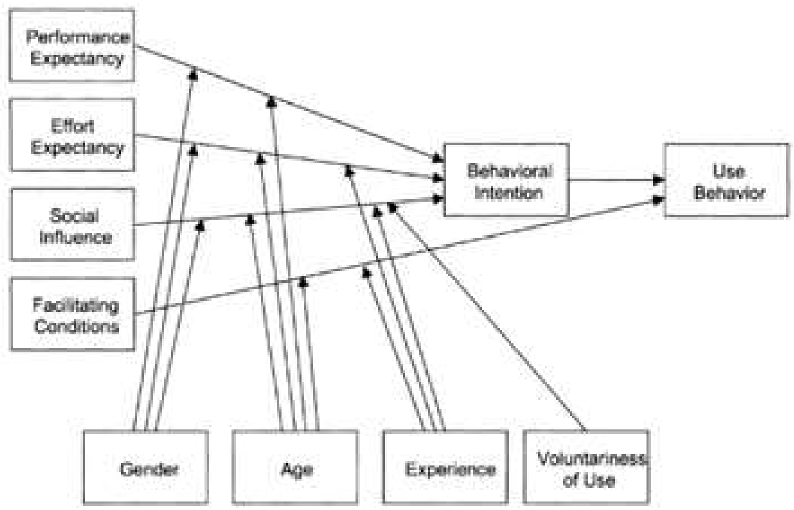

Fig. 1. An overview of UTAUT's determinants and moderators (Venkatesh et al., 2003).

Hypotheses

The proposed UTAUT model is shownin Figure2. Performance Expectancy, Effort Expectancy, Social Influence, facilitating conditions, Trust in AI, and Perceived value are proposed to be the determinants of Behavioral Intention.

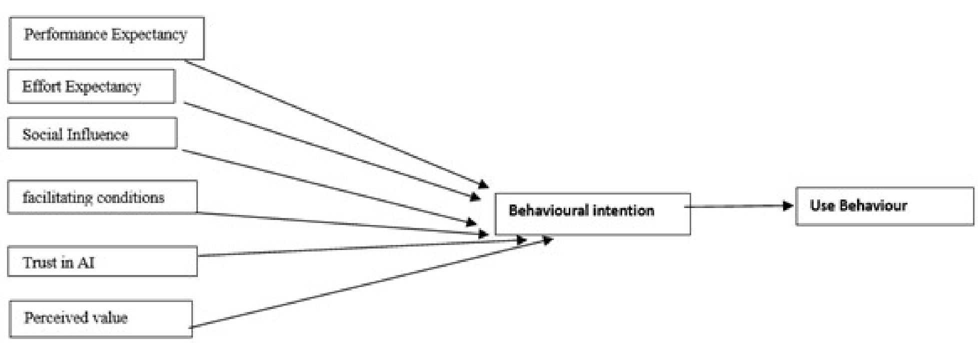

Fig 2: Proposed Model

Source: Primary Source

PerformanceExpectancy from candidate's perspective

AI-driven irecruitment processes are expected to perform with accuracy with numerous advantages, such as Increased efficiency ithat is achieved by automating repetitive operations such as resume screening, candidate isourcing, scrutinizing extensive datasets and minimizing human prejudice, mistakes during early evaluations, icost saving due to less time and improved candidates overall iexperience of job application and selection [25].According to [43]. A new technology user expects performance to the extent that they believe that iusing technology will help them attain better performance. The term "performance expectancy" relates to the extent to which using AI-powered recruiting services iwould help job candidates with their job applications. Several models have discovered factors that represent this idea, including iperceived usefulness (TAM/ TAM2 and C-TAM-TPB), extrinsic imotivation (MM), job fit (MPCU), irelative advantage (IDT), and outcome expectations (SCT). iAccording to studies, performancei expectancy is a strong predictor of the willingness to use technology [43].iAmong the 116 studies analyzed by Williams et al. (2015) to investigate the iinteraction between performance expectancy and behavioral intention, a significant iassociation was observed in 93 istudies (80%). The correlation between Performance Expectancy and Behavioral Intentionihas been substantiated in numerous additional research istudies. Hsu and Ju [15] conducted a study on the factors that affect users' intention to continue using mobile banking in Indonesia and ialso validated the relation. They found that factors such as innovation expectancy (similar to performance expectancy) and outcome expectancy (related to behavioral intentions) play prominent a role in users' acceptance of Google Glass, as examined by [26].The hypothesis formulated for this construct is stated below

H1:iPerformance expectancy of the AI-powered recruitment process is statistically isignificantly related to the behavioral iintention to use it

Effort Expectancy

Effort expectancy, like performance expectancy, was recognized as a significant element in the UTAUT model that affects user intentions to adopt new information technology. The foundation of this is built upon three key principles: the perceived ease of use as defined by [11]the complexity model proposed, and the ease of use framework provided by [28]. From the applicant's standpoint, this implies that the utilization of AI-driven hiring processes for job applications is easily accessible, the interaction with the process is transparent and clear. The study conducted by H., Kassim, N., & Hassan, M. M. (2021) validates the relationship between effort expectancy and behavioral intention for mobile learning in higher education. It examines how individuals' behavioral intentions are influenced by their perception of effort expectancy when using cloud computing services [34].In a study conducted by Williams et al. in 2015, out of 110 investigations, 64 of them, or 58%, discovered a substantial correlation between effort expectancy and behavioral intention.In this study, effort expectancy refers to the level of comfort linked to using of AI-powered recruitment procedure. The second hypothesis is formulated as follows, drawing on evidence from the literature:

H2:iEffort expectancy of AI-powered recruitment process is istatistically significantlyi related to the behavioral intention to adopt it

Role of SocialInfluence on job applicant's perception

[43] suggests that an individual's perception of how others will see them upon accepting a new technology impacts their choice to use it. Social influence refers to the mechanism via which individuals mold the thoughts, emotions, and behaviors of others [33].Among

the 115 istudies that investigated the correlation between social influence and behavioral intention, 86 studies (75%) discovered a significant association (Williams et al., 2015). In their study, [44] examined how social networks affect the job search behavior and intentions of recent college graduates in China. This study examines the impact of social influence, including guidance and assistance from family, friends, and other social networks, and establishes a correlation between them. Moreover, the correlation between these factors has been established across several fields, including studies on the impact of social media on the purchasing choices of millennials,[30].This analysis specifically examined the effects of social factors on behavioral intentions.The association between Social Influence and Behavioural Intention has been determined to be statistically significant based on the studies conducted by Al-Shafi & Weerakkody (2009), Hung, Wang, & Chou (2007), and Kourouthanassis, Georgiadis, Zamani, & Giaglis (2010).The third hypothesis is formulated as follows,

H3:ISocial influence is statistically isignificantly related to the behavioral intention to use the AI-powered recruitment process

FacilitatingConditionsi

Facilitating Conditions are the iuser's preferences for the resources and support available to carry out a behavior [7].Williams reviewed 48 studies on the association between enablingi conditions and behavioral intention and discovered that 33 studies (69%) ifound this relationship to be significant [45].[6,7] offer insights on creating favorable conditions for job applicants in the context of AI-powered recruiting, emphasizing the relevance of transparency, accessibility, and trust in AI systems. While particular research may be restricted due to the nascent nature of AI in recruiting, this paper provided significant insights into how facilitating conditions can influence job candidates' experiences and behavioral intentions in AI-driven hiring procedures.[47] investigated the relationship between human resource practices, perceived organizational support (a notion closely related to facilitating conditions), and workiintention among employees in the Chinese healthcare sector, and found that the association is significant. The connection between Facilitating Conditions and Behavioural Intention is relevant in numerous contexts (Schaupp & Hobbs, 2009; Sok Foon & Chan Yin Fah, 2011; Teo, 2011; Biljon & Kotzé, 2008; Y. L. Wu, Tao, & Yang, 2007).

H4:Facilitating conditions are statistically significantlyirelated to the ibehavioral intention to use the AI-powered recruitment processi

Trust in AI

Establishing trust in AI necessitates a thorough approach that incorporates technical, ethical, and societal considerations. Trust in AI encompasses individuals' assurance in the consistent accuracy of results, transparency in the utilized methodology, understanding of trustworthiness, and moral operation of artificial intelligence systems. The framework encompasses the attributes of reliability, transparency, explainability of AI-driven decision-making, impartial treatment of individuals, safeguarding of sensitive data, and the creation of a positive user experience for repeat use. Several studies have also analyzed this phenomenon to explore the correlation between AI-powered decision-making systems and the behavioral intents of job seekers. G. K. C. and Lu, R. (2020). Puaschunder, J. M., and Kutarna, C. (2021). Scobie, N. V., Demirtas, D., and Peko, G. (2020) investigated the impact of explainability and algorithm transparency on enhancing trust in AI recruitment tools. This study examines the impact of providing clear explanations about how AI algorithms make decisions and ensuring transparency in the recruiting process on the levels of trust displayed by job applicants. The influence of several factors, including the transparency of

AI algorithms, the perceived dependability of AI evaluations, and the familiarity with AI technology, on the amount of trust exhibited by applicants and their following behavioral intentions, such as submitting job applications and accepting job offers. For this study, researchers are firmly convinced to incorporate it as an attribute in the ATUAT framework. Therefore, the hypothesis is formulated as follows:

H5: Trustiin AI is statistically significantly irelated to the behavioral intention to use the AI-powered recruitment process

Perceived value

Perceived value can be understood through social cognitiveitheory that depicts iindividual expectations are the primaryi determinant of attractive outcomes, as defined by social cognitive theory, which assumes that individual perceived valuei is the iprimary determinant of affective outcomes (Bandura, 1978). iPerceived value has played the role of the antecedent of many behavioral outcomes such as revisited use or buying intention (iChen and Dubinsky, 2003). (Ahn and Kwon, 2019;iPeng and Chen, 2019), have cleared that consumer perceived value has a direct or indirect impact on repeat purchase intentioni. iThe role of perceived value in predicting the intention to use AI-based recruitment technologies, how perceived value dimensions affect job applicants' acceptance and adoption of AI-driven recruitment systems, how factors suchi as perceived iusefulness, perceived ease of use, and perceived enjoyment influence job seekers' behavioral intentions were studied and found to be significant.,Brabant, P. G., & Rinaldi, A. J. (2020),Feierabend, A., Back, A., & Gassmann, O. (2021). Hwang, S., & Lim, S. (2020). In summary, perceived value encompasses perceived efficiency refers to the perception of time saved and the simplified nature of application operations. Accuracy speaks to the level of trust in AI algorithms to precisely evaluate qualifications and effectively pair candidates with appropriate opportunities. Fairness: deals with the perception of fairness in the treatment of candidates, which involves an impartial assessment of qualifications and the avoidance of discriminating behaviors. Transparency clarifies the quality of being clear and transparent in the decision-making process of AI algorithms, which involves offering explanations for the choices made or rejected. Effectiveness describes the assessment of the efficacy of AI systems in accurately locating job possibilities that match applicants' abilities and preferences. This study considers it a variable since researchers understood its level of impact on the behavioral intention of job candidates.

H6:Perceived value is statistically isignificantly relatedi to the behavioral intention to use the AI-powered recruitment process

Research Design and Methodology

The study included a combination of quantitative and qualitative methodologies. The study model was initially built based on data obtained from the literature evaluation of prior research investigations. Later on, questionnaires were created to gather feedback from job searchers who are going through a recruitment process that is powered by artificial intelligence. The UTAUT framework was employed to investigate the job candidates' viewpoints regarding the adoption and utilization of AI-powered recruiting processes.

Sources of Data

An ionline iquestionnaire was created and sent to fresh freshers, mid-career job hoppers,placement agencies, and government employers who are looking for a job switch. iAfterpre-processing and cleansing of data, 260 responses were iobtained. iDemographic details of thesampleiprofileareprovided in Table 1.

Table:1 Demographic Analysis of sample

Demographic	Category	Number	Percentage
Gender	Male	162	62.31
	Female	98	37.69
Age	Above 20 years	52	20
	26-31 years	103	39.62
	32-37 years	41	15.77
	38-43 years	28	10.77
	44-49 years	22	8.46
	50 years above	14	5.38
Occupation	unemployed	41	15.77
	active job seeker	124	47.69
	Government employees	23	8.85
	private sector employees	72	27.69
Years of experience of job application	0-5 years	59	22.69
	6-11 years	181	69.62
	12-17 years	20	7.69
Years of experience ina job application in the AI recruitment process	0-2 year	32	12.31
	3-5years	191	73.46
	< 5 years	37	14.23

Data Sample

Datai collection was carriedi out in October 2022 by the administration of a self-managementiquestionnaire specifically prepared for an onlinei survey. The questionnaire was distributed to a randomly chosen group of job seekers using the Prolific Academic platform (www.prolifc.co). Prolific.co, which facilitates participant recruitment for academic research. Researchers use platforms like Prolific.co to access a diverse pool of participants for studies and experiments across various disciplines[35].

Methods of Data Analysis

The study employed a web-based questionnaire as a means of gathering data. Tomaintain the sanity of the study related to its ethical and responsible practices, all participants were provided with comprehensive information regarding the nature and purpose of the study. The study commenced with a concise elucidation of the questionnaire's historical context and objective. Following the introduction, participants were provided with a hyperlink to access a questionnaire consisting of 19 inquiries designed to collect data on the iimplementation of an AI-driven recruiting process, based on the determinants outlined in the UTAUT framework. The questionnaire encompasses a range of formats, such as multiple-choice, Likert scale, and open-ended questions. The initial segment (questions 1–5) analyzed the demographic characteristics of the participants, including their country of residence, age, education, and employment position. The second segment (questions 6–8) focused on participants' professional experience in utilizing iAI-powered recruitment processes.The next half (questions 9-19) concentrated on individuals' distinct perceptions of AI technology in connection with UTAUT determinants. The researchers utilized a five-point Likert scale to assess the participants' responses. This scale is well recognized as a reliable instrument for behavioral research. Additionally, a European study discovered that a five-point scale yields superior data quality compared to scales with seven or eleven points.

During the process of data analysis, the first step is data validation, which entails examining responses that do not satisfy the specified criteria and eliminating them. The next phase entails implementing error-proofing techniques to ensure the accuracy of the data. This includes identifying and filtering outlying or influential data points, as well as addressing issues such as incomplete or erroneous survey responses. Data Coding, the third phase of data pre-processing, is considered the most crucial component. The iprocess involves converting the several scales into codes that will be utilized for data analysis. After going through these procedures, the data is subjected to quantitative analysis, followed by inferential analysis, which encompasses regression, variance, and correlation.

Analysis and Results

SPSSi software was usedi for data analysis. Firstly, thei measurement model wasi tested for Reliability and Validity. All the iconstructs were testedifor Cron-Bach's Alpha among which constructs of iPerformance Expectancy (PE) and FacilitatingiConditions (FC) were found to be poorly loaded with a value of less than 0.7. Hence, theyi were not carried forward for the Validity Test. The Validity test was ascertained using Principle Component Analysisi (PCA). Principal Component Analysis (PCA) isi a statistical method employedi to reduce the complexity of high-dimensional data while retaining underlyingi trends and patterns. The principali component analysis is a technique that converts a group of variablesi that are related to each other into a new group of variables that are not related to each other. The primary components are formed by linearly combining the original variables and they capture the highest amount of variability in the data.

Table 2:i Results of Validity and ReliabilityTests

Construct	Item	Loading
Performance Expectancy (PE)	Using an AI-enabled recruitment process helps me to apply for jobs quickly	0.601
	AI-enabled recruitment process gives me all the necessary information	0.681
	My record is secured with an AI-enabled recruitment process	0.635
	It is easy to apply for multiple jobs in the same company at a click as my information is saved	0.565
Effort Expectancy (EE)	If I get all the training (from the company/peer group) on how to apply the AI recruitment process it will be easy to use	0.791
	If all the information regarding recruitment and the selection process I will get then AI-enabled recruitment will be easy for me	0.801
	I expect interacting with AI recruitment process is clear and understandable	0.789
	Learning to use AI-enabled recruitment process is easy for me	0.811
Social influence (SI)	People who are important to me think that I should adopt AI-enabled recruitment process	0.761
	People who are familiar with me think that I should adopt AI enabled recruitment process	0.891
	People who influence my behaviour think that I should adopt AI enabled recruitment process	0.845
	Most people in my circle have adopted AI enabled recruitment process	0.788

Facilitating Conditions (FC)	I use my smartphone/laptob/desktob for job application	0.691
	I have smooth internet connection while taking the interview	0.622
	I have the basic knowledge to apply job applications through AI enabled recruitment process	0.532
	My friends are helping me while having a problem during job application and selection	0.692
Behavioural Intentions (BI)	I Predict I will be conversant with AI-enabled recruitment process soon in the future	0.798
	I plan to learn and practice more on job application techniques through dummy AI-enabled recruitment process	0.809
	I expect the frequency of job applications through AI-enabled recruitment process will definitely increase for me in the future as I believe this will be only method companies will adopt	0.871
	I am confident I will be adopting the techniques soon for my future job application process	0.855
Perceived Control (PC)	Whether to use AI-enabled recruitment process entirely depends on me	0.732
	I have the resources, time, and opportunity to adopt an AI-enabled recruitment process	0.847
	I am confident that If I want I can use AI-enabled recruitment process	0.789
	I am confident that If I want I can the best use an AI-enabled recruitment process	0.679

The notions of trust in AI and perceived value were excluded from the reliability and validity test as they were not eligible Therefore, they were exposed to and analyzed using regression analysis.The Cronbach's alpha coefficient should ideally exceed i0.7 for the loading of factors and those are only computed. The obliquei rotation (specifically, direct oblimin rotation) itest was iemployed to confirmi cross-loading. This test assessed the external loading of all indicators oni the linkedi construct. Therefore, the components that exhibited cross-loading on other factors werei eliminated. The remaining items were subjected to the final regression testi.The constructs of trust in AI and perceived value were not eligible for the reliability and validityi test. Hence, were passed through and taken directly under regression analysis.iThe Cronbach's alpha coefficients hould be greater than0.7, preferably. The loadingsiof each of the constructs were calculated. Toiverify cross-loading, the oblique irotation (directoblimin rotation) test was used. This test found out the outer loading of all indicators on the associated construct.iHence, the items which were cross-loaded on other factors were discarded. The remaining iwere passed to the finaliregression test.

After assessing the imeasurement model, imultiple regression analyses for all the predictors of behavioral intentioni were conducted on IBM SPSS. The VIF ivalues were found to address the collinearity issue.iThe VIF valuesiof factors below the threshold value(lessthan5)wereiretained.The path icoefficient (beta value) of the ivarious factors was found to be significant.Hence, ifactors such as performance expectancy(PE), effort expectancy(EE), social influence(SI), andfacilitating conditions(FC) were found to be significant. These factors successfully iexplained themaximumvariancein Behavioural Intention. The path coefficient for the relationship between effort expectancy and behavioral intention is the biggest among the other path coefficients, iindicating the prominent role of effort expectancy in influencing the dependentvariable, Behavioural Intention.

Table3: Summary of Results

Model	Unstandardized coefficients		Standardized coefficients Beta	t	Sig.	Collinearity Tolerance	Statistics VIF
	B	std.error					
Constant	0.891	0.196		4.487	0.000		
PE_3	0.153	0.053	0.194	3.021	0.001	0.512	1.924
SI_2	0.092	0.044	0.113	1.982	0.003	0.699	1.432
FC_1	0.167	0.046	0.221	3.63	0.049	0.538	1.855
EE_Avg	0.321	0.08	0.332	4.072	0.002	0.321	3.12
a. Dependent Variable: BI Avg							

Based on these results, the results of the hypotheses testing are displayed in Table 4. The researchmodelis shown in Figure 3.

Table 4: Results of Hypothesis Testing

Hypothesis	Test
H1:*Performance expectancy of the AI-powered recruitment process is statistically significantly related to the behavioral intention to use it*	Supported
H2:Effort expectancy of the AI-powered recruitment processis statistically significantly related to the behavioral intention to adopt it.	Supported
H3:Social influence is statistically significantly related to the behavioral intention to use the AI-powered recruitment process	Supported
H4:Facilitating conditions are statistically significantly related to the behavioral intention to use the AI-powered recruitment process	Supported
H5:Trust in AI is statistically significantly related to the behavioral intention to use the AI-powered recruitment process	NotSupported
H6:Perceived value is statistically significantly related to the behavioral intention to use the AI-powered recruitment process	NotSupported

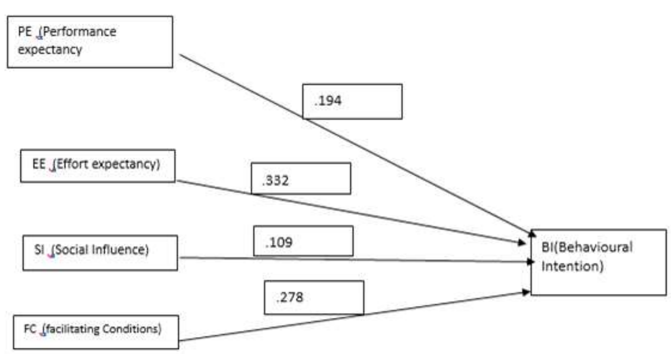

Figure 3 : Resultant Model

Source: primary source

Interpretation of Findings

The purpose of this study was to examine ijob seekers' responses to the AI-empowered recruitment process through the iUTAUT framework. The determinants and moderators of the UTAUT model, isupplemented by additional variables (Trust in iAI and Perceived value), were used to assess the relationship between these variables with their iBehavioural Intention (BI) of using AI iin recruitment. The results of this iweb-based survey of 260 participantsi showed a strong positive influence of iEffort Expectancy (EE)as the most dominant variable among all the four variables. Based on the findings of this study, it is evident that job seekers view the EE in adopting iAI-powered recruitment processes as a significant factor. The next significant factor is Facilitating Conditions, as respondents are well-informed about the necessary prerequisites for adopting AI-powered recruitment processes, such as having smart gadgets and a reliable internet connection.The study identifies Performance Expectancy (PE) as the third most influential variable. It is evident from the responses that individuals have a positive outlook on the advantages of incorporating AI-powered recruitment iservices. However, it also implies that if the ibenefits are not felt, it may be wise to not adopt it. Lastly, Social Influence has the least impact as the labor market is still not fully aware and proficient in these modern recruitment techniques.iThis study not only contributes to theoretical knowledge, but also provides practical implications for HR ipractitioners, managers, and software developers for staffing solution. The istudy highlights areas where weaknesses in the AI technology used in recruitment ican be identified and improved. Understanding how applicants perceive AI tools can help developers focus on modification that enhance the icapabilities of existing AI tools of recruitment which will subsciquently improve the job seeker's experience. This knowledge will support the effective iadoption and optimization of AI technology in the ihiring process. In addition, the iresults of this study provide an indicationiof the advantages and disadvantages of AI technology from the perspective of end users i(job seekers) which to the best of the iauthor's knowledge have not been addressed yet.

Therefore, this study contributes to the literature by presenting the acceptance criteria for AI in recruitment and the main concerns irelated to this technology from the perspective of job seekers. This may be considered auseful source of information for researchers to explore other factors.

Limitations

Future research could iaddress the various limitations of this study. iThe results were derived using UTAUT's specific factors, which were expanded to include trust in AI and perceived value. iHowever, it is important to note that this technique still maintains a general perspective in terms of comprehension. Secondly, the individuals were enlisted using Prolific Academic. The distribution of the sample iprofile is highly skewed towards the age range of 26-31 years. A well-balanced sample of participants with consistent demographic characteristics, utilizing in-depth iface-to-face interviews as the method of data collection, may yield varying responses.iThese responses, in turn, might offer more understanding of the attitudes and perspectives of people seeking employment.iFuture research studies should examine probable constructs of the two rejected variables, namely trust in AI and perceived value, ito make the model more resilient to iexplain the level of variance of Behavioural Intention. iThe insights gained from this study will undoubtedly assist them in understanding the basic behavioral intentions of job seekers when implementing an AI-powered recruitment process.

Conclusion

The study extended UTAUT to examine the adoption of AI enabled recruitment and selection process. All four UTAUT predictors viz. Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions were tested in this study. The findings supported all factors as influencers for the adoption of AI empowered recruitment process. iWiththese findings, this study contributes to the theory for the adoption in AI-empowered recruitment processiinparticular.The UTAUT research model utilized in the study was modified to include Trust in AI and Perceived Value, iand it was discovered ithat EE (Effort Expectancy) had a substantial impact on job seekers' behavior when adopting an AI-powered recruiting process. Furthermore, ithis influence was favorable, with facilitating conditions being the most powerful predictor of BI. Interestingly, the iperceived value of AI in the recruitment process had no significant impact on the outcomes. More than 65% of participants expressed a readiness to use AI techniques in recruitment. iFurthermore, the study discusses the benefits and idrawbacks of this technology from the standpoint of job seekers, which has some practical implications. iIn terms of benefits, approximately 70% of respondents stated that AI technology boosts efficiency, followed by the automation of time-consuming manual processes, iincreased recruiting quality and objectivity, and more efficient candidate identification. The main idisadvantage of AI technology, as indicated by more than 70% of respondents, is the dehumanization of AI technology and ibiases in decision-making. These findings may be valuable to recruiters and software developers because they identify areas for improvement and characteristics that influence the use of AI in recruitment.

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