Factors Affecting the Intention to Use Artificial Intelligence-Based Recruitment System: A Structural Equation Modeling (SEM) Approach

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Abstract The controversy over fairness and objectivity in the job market, due to hiring irregularities, has led to calls for transparent and fair recruitment procedures. Advances in IT technology have led to the emergence of a non-face-to-face "AI recruitment system" in which artificial intelligence (AI) conducts interviews, instead of human interviews. As the introduction of the non-face-to-face method is encouraged in the hiring process due to the COVID-19 virus pandemics, the number of companies introducing AI recruitment systems is steadily increasing. In this study, the factors affecting the intention of use of AI-based recruitment system were analyzed by utilizing TOE and TAM. As a result, it was shown that the reliability, security, suitability, new technology, partiality, readiness, and legal and policy environment of the TOE affected the intention of using the system. It was also identified to have the moderating effect of the number of employees in the firm.

Keywords Artificial intelligence · AI recruitment system · AI interview job suitability · Recruitment procedure act

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1   Introduction

The AI recruitment system reduces the time and cost of securing interview locations, provides recruitment services comparable to hiring professionals for small and medium-sized enterprises, and expands the scope of employees to be hired as applicants. As long as the Internet is connected to them regardless of the location, eliminating the room for human preferences of recruiters and increasing fairness [1]. For example, in the United States, they use programs such as IBM's Watson to identify personality and values through resume and social media analysis [2].

In 2020, a non-face-to-face approach was particularly recommended in recruitment due to the Pandemic of the COVID-19 virus, and the AI recruitment system began to be introduced in the hiring process. If the AI recruitment system can be included in the existing recruitment process and the non-face-to-face recruitment method can be implemented, it is necessary to examine the factors affecting intention to use of AI recruitment system. To proceed with the research, we analyze which factors affect the intention to use of the AI recruitment system using TAM and TOE.

2   Theoretical Background

2.1   Artificial Intelligence and Recruitment

Artificial intelligence (AI) is currently being used in various industries and the origin of the concept is quite old. At the 1956 American Conference of Dartmouth, cognitive scientists proposed the term "artificial intelligence," meaning "science and engineering making intelligent machines" [2]. Artificial intelligence is divided into strong and weak artificial intelligence depending on the autonomy of cognitive abilities [3]. In the past, "weak artificial intelligence" was the mainstream to replace repetitive tasks, but in recent years, consumers are increasingly interested in "strong artificial intelligence" technology as AI technology has been applied to various areas and consumers demand a higher level of intelligence [4].

This technological advance of AI constantly changes the company's recruitment strategy, such as the application selection process. AI based recruitment can be an effective process of human resource management [5]. In the U.S., 50 of Fortune 500 companies, including Unilever and Hilton Hotels, implemented the recruitment process using artificial intelligence [6].

2.2   Recruitment Procedure Act in Korea

Act on the Fairness of State Laws, abbreviated as the Recruitment Procedure Act, is a law that bans unfair solicitation, pressure, and coercion in hiring human resources
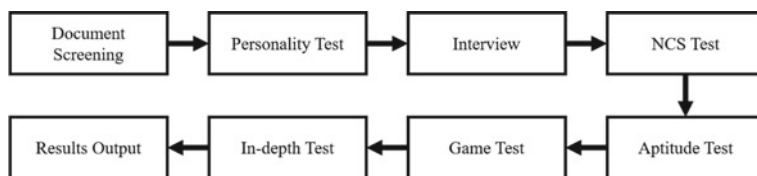
Fig. 1 Process of AI-based recruitment system (7 phase example)

and prohibits job seekers from requesting personal information, such as physical conditions unrelated to job performance.

A work-seeker shall not require a work-seeker to enter information not necessary for the performance of his/her duties in the application form, resume, or a letter of self-introduction, or collect evidence. Following personal information is prohibited from collecting and requesting: physical condition such as appearance, height, and weight, area of origin, marital status, and lineal ascendants of property, and educational background, occupation, and property of brothers and sisters. However, even if personal information is prohibited by law, collection and request can be made if necessary for the performance of duties.

2.3 AI Recruitment System

AI recruitment system is a system that can identify job suitability of applicants by using artificial intelligence and machine learning, and in the entire process of recruitment, the AI image analysis system uses facial recognition technology to analyze empathy, anomalies, confidence, positivity, criticality, curiosity, concentration, and sociality, and the AI voice analysis system detects even the smallest sounds around and analyzes the frequency of use of positive words, negative words, neutral words, and words. If the existing recruitment process was usually done through documents (i.e. resume, applications) screening, written test, and interview, the AI interview process depends on the needs of the company, but this study will give an example of the seven-step recruitment process. The process is shown in Fig. 1.

2.4 Technology, Organization, and Environment (TOE) Framework

The TOE framework proposed by Tornatzky et al. [7] describes the factors influencing the organization's adoption of information technology from three perspectives: technological context, organizational context, and environmental context. The summary of TOE framework is shown in Table 1 [8].

Table 1 TOE framework and the measurement

Context	Description	Measurement
Organizational context	Refers to the unique organizational characteristics and resources that a company has and affects technology adoption by itself	Firm size, firm scope, top management support, staff capacity/competence, surplus resources
Technological context	It is important to determine whether technology can be introduced and if the technology currently being applied is suitable for the firm	Relative advantage, compatibility, complexity, trialability, perceived barriers, IT/IS infrastructure
Environmental context	Means the business activities of a company and includes the industry, competitors, government regulations, business partners, etc. to which the company belongs	Competitive pressure, environmental uncertainty, government incentives and regulations

2.5 Technology Acceptance Model (TAM)

Davis et al. [9]'s Technology Acceptance Model is a proposed model for predicting users' acceptance in the introduction of new technologies and modifies the proposed reasonable theory of behavior in Fishbein and Ajzen to explain and predict people's behavior [10]. The perceived usefulness that the TAM model expects to improve work performance by using a new information system and the perceived ease of use that it considers easy to use a new information system are used in conjunction with the intention to accept the technology. While traditional technology acceptance models include attitude variables as parameters, many prior researches have shown that attitude are not important parameters [11].

3 Research Design

The recruitment industry is one of the latest service industries where the convergence of existing NCS based blind hiring regulations and IT is evolving into AI recruitment systems. The system is an integrated form of 4th industrial technology. To identify the factors affecting the intention to use of AI recruitment system in the organization, this research designed the research model which is presented in Fig. 2. Also, the research examined moderating effect of the number of employees in the firm.
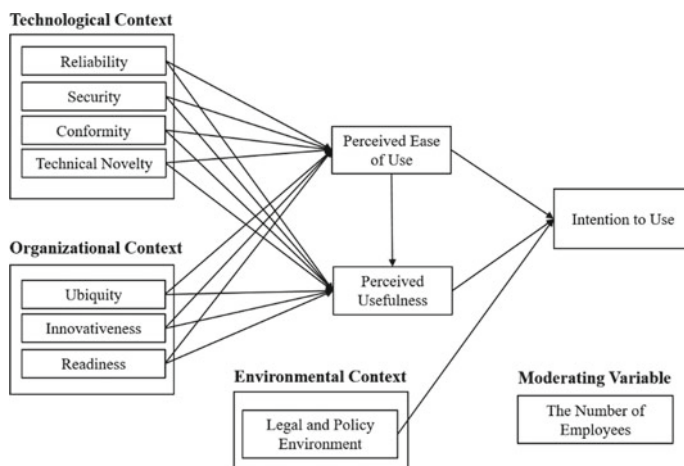
Fig. 2 Research model

3.1 Research Hypothesis

Reliability suggests in previous studies that people have different degrees of trust in other people or objects, are considered individual characteristics, and that services have a positive relationship to the use and acceptance of new technologies [12]. In this study, reliability is defined to the extent that AI recruitment system are believed to be reliable.

Security means the degree to which new approaches are prevented from hacking attacks in the information technology area, and the degree to which authentication errors are blocked [13]. In this study, security was defined as the degree of belief that the use of AI recruitment systems would be safe without personal information infringement or leakage.

Tornatzky and Klein [14] conducted a study that comprehensively compares previous prior studies, explaining that conformity, along with relative advantages and complexity, is a major influence on innovation acceptance. In this study, conformity was defined to the extent that the recruitment system is appropriate for the organization.

Technical novelty was adopted as a construct to determine the effect of the novelty on acceptance within AI recruitment systems where research is not actively conducted. In this study, we defined technical novelty as the degree of novelty that users feel about the technology that AI recruitment systems have.

Kannan et al. [15] addressed that the ubiquity enables customers to reach customers regardless of location in real time, receive diverse information regardless of their location, and enable real-time communication. Meanwhile, Ku and An [16] found that ubiquitous convenience affects perceived ease of use and that there is no significant impact on perceived usefulness in the study of factors affecting

the acceptability of u-Commerce. This study defined the ubiquity to the extent that the organization believes that AI recruitment system services can be applied well anywhere.

Innovativeness refers to the extent to which individuals and organizations are able to explore new information technology and experiment on their own to exercise their power to accommodate new technologies and services relatively faster than other consumers [17]. In this study, innovativeness was used as the same measurement.

Readiness is a variable for measuring the degree to which an organization is prepared to adopt a new technology [8]. In this study, readiness is defined to the extent that the organization is prepared to adopt an AI recruitment system.

Dasgupta [18] defined government support for personnel regulations as encouraging the introduction of new IT systems for the development of the company. Teo et al. [19] confirmed that the greater the support for policy, the greater the intention of the organization to introduce a human resource information system. In this study, the legal and policy environment was defined as extent to which law and policy are important for the introduction of AI recruitment systems.

Perceived ease of use is a factor that directly affects perceived usefulness, and the easier and more convenient users perceive the new technology or system to be, the more useful it is [20]. Accordingly, this study defined perceived ease of use to the extent that user feel easy to use the systems. Perceived usefulness refers to the degree to which users believe that the use of information systems can increase performance and is useful in their daily lives [9]. Bhattacherjee [21] explained that perceived usefulness had a significant effect on the intention to use. This research defined usefulness to the extent that it is believed to be beneficial for the purpose of use.

Lastly, a hypothesis was established with the number of employees as a moderating variable to find that the number of employees in the firm makes difference in the relationship of the factors. The summary of the hypothesis is presented in Table 2.

4   Empirical Analysis

To collect the data for the analysis, an online survey was conducted to measure the variables. The survey targets include personnel department workers who understand the artificial intelligence recruitment system or decision makers of corporation in the team of management, planning and strategy. Of the total 216 survey responses, 187 data were used for the final analysis, except for those that were missing or insincere response. A frequency analysis was conducted to examine the demographic characteristics of the respondents, and the results were shown in Table 3. For statistical analysis of all process, the SPSS and AMOS tools were used.

Table 2 Summary of the research hypothesis

Hypothesis
H1: Reliability of AI recruitment systems has a positive impact on perceived ease of use
H2: Reliability of AI recruitment systems has a positive impact on perceived usefulness
H3: Security of AI recruitment systems has a positive impact on perceived ease of use
H4: Security of AI recruitment systems has a positive impact on perceived usefulness
H5: Conformity of AI recruitment systems has a positive impact on perceived ease of use
H6: Conformity of AI recruitment systems has a positive impact on perceived usefulness
H7: Technical novelty of AI recruitment systems has a positive impact on perceived ease of use
H8: Technical novelty of AI recruitment systems has a positive impact on perceived usefulness
H9: Ubiquity of AI recruitment systems has a positive impact on perceived ease of use
H10: Ubiquity of AI recruitment systems has a positive impact on perceived usefulness
H11: Innovativeness of AI recruitment systems has a positive impact on perceived ease of use
H12: Innovativeness of AI recruitment systems has a positive impact on perceived usefulness
H13: Readiness of AI recruitment systems has a positive impact on perceived ease of use
H14: Readiness of AI recruitment systems has a positive impact on perceived usefulness
H15: Legal and policy env. of AI recruitment systems has a positive impact on perceived usefulness
H16: Perceived ease of use of AI recruitment systems has a positive impact on the perceived usefulness
H17: Perceived ease of use of AI recruitment systems has a positive impact on the intention to use
H18: Perceived usefulness of AI recruitment systems has a positive impact on the intention to use
H19: The number of employees in the company (less than 100 employees, more than 100 employees) moderate the relationship of factors affecting the intention to use of the AI recruitment system

4.1 Reliability, Convergence Validity, and Discriminant Validity

Table 4 show the values of factor loading, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) for all constructs. Reliability assessments indicate the stability and consistency of instrument's measurement in a research model, and the reliability of the measurement is commonly evaluated through Cronbach's Alpha. If the Cronbach's Alpha is 0.7 or higher, it can be evaluated that internal consistency of the extracted constructs has been obtained [22], and the Cronbach's Alpha values of all the structures has exceeded the criteria.

For the convergence validity assessment, CR and AVE were used to evaluate the assessment. All the values of CR are satisfied the recommended 0.7 criteria. Also AVE for each construct are acceptable by exceeding the threshold 0.5 [23].

Correlations and AVE were used to test the discriminant validity. AVE should be higher than the square of the highest value of the correlations [23]. The diagonal

Table 3 Demographic characteristics of survey respondents

Section		Freq.	%
Individual			
Work area	Personnel	39	20.9
	Planning/Strategy	45	24.1
	Accounting/Finance	39	20.9
	R&D	19	10.2
	Others	45	24.1
Position	Clerk	40	21.4
	(Assistant) Manager	48	25.7
	(Deputy) General Manager	35	18.7
	Director and above	53	28.3
	Others	11	5.9
Industry	Finance	12	6.4
	Public institution	23	12.3
	IT	31	16.6
	Manufacturing	16	8.6
	Distribution	19	10.2
	Service	39	20.9
	Others	47	25.1
Number of employees in their firm (person)	1–100	110	58.8
	+100	77	41.2

values in Table 5 represent AVE for each constructs, off-diagonal values indicate the correlations between each latent variable. The highest correlation is 0.851 and the squared value is 0.724. AVE for each construct was higher than the threshold of 0.724, so the discriminant validity was satisfied.

4.2 Goodness of Fit

This assessed the measurement model by conducting a CFA. Through the analysis of measurement model, goodness of fit indexes for the model are extracted and they can estimate how well the model represents the data. The values of indexes with recommended criteria are shown in Table 6. While the GFI and RMR were below the recommended levels, the overall model fit was considered to be fine because other indices were significantly higher or lower than the threshold [24–26].

Table 4 Construct reliability and convergent validity

Constructs	Indicator	Factor loading	Cronbach's α	CR	AVE
Ubiquity	UB1	0.831	0.912	0.902	0.756
	UB2	0.806			
	UB3	0.755			
Innovativeness	IV1	0.875	0.932	0.888	0.726
	IV2	0.833			
	IV3	0.783			
Readiness	RD1	0.829	0.928	0.898	0.745
	RD2	0.816			
	RD3	0.779			
Reliability	RA1	0.783	0.957	0.939	0.756
	RA2	0.763			
	RA3	0.755			
	RA4	0.739			
	RA5	0.735			
Security	SC1	0.829	0.938	0.905	0.761
	SC2	0.824			
	SC3	0.783			
Conformity	CF1	0.684	0.938	0.920	0.741
	CF2	0.651			
	CF3	0.639			
	CF4	0.548			
Technical novelty	TN1	0.800	0.900	0.887	0.723
	TN2	0.784			
	TN3	0.717			
Legal and policy environment	LPE1	0.775	0.931	0.899	0.749
	LPE2	0.712			
	LPE3	0.693			
Perceived ease of use	PEU1	0.801	0.959	0.945	0.810
	PEU2	0.787			
	PEU3	0.784			
	PEU4	0.778			
Perceived usefulness	PU1	0.850	0.964	0.933	0.777
	PU2	0.824			
	PU3	0.820			
	PU4	0.774			
Intention to use	IU1	830	0.967	0.942	0.765

Table 4 (continued)

Constructs	Indicator	Factor loading	Cronbach's α	CR	AVE
	IU2	0.816			
	IU3	0.814			
	IU4	0.792			
	IU5	0.751			

Table 5 Construct correlations and discriminant validity

	UB	IV	RD	RA	SC	CF	TN	LPE	PEU	PU	IU
UB	0.756										
IV	0.51	0.726									
RD	0.423	0.511	0.745								
RA	0.692	0.643	0.532	0.756							
SC	0.536	0.539	0.487	0.739	0.761						
CF	0.693	0.633	0.661	0.851	0.713	0.741					
TN	0.612	0.483	0.730	0.544	0.469	0.629	0.723				
LPE	0.562	0.633	0.719	0.671	0.516	0.703	0.764	0.749			
PEU	0.744	0.604	0.583	0.843	0.732	0.842	0.668	0.774	0.81		
PU	0.689	0.627	0.595	0.795	0.694	0.799	0.536	0.644	0.797	0.777	
IU	0.614	0.606	0.529	0.745	0.654	0.761	0.533	0.72	0.782	0.826	0.765

Table 6 Goodness of fit indexes for the model

Indexes	Result value	Recommend
Chi-square/degree of freedom	1.434	<3
Goodness of fit index (GFI)	0.802	>0.9
Normed fit index (NFI)	0.902	>0.9
Comparative fit index (CFI)	0.968	>0.9
Incremental fit index (IFI)	0.968	>0.9
Root mean square error of approximation (RMSEA)	0.048	<0.08
Root mean square residual (RMR)	0.051	<0.05

4.3 Structural Model for Hypotheses Testing

The tests for each hypothesis in the research model were conducted using structural equation modelling via AMOS. The path analysis results are shown in Table 7, and the path coefficients are listed as standardized coefficients.

As a result of the analysis in the organizational context, only the ubiquity and readiness have a positive impact on the perceived ease of use. This means that laying

Table 7 Summary of hypothesis test results

Hypothesis	Path coefficient	p	Result
H1: Reliability → perceived ease of use	0.243	0.001	Supported
H2: Reliability → perceived usefulness	0.107	0.103	Rejected
H3: Security → perceived ease of use	0.1	0.098	Rejected
H4: Security → perceived usefulness	−0.012	0.81	Rejected
H5: Conformity → perceived ease of use	0.2	0.015	Supported
H6: Conformity → perceived usefulness	−0.088	0.207	Rejected
H7: Technical novelty → perceived ease of use	0.243	0.018	Supported
H8: Technical novelty → perceived usefulness	0.28	0.001	Supported
H9: Ubiquity → perceived ease of use	0.15	0.029	Supported
H10: Ubiquity → perceived usefulness	0.133	0.021	Supported
H11: Innovativeness → perceived ease of use	0.215	0.053	Rejected
H12: Innovativeness → perceived usefulness	0.22	0.018	Supported
H13: Readiness → perceived ease of use	−0.146	0.081	Rejected
H14: Readiness → perceived usefulness	0.247	***	Supported
H15: Legal and policy environment → intention to use	0.232	***	Supported
H16: Perceived ease of use → perceived usefulness	0.159	0.032	Supported
H17: Perceived ease of use → intention to use	0.533	***	Supported
H18: Perceived usefulness → intention to use	0.185	0.021	Supported

the foundation for adopting the AI-based recruitment system from an organization's perspective makes it easier to use the system. In contrast, the variables in technical context had a significant impact on perceived ease of use and usefulness, except for the two paths. This address that at the period when the AI-based recruitment system has yet to be actively utilized, the automation of recruitment process requires confidence in technical trust and security, and acceptable technical novelty and system suitability are considered as important point for the performance. The recruitment procedures are generally regulated by the government's law and policy for the fairness of the process and selection. In the results, Law and policy environment in the environmental context had a direct effect on intention to use. In the path associated with the TAM constructs, all the relations have a significant effect. In particular, the coefficient between the path of ease of use and intention to use was 0.533, which indicates that convenience of application is most important attributes to the workers at the corporates.

Table 8 Summary of multi-group analysis (PLS-MGA)

Relationship	Difference	p	Number of employees			
			1–100		+100	
			β	p	β	p
H2: RA → PU	−0.319*	0.037	0.129	0.177	0.447	***
H15: LPE → IU	0.374*	0.022	0.341	***	-0.032	0.81
H17: PEU → IU	0.386*	0.027	0.622	***	0.236	0.121
H18: PU → IU	−0.555**	0.004	0.043	0.614	0.599	***

Note: *p<.05, **p<.01, ***p<.001

4.4 Moderating Effect Analysis

A multi-group analysis (PLS-MGA) was conducted using smartPLS 3.3.2 as the last step of the empirical analysis. The groups were divided into two groups with under 100 employees group and more than 100 employees group. First, we confirmed the possibility of a moderating effect analysis through the Measurement Invariance Assessment (MICOM) and conducted a PLS-MGA. The results suggested that there were differences only for the four paths as shown in Table 8.

5 Conclusions

In this study, the factors that affect the intention to use of the artificial intelligence recruitment system were examined. The social environment changes and the rapid development of the IT environment caused by the COVID-19 around the world have brought many changes in the recruitment culture as well. Moreover, the government has revised the Recruitment Procedure Act, as controversy mounts over the fairness of hiring irregularities day after day.

In addition, at a time when there is a growing debate among job seekers about the fairness of the recruitment process, research has been conducted. But the research for the view of work-seeker is still in the beginning stage and should be studied after the implementation process. For job seekers, negative and positive public opinion exists together because AI systems that apply artificial intelligence technology are not fully generalized and lack understanding. In this study, we conducted the research only from the perspective of the company and conducted a survey of all departments' workers, but in future research, the researches to conduct a survey of the company's personnel managers and job seekers to study from other perspectives are needed, and the social impact or effectiveness in terms of the AI recruitment system adoption.

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