DEVELOPMENT AND VALIDATION OF ARTIFICIAL INTELLIGENCE-BASED RECRUITMENT ACCEPTANCE MODEL: AN EMPIRICAL INVESTIGATION AMONG CANDIDATES

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ABSTRACT

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The utilization of artificial intelligence (AI) technologies in various areas rising exponentially year by year and is expected to continue its growth in the future. Human resources (HR) function is one of the areas that is still at the beginning of AI utilization. Since the recruitment phase is one of the important functions of HR with the duty of determining the most valuable source for a company, employees; benefits attained by using AI technologies will be critical for this phase. For companies to invest in such technologies, on the other hand, they should understand what are the factors influencing the job candidates' adoption of the recruitment process equipped by AI technologies. This study aims to empirically investigate the job candidates' AI-based recruitment acceptance by developing a model presenting the factors affecting their behavioral intention to participate in AI-based recruitment. For this purpose, to form a pool of factors the literature on AI-acceptance in recruitment is systematically reviewed, and additional research is made on other related topics. For model development, UTAUT2 including the passive use decision is used as the base model. To form a compact model and achieve content validity, a HR expert panel analysis is conducted. Data is collected from 324 Turkish participants via an online questionnaire to test the model of AI-based recruitment acceptance among candidates in Turkey. Data is analyzed by implementing the partial least squares path modeling of the structural equation model; the influential factors and inter-factor relationships are identified, and the final model is formed.

Keywords: Acceptance, Technology Acceptance, UTAUT2, AI-Based Recruitment, Acceptance of AI

ÖZ

YAPAY ZEKÂ TABANLI İŞE ALIM KABUL MODELİNİN GELİŞTİRİLMESİ VE DOĞRULANMASI: ADAYLAR ARASINDA AMPİRİK BİR ARAŞTIRMA

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Yapay zeka (YZ) teknolojilerinin çeşitli alanlarda kullanımı her geçen yıl katlanarak artmakta ve gelecekte de büyümesini sürdürmesi beklenmektedir. İnsan kaynakları (İK), fonksiyonu yapay zeka kullanımının henüz başında olan alanlardan biridir. İşe alım aşaması, bir şirket için en değerli kaynak olan çalışanları belirleme görevi ile İK'nın önemli işlevlerinden biri olduğundan, yapay zeka teknolojilerini kullanarak elde edilen faydalar bu aşama için kritik olacaktır. Öte yandan, şirketlerin bu tür teknolojilere yatırım yapabilmeleri için, iş adaylarının YZ teknolojileri ile donatılmış işe alım sürecini benimsemelerini etkileyen faktörlerin neler olduğunu anlamaları gerekmektedir. Bu çalışma, iş adaylarının YZ tabanlı işe alım sürecine katılma konusundaki davranışsal niyetlerini etkileyen faktörleri ortaya koyan bir model geliştirerek iş adaylarının YZ tabanlı işe alım kabulünü ampirik olarak araştırmayı amaçlamaktadır. Bu amaçla, bir faktör havuzu oluşturmak için işe alımda yapay zeka kabulüne ilişkin literatür sistematik olarak incelenmiş ve diğer ilgili konularda ek araştırmalar yapılmıştır. Model geliştirme için, pasif kullanım kararını içeren Teknoloji Kabul ve Kullanım Birleştirilmiş Modeli-2 (TKKBM2) temel model olarak kullanılmıştır. Kompakt bir model oluşturmak ve içerik geçerliliğini sağlamak için İK uzman paneli analizi yapılmıştır. Türkiye'deki adaylar arasında yapay zeka tabanlı işe alım kabul modelini test etmek için 324 Türk katılımcıdan çevrimiçi bir anket aracılığıyla veri toplanmıştır. Veriler, yapısal eşitlik modelinin kısmi en küçük kareler yol modellemesi uygulanarak analiz edilmiş; etkili faktörler ve faktörler arası ilişkiler belirlenmiş ve nihai model oluşturulmuştur.

Anahtar Sözcükler: Kabul, Teknoloji Kabulü, Teknoloji Kabul ve Kullanım Birleştirilmiş Modeli-2, Yapay Zeka Tabanlı İşe Alım, Yapay Zekanın Kabulü

To My Lovely Mother

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Networks
AVE	Average Variance Extracted
AVR	Average
BIP	Behavioral Intention to Participate
C	Creepiness
CA	Cronbach's Alpha
CB-SEM	Covariance-Based Structural Equation Modelling
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
CV	Curriculum Vitae
DL	Deep Learning
DOI	Diffusion of Innovation
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
ETAM	Extension of the Technology Acceptance Model
F	Fairness
FC	Facilitating Conditions
HM	Hedonic Motivation
HR	Human Resources
IT	Information Technology
KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
MSA	Measures of Sample Adequacy
NLP	Natural Language Processing
PC	Privacy Concerns
PE	Performance Expectancy
PEE	Performance and Effort Expectancy
PLS-SEM	Partial Least Squares Path Modeling Method of Structural Equation Modelling
R&S	Recruitment and selection
SEM	Structural Equation Modeling
SI	Social Influence
T	Trust

TAM	Technology Acceptance Model
TC	Two-way Communication
TOE	Technology Organization Environment
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Consumer Acceptance and Use of Information Technology

CHAPTER 1

INTRODUCTION

In this first chapter of the thesis, an introduction to problem statement will be provided and the purpose, scope, and significance of the study and the research questions will be introduced. In addition, the main steps of the study will be presented.

1.1. Introduction to Problem Statement

The advancements in technology and digitalization have begun to affect various areas of businesses increasingly. AI is one of those developments in the information era. Although its roots date back to the 1940s, half a century has passed with scientific obscurity and lack of practical application and it has come to the forefront recently due to big data and advancements in computational power (Haenlein & Kaplan, 2019). The concept of AI was set forth by the English mathematician Alan Turing in his article “Computing Machinery and Intelligence” in which he questioned the intelligence of a machine and tested it with the “imitation game” in 1950 (Turing, 1950). AI was then defined as “making a machine behave in ways that would be called intelligent if a human were so behaving” by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon when they were studying a research project on AI at Dartmouth College (McCarthy, Minsky, Rochester, & Shannon, 2006). In the 2000s new definitions for AI were introduced. Russell and Norvig expressed it as “an effort to create rational agents.” (Russell & Norvig, 2010). More recent definitions underlined different aspects of AI. For example, Castelvecchi (2016) focused on its ability to learn while Brynjolfsson and Mitchell (2017) underlined its emulation capacity – how it is designed to copy human capabilities and skills (Berente, Gu, Recker, & Santanam, 2021). After the Dartmouth Conference, achievements in the field followed one another. A natural language processing (NLP) tool simulating a conversation with a human called ELIZA, a program solving simple problems called General Problem Solver Program, and a chess-playing program Deep Blue by IBM were developed as expert systems that are defined as the systems developed with the assumption that formulating human intelligence can be done with a top-down set of rules. On the other hand, with the goal of machines to interpret external data, learn from it, and use what they learned to achieve some goals, artificial neural networks (ANN) have been studied by researchers. In 2015, when Google developed AlphaGo which was able to beat the world champion in a more complex game, a deep learning (DL) concept emerged. Today, ANN and DL form the basis for the image or speech recognition algorithms which are then used to develop smart speakers and self-driving cars. (Haenlein & Kaplan, 2019)

The usage of AI in various business areas is rising exponentially. According to the global survey done by McKinsey & Company in 2022, organizations' adoption of AI in at least one function has more than doubled from 2017 to 2022 (Chui, Hall, Mayhew, Singla, & Sukharevsky, 2022). Based on the report of Fortune Business Insight, while the global market size of AI was USD 428.00 billion in 2022, it was estimated to reach USD 2,025.12 billion in 2030 from 515.31 billion in 2023 (Fortune Business Insight, 2023). Healthcare, automotive, financial services, logistics, communications media, and retail industries are the leading industries highly using AI (Rao & Verweij, 2017).

The human resource function (HR) is one of the areas where AI is deployed and still has room for further digitization. According to the "Global Talent Trends Study" of Mercer in 2019, over 80 percent of the companies already operate AI in practice across various HR tasks (Mercer, 2019) and 39 percent of the leaders who are the respondents in the PWC's "AI Business Survey 2022" say that they plan to use AI simulations to hire and train their employees (Rao & Greenstein, 2022). The amount of organizational, personnel, and task-oriented data HR is inherently responsible for has led to the incorporation of AI in many tactical HR processes (Di Vaio, Palladino, Hassan, & Escobar, 2020; Votto, Valecha, Najafirad, & Rao, 2021). Talent acquisition, screening, interviewing, selecting, onboarding, career development, succession planning, and compensation management are these HR processes AI benefited from (Oracle Corporation, 2019). However, according to several surveys, recruiting and hiring are among the main areas where AI and data analytics are being used the most to enhance management decisions regarding the workforce (Littler, 2018). When we look into its effect in the phases of recruitment in detail, it is found more useful in sourcing candidates with 68% and screening candidates with 57% (Bongard, 2019). There are many forms of AI usage in recruitment from sourcing to screening stages which are identifying profiles, matching profiles, pre-selection, and selection (Achchab & Temsamani, 2021).

The researchers have studied the factors influencing the success of an information system dating back to 1949 (Delone & McLean, 1992). While the success of an information system is dependent on some measures on a technical level showing the quality of the system, other measures such as "the use of the system" or "the user satisfaction" related to the interaction of the output of the system with its recipients have been also found a place in the literature (Delone & McLean, 1992). The acceptance of a user has been defined as the attestable voluntariness to use information technology for the purposes it has been designed (Dillon & Morris, 1996). It has been viewed as the main factor to decide on the success of any information system and many researchers worked on models to design, examine, and predict how users would respond to a new technology (Dillon & Morris, 1996). The basic concept underlying most of the user acceptance models is predicting the actual use of a new information technology by looking at individual reactions of users regarding that technology and how they affect their intention to use that technology (Venkatesh, Morris, Davis, & Davis, 2003).

In light of all this information, since AI utilization has been rising and expected to rise exponentially in the future and companies are at the beginning of use of AI technologies in their recruitment processes, it is important to understand how AI-based recruitment will be welcomed by the job candidates and what are the factors to emphasize in order to attract job candidates to such recruitment processes and order these technologies to become successful and worthwhile to invest in.

1.2. Purpose of the Study

The purpose of this study is to investigate how Turkish job candidates will respond to AI-based recruitment which is relatively new to the country. This study aims to identify the factors influencing the job candidates' behavioral intention to participate in an AI-based recruitment which includes passive use decisions. By doing so, it is asserted that the factors affecting the actual participation can be predicted. This study also tries to understand the relationships among these factors.

1.3. Research Questions

The research questions this study tries to answer are "What are the factors influencing the job candidates' behavioral intention to participate in AI-based recruitment in Turkey?", "Which factor affects most the behavioral intention to participate in AI-based recruitment?", "Are there any significant relationships between factors influencing the behavioral intention to participate in AI-based recruitment?".

1.4. Scope of the Study

This study is conducted in Turkey; therefore, the sample of potential job candidates are all from Turkey and above the age of 18. The systematic literature review on the research subject in this study covers studies from 2000 to 31st May 2023, written in English. In the recruitment scenario within the scope of this research, the job posting is announced to the candidates via social media and the corporate website, and CV information is collected through the format in the link provided. Resumes are scanned without any human effort via artificial intelligence and matched based on the criteria previously determined for the job position again by artificial intelligence, and an online exam link and personality inventory test are sent to the candidates. After the tests are completed, interview invitations are automatically sent to a certain number of candidates based on personality matches and exam scores. Candidates can schedule the interview date and time from the calendar application on the institution website by also benefitting from the chatbot serving 7/24 for aid. In the final stage, artificial intelligence-supported recruitment robots interview the candidates and calculate the correctness percentage of the candidates' answers to the questions based on the previously defined answers and analyze the tone of voice and facial expressions. When the interviews end, the candidates' recruitment results are notified by phone by human resources employees. In summary, this study is based on a recruitment scenario including AI technologies in all phases of the process. In addition, information regarding the industry, type or size of the organization which utilize AI technologies in recruitment are not specified in the scope of this study. Since no analysis will be carried out, such information is not included in the scenario so as not to influence the choice of candidates to be recruited.

1.5. Significance of the Study

As mentioned in section 1.3. if an information system is wished to be successful, one of the factors that should be taken into consideration is user acceptance. Since AI utilization in recruitment is relatively new and predicted to grow exponentially year by year, it is important to understand the factors influencing the acceptance of it by the job candidates. According to the limited literature review carried out for this study with some constraints and criteria, the literature lacks on this topic. On the other hand, most of the studies in the literature base their studies on AI utilization in some parts of the recruitment process and factors either directly taken by pre-proposed models or qualitative research on subjects. This research fills the gap in the literature by studying a recruitment scenario utilizing AI as a whole and using HR experts who have considerable experience in recruitment while determining the factors. The pool of the factors is formed by a systematic literature review not only on the acceptance of AI in recruitment but also on similar concepts such as the acceptance of chatbots, service robots, robot instructors, and voice assistants. This is another contribution of the research to the literature. Along with the researchers, the implications taken from this study can be used by companies considering investing in AI for their recruitment processes.

1.6. Main Steps of the Study

The main steps followed throughout the study are illustrated in Figure 1 below.

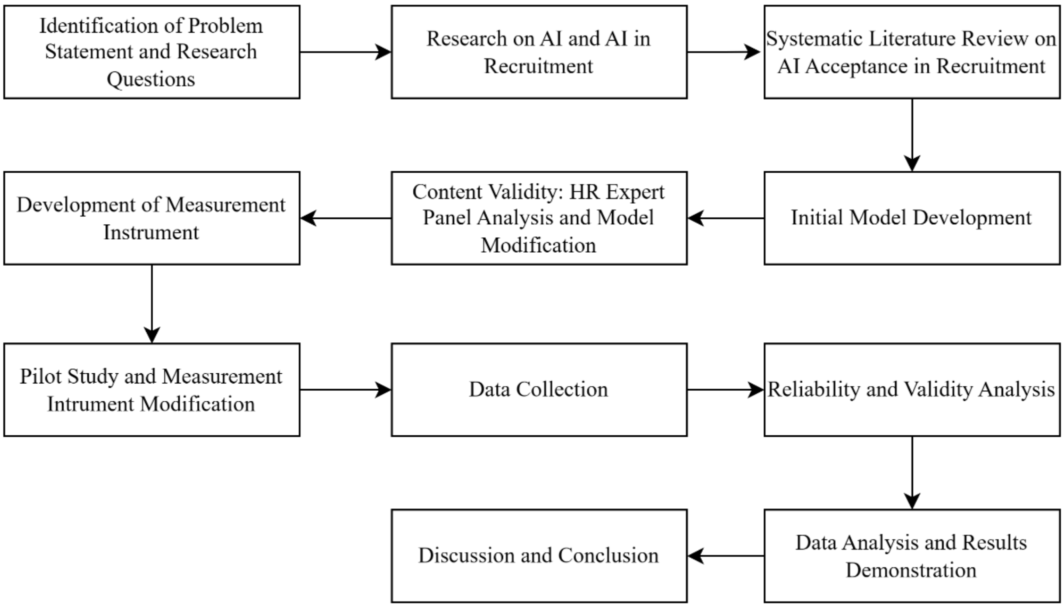


Figure 1: Main Steps of the Study

1.7. Outline of the Thesis

In this chapter, chapter 1, the information regarding the history of AI, its usage, and its share in the HR field and recruitment are expressed. The research questions, purpose, significance, and main steps of the study are provided.

Chapter 2 presents the literature review regarding artificial intelligence in recruitment, main technology acceptance models, and AI acceptance in recruitment.

In Chapter 3, the research methodology including model formation, expert panel analysis, pilot study, research instrument, sample characteristics, and data collection and analysis methods are presented.

In Chapter 4, the data analysis results are demonstrated.

In Chapter 5, the results of the study are examined and inferences are made. Limitations of the study and insights for future research are shared.

The “References” part shows the resources benefitted throughout the study.

The “Appendices” part demonstrates the tables and forms which are not given in the thesis text for simplicity and better visualization.

CHAPTER 2

LITERATURE REVIEW

This chapter is devoted to the literature review on AI in recruitment, technology acceptance models, and acceptance of AI in recruitment.

2.5. Artificial Intelligence in Recruitment

Recruitment and selection (R&S) are crucial organizational practices that encompass various phases, such as job analysis, candidate profiling, interviews, and contract signing. Traditionally, these processes heavily relied on human effort and judgment. However, with the advent of advanced technologies, AI-enabled tools have emerged to perform tasks beyond human capabilities, revolutionizing the field of R&S (Chamorro-Premuzic & Furnham, 2010; Lucci & Kopec, 2016; Rezzani, Caputo, & Cortese, 2021)

Organizational, cultural, technological, and financial constraints often impede recruiters from accessing and adopting modern tools, leading to a discrepancy between recruiters and candidates in terms of technology usage (Carrillat, d'Astous, & Grégoire, 2014; Allal-Chérif, Aránega, & Sánchez, 2021) With the growing interest of job seekers on new technologies and reliance on social networks and dedicated applications to find jobs, recruiters need to bridge this gap and embrace AI-driven solutions (Allal-Chérif, Aránega, & Sánchez, 2021; Parry & Tyson, 2010).

AI tools, including big data analytics, intelligent robots, face recognition, and voice interaction, have the potential to automate several aspects of the R&S process, such as data extraction, profile analysis, candidate engagement, and interviews (Jia, Guo, Li, Li, & Chen, 2018; Rezzani, Caputo, & Cortese, 2021).

The evolution of recruitment practices from analog to digital processes, facilitated by the Internet, has revolutionized the industry (Black & van Esch, 2020). Digital Recruiting 2.0 introduced advancements such as job aggregation and digital professional networks, leading to the rise of Digital Recruiting 3.0, which incorporated AI applications (Black & van Esch, 2020; Haenlein & Kaplan, 2019). The sheer volume of job applications generated by digital recruitment necessitated the use of AI for sourcing and screening candidates, enabling time savings and talent mapping (Achchab & Temsamani, 2021; Black & van Esch, 2020).

The shift in the source of firm value from tangible to intangible assets has elevated the importance of human capital and turned the adoption of AI-enabled recruiting tools from nice to have to imperative (Black & van Esch, 2020). In other words, it is understood that the adoption of AI-driven recruitment tools depends not only on their technical capability to identify and attract candidates but also on the worth of those candidates themselves correlated with the value they bring to the company (Cabrera & Fritts, 2021). Now companies believe that recruiting top-notch employees gives them a competitive edge that is challenging for their rivals to replicate (Harris, 2018). To reap the positive impacts in the future, business leaders need to find the optimal balance of manpower and automation by keeping up with HR 4.0 (World Economic Forum, 2019).

2.1.1. Advantages of Use of Artificial Intelligence in Recruitment

AI utilization in recruitment brings many advantages to companies.

The primary advantage of using AI in R&S is the significant time and cost savings, leading to improved efficiency and effectiveness (Rezzani, Caputo, & Cortese, 2021; Achchab & Temsamani, 2021). For example, AI-enabled tools can analyze applicant information and skills, helping to identify the most suitable candidates for a given position in a very short period of time (Chakraborty, Giri, Aich, & Biswas, 2020).

Moreover, AI in recruiting offers additional benefits, such as automating data collection, expanding the applicant pool, providing timely feedback, and facilitating flexible interview scheduling (Nawaz & Gomes, 2019). Recruiters acknowledge the potential of AI, particularly in the initial stages of the R&S process, for information analysis and scheduling (Nawaz, 2019). However, there is an ongoing debate about the extent to which AI should be involved in decision-making, with many applications still requiring human verification (Jia, Guo, Li, Li, & Chen, 2018).

AI-enabled recruiting tools not only allow HR professionals to focus more on monitoring and strategic decision-making aspects, reducing cognitive stress and turnover within the HR area but also enhance the candidate experience (Bhardwaj, Singh, & Kumar, 2020; Rezzani, Caputo, & Cortese, 2021). The integration of AI technologies enables candidates to have interviews at their convenience, increasing their perception of a faster and less biased selection process due to the removal of prejudice, discrimination, and emotional factors (Rezzani, Caputo, & Cortese, 2021; Black, van Esch, & Ferolie, 2019; Hemalatha, Nawaz, Kumari, & Gajenderan, 2021). A company needs to remain aware of the quality of candidates' experiences to effectively capitalize on the positive aspects or address the negative ones (Black & van Esch, 2020). In a study conducted by Talent Board in 2017, it has found that a significant percentage of candidates, specifically 77% with positive experiences and 61% with negative experiences, tend to share their impressions with their friends and family, also 81% of rejected candidates with a highly positive experience still have the willingness to recommend or refer individuals they knew to the company (Black & van Esch, 2020).

2.1.2. Artificial Intelligence in Sourcing and Engagement of the Candidates

The rise in the number of applicants per job position in recent years has led companies to adopt AI-enabled tools for sourcing candidates. AI tools have proven to be more efficient and effective than humans, particularly in the early stages of recruitment like sourcing. (Rezzani, Caputo, & Cortese, 2021)

AI technology can automatically generate job requirements for a specific position based on the tasks, expected performance, and role classification of each department to gain insights into the characteristics associated with each position. By combining diverse sets of applicant information such as job experience, capacity assessment, and performance, AI technology can suggest candidates who are projected to excel well in the assigned job. (Lee & Kim, 2021)

Social networks play a crucial role in facilitating recruitment through various mechanisms such as direct contact between job seekers and recruiters, building employer brand reputation, transparency in relationships, and specifying job data. However, social networks also bring challenges in managing the influx of talent and maintaining control over talent flows. (Allal-Chérif, Aránega, & Sánchez, 2021)

Major global companies and recruitment firms actively use social networks like Facebook and LinkedIn for talent acquisition, maintaining constant interaction with potential candidates. MOOCs, or Massive Online Open Courses, not only provide training but also serve as platforms for networking and recruitment (Dotsika & Watkins, 2017) They offer opportunities for social businesses to present their missions, attract talented individuals, and provide social training to assess potential employees. Artificial intelligence enables the analysis of diverse and unstructured data from social networks, facilitating the matching of candidate skills with company needs (Pasat & Vasilescu, 2019). AI tools employed by companies like Pandologic, Talenya, and HireScore scrape data from various social networks and match candidates to job positions, enabling targeted recruitment (Campbell, Sands, Ferraro, & Tsao, 2019).

AI-powered chatbots are valuable tools in the sourcing process, complementing the tasks of human recruiters. They can handle a large number of CVs that often go ignored, allowing companies to engage with 100% of candidates (Allal-Chérif, Aránega, & Sánchez, 2021). Chatbots powered by AI also contribute to candidate engagement and provide information about the recruitment process, company, and job details on a 24/7 basis (Black & van Esch, 2020). This improves the employer brand by facilitating interactions with all candidates (Allal-Chérif, Aránega, & Sánchez, 2021). They simulate human-like interactions, aid candidates, and free up HR professionals' time (Votto, Valecha, Najafirad, & Rao, 2021).

AI tools can also optimize job advertisements by adjusting the wording to increase the number of applicants and enhance diversity (McIlvaine, 2018) Unilever is one of the companies that has successfully leveraged AI to increase the number of applicants and improve the diversity of their candidate pools (Feloni, 2017). Other examples are Johnson & Johnson and L’Oréal. Johnson & Johnson implemented an AI tool developed by Textio to eliminate language in their job descriptions and proactive recruitment strategies that was biased towards males. This initiative resulted in a notable increase in gender diversity, as it attracted an additional 90,000 female candidates within a year. On the other hand, L'Oréal utilized Textio's AI-enabled tool to remove previously biased language favoring females, leading to an equal distribution of male and female job applicants and achieving a level of gender diversity that had not been attained before. (Duan, Edwards, & Dwived, 2019)

AI-enabled tools excel at screening and matching candidates by utilizing machine learning techniques and natural language processing (Paschen, Kietzmann, & Kietzmann, 2019). They can analyze profiles on social media and professional networks to identify suitable candidates (Black & van Esch, 2021). With all the services it provides, AI systems transform the application process by eliminating the need for traditional resumes and applications (Black & van Esch, 2020). The use of AI in the sourcing stage reduces costs and saves time, which is particularly beneficial for social businesses with limited resources (Allal-Chérif, Aránega, & Sánchez, 2021; Achchab & Temsamani, 2021).

The AI capabilities can be used in candidate sourcing and engagement in recruitment and their outcomes are summarized in Table 1 below.

Table 1: AI Capabilities in Candidate Sourcing and Engagement

AI Capability	Outcomes	Reference
Predicting job vacancies	Enhanced employee retention Enhanced corporate reputation as an employer Decreased hiring time	(Albert, 2019; Achchab & Temsamani, 2021)
Optimizing job descriptions	Enhanced workplace diversity Minimized potential for indirect bias or discrimination Increased candidate involvement or interaction	(Albert, 2019; Lee & Kim, 2021)
Targeted job advertising	Enhanced candidate experiences Optimized opportunities for candidate involvement Reduced expenditure on advertising	(Albert, 2019; Saad, Nugro, Thinakaran, & Baijed, 2021)
Multi-database candidate sourcing	Accelerated sourcing efficiency Increased focus of recruiters on critical tasks and enhanced recruiter task allocation and prioritization Enhanced quality and quantity of talent pool	(Albert, 2019; Saad, Nugro, Thinakaran, & Baijed, 2021)

Table 1 (cont.)

Screening CVs	Mitigated human fatigue-related biases Increased diversity Cost reduction Increased focus of recruiters on critical tasks and enhanced recruiter task allocation and prioritization	(Albert, 2019; Saad, Nugro, Thinakaran, & Baijed, 2021; Lee & Kim, 2021; Achchab & Temsamani, 2021)
AI-Powered background checking and personality analysis	Increased focus of recruiters on critical tasks and enhanced recruiter task allocation and prioritization Minimized expenses due to human errors	(Albert, 2019; Saad, Nugro, Thinakaran, & Baijed, 2021)
Monitoring employer branding	Enhanced talent pool quality through a robust employer brand Favorable client perception Decreased time-to-hire, turnover, and cost reduction	(Albert, 2019)
Candidate engagement (chatbot)	Decreased time-to-hire Increased focus of recruiters on critical tasks and enhanced recruiter task allocation and prioritization Enhanced candidate experience and employer brand	(Albert, 2019; Saad, Nugro, Thinakaran, & Baijed, 2021)

2.1.3. Artificial Intelligence in Assessment of the Candidates

AI technologies such as Natural Language Processing (NLP) and computer vision offer powerful tools for evaluating candidates' integrity, personality traits, and communication skills (Black & van Esch, 2019; Gupta, Fernandes, & Jain, 2018).

Serious games are one of the ways to implement AI for the assessment of the candidates for a job position. They are the simulations in which the candidates are challenged by AI with various pre-created job scenarios to evaluate their behaviors. Serious games are used by recruiters to test the communication and coordination skills, response time, degree of adaptability, and creativity of the candidates (Allal-Chérif & Makhlouf, 2016; Yannakakis & Togelius, 2015) By staying behind the computer screen candidates are protected from any judgments affected by human prejudices (Zelenskaya & Singh, 2011). Unilever is one of the companies implementing 12 neuroscience-based AI games to screen candidates (Feloni, 2017).

AI-powered chatbots have been used in the assessment stage of recruitment in addition to attracting and communicating with candidates as mentioned in the previous section. They can also schedule and conduct interviews with candidates on digital platforms with a communication language tailored to company needs on a 7/24 basis. (Allal-

Chérif, Aránega, & Sánchez, 2021; Callejas, Ravenet, Ochs, & Pelachaud, 2014). For instance, the US military pioneered chatbot technology with Sergeant Star, a virtual recruiter who has asked millions of questions (Allal-Chérif, Aránega, & Sánchez, 2021). To enhance users' perception of social presence and foster positive attitudes toward chatbots, a social-oriented interaction style is recommended (De Cicco, Silva, & Alparone, 2020).

It is also possible for companies to practice AI with video recording interviews. They have become increasingly common, enabling the analysis of facial expressions, body language, and keywords (Raghavan, Barocas, Kleinberg, & Levy, 2019; Cabrera & Fritts, 2021). AI interview systems developed using deep-learning technology utilize visual, vocal, verbal, and vital (biological) data to evaluate candidates' competencies, emotional states, linguistic behaviors, and tendencies (Lee & Kim, 2021). While traditional selection mechanisms, namely unstructured and structured interviews both show limited accuracy of %14 and 30% respectively in identifying candidates who perform well in the long term (Hunter & Schmidt, 1998; Huffcutt, Culbertson, & Weyhrauch, 2013), according to Midas IT, an agency specializing in AI analysis, AI interviews offer the accuracy of nearly 82% in determining talented applicants (Nawaz, 2019). For example, one of the studies presents an AI-based interview system that is implemented in several enterprises, including five major public enterprises in Korea, trained on more than 100,000 evaluation data sets derived from 400,000 interview image data and achieved a reliability score of 0.88 Pearson. According to the study, the system received high satisfaction ratings of 85% in terms of fairness and efficiency, considering aspects such as evaluation processes, job fitness, and organization fitness (Lee & Kim, 2021). With the help of tone of voice, microfacial movement, and gesture analysis, AI-based interviews enable companies to understand whether the candidate is appropriate to the organizational culture or not (Cabrera & Fritts, 2021).

AI technologies also allow predictive hiring (Achchab & Temsamani, 2021). Based on the past data retrieved from high-performer employees, it is possible to transform the training, skills, and experiences of the candidates into measurable data and compare them with those of the referent employees (Faliagka, Tsakalidis, & Tzimas, 2012).

The AI capabilities can be used in candidate assessment in recruitment and their outcomes are summarized in Table 2 below.

Table 2: AI Capabilities in Candidate Assessment

AI Capability	Outcomes	Reference
AI-powered psychometric testing	Increased focus of recruiters on critical tasks and enhanced recruiter task allocation and prioritization Enhanced workplace diversity Improved candidate to hire ratio	(Albert, 2019; Saad, Nugro, Thinakaran, & Baijed, 2021)
Video screening	Bias and discrimination reduction Increased focus of recruiters on critical tasks and enhanced recruiter task allocation and prioritization Enhanced candidate experience	(Albert, 2019; Lee & Kim, 2021)
Automated interview scheduling	Increased focus of recruiters on critical tasks and enhanced recruiter task allocation and prioritization	(Albert, 2019)
Profile matching	Minimized costs due to human errors Bias and discrimination reduction	(Lee & Kim, 2021; Achchab & Temsamani, 2021)
Facial, voice pattern recognition, sentiment and word choice analysis	Minimized costs due to human errors Bias and discrimination reduction	(Saad, Nugro, Thinakaran, & Baijed, 2021; Lee & Kim, 2021; Achchab & Temsamani, 2021)
Predictive hiring analysis (analyzing the probability of success in the job)	Increased employee performance Enhanced employee retention	(Achchab & Temsamani, 2021)

2.2 Technology Acceptance Models

In this part, some of the major technology acceptance models will be discussed briefly.

2.2.1. Diffusion of Innovation (DOI) Theory

The diffusion of innovation (DOI) theory has grounds in anthropology and communication research. Everett M. Rogers explained the attributes of innovation and the variables determining the widespread use of such an innovation in his book "Diffusion of Innovations", published first in 1962. Diffusion was defined as "the process by which an innovation is communicated through certain channels over time among the members of a social system “. Therefore, the four main elements of diffusion described are innovation, communication channels, time, and the social system (Rogers, 2003). “The rate of adoption” on the other hand, was defined as “the relative speed with which an innovation is adopted by members of a social system” (Rogers, 1995). It is viewed as the main theoretical base for technology acceptance but from a global perspective (Dillon & Morris, 1996). The perceived characteristics of innovations to explain the changing rate of adoption of an innovation are shown in Figure 2.

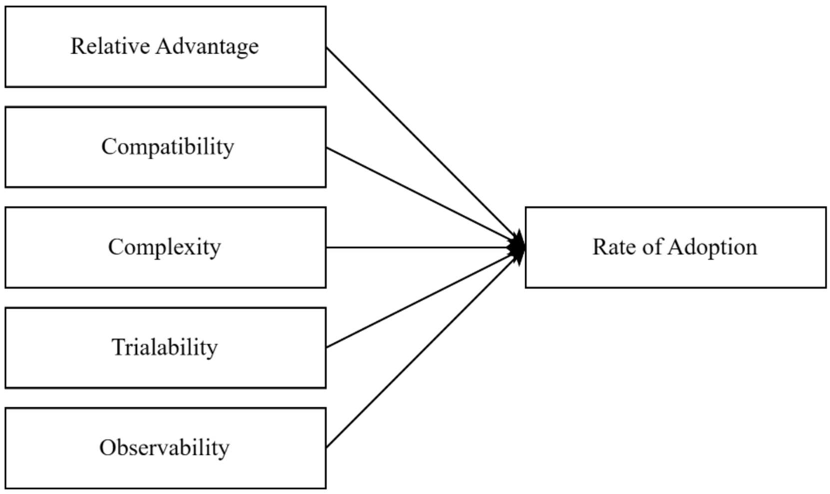


Figure 2: Diffusion of Innovation Theory

As can be seen in Figure 2, relative advantage, compatibility, complexity, trialability, and observability are the five elements of innovations determining the rate of adoption based on the DOI theory (Rogers, 2003). Their definitions are given below (Rogers, 2003):

- Relative Advantage is defined as “the degree to which an innovation is perceived as being better than the idea it supersedes”,
- Compatibility is defined as “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters”,
- Complexity is defined as “the degree to which an innovation is perceived as relatively difficult to understand and use”,
- Trialability is defined as “the degree to which an innovation may be experimented with on a limited basis”

- Observability is defined as "the degree to which the results of an innovation are visible to others."

2.2.2. Theory of Reasoned Action (TRA)

The theory of Reasoned Action (TRA) is based on the social behavior studies of Martin Fishbein and Icek Ajzen who joined him later (Fishbein & Ajzen, 1972). Although this theory originally has grounds in sociology and psychology, it became a foundation to explain IT usage behavior (Taherdoost, 2018). According to the theory, a single act is determined by the behavioral intention of the person in the subject. The behavioral intention to act in a specific way, on the other hand, was found to be predicted by the subject's attitude toward that specific act and normative beliefs that the subject's family and friends expected him or her to perform that act (Fishbein & Ajzen, 1972). Determinants of the probability to act in a specific way are demonstrated in Figure 3 below.

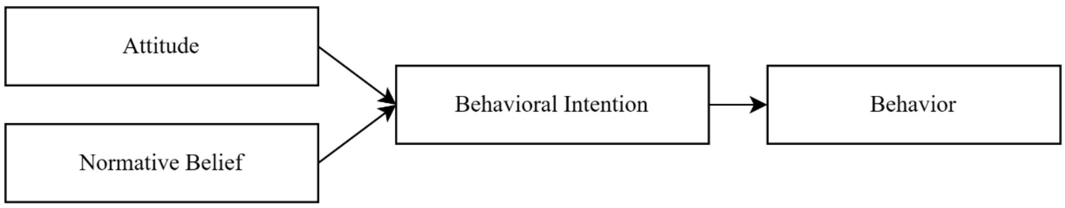


Figure 3: Theory of Reasoned Action

Based on this model, volitional and rational human behavior can be explained by three cognitive factors which are the favorableness of a person's feelings, social influence, and a person's decision to do or not to do that behavior (Taherdoost, 2018). Not addressing the role of habits, cognitive deliberation, and the moral factors may be considered as the disadvantages of the model (Taherdoost, 2018).

2.2.3. Theory of Planned Behavior (TPB)

This theory is an extension of the TRA. Intention to perform a specific behavior is the main factor and it is the measure of motivation to exert an effort to perform a behavior. The stronger the behavioral intention, the more likely that person engages in behavior action. The behavior mentioned here is considered to have a voluntary nature and the person in question should have all the opportunities and resources such as time, money, skills, and cooperation of others to perform that behavior.

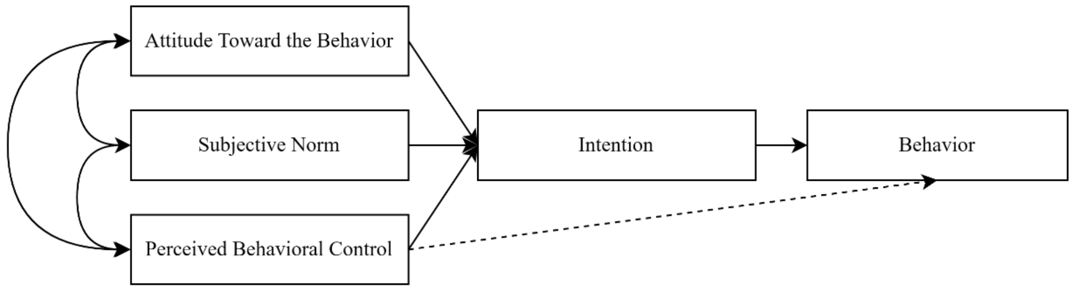


Figure 4: Theory of Planned Behavior

Based on the framework of the model shown in Figure 4, attitude toward the behavior, subjective norm referring to social pressure felt to act or not to act, and perceived behavioral control which means perceived easiness of acting are the strong predictors of the intention to behave (Ajzen, 1991). “The perceived behavioral control” in the model is what differentiates the TPB from the TRA.

2.2.4. Technology Organization Environment (TOE) Framework

In the book “The Processes of Technological Innovation” published in 1990 by Tornatzky and Fleischer, the life cycle of technological innovation is researched and they analyzed the innovation from the perspectives of individuals, work groups, organizations, and the environment (Tornatzky, Fleischer, & Eveland, 1990). The “Technology Organization and Environment” framework emerges as a part of the innovation process representing the organization-level context influencing the adoption and implementation of an innovation (Baker, 2012). The framework is shown in Figure 5.

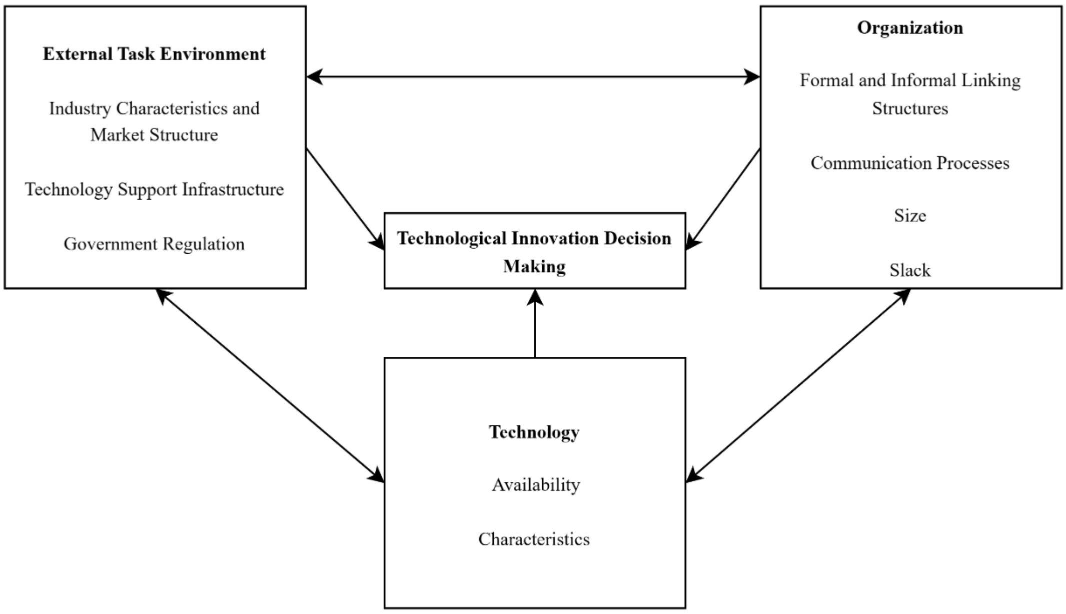


Figure 5: Technology Organization Environment Framework

As it is shown in Figure 5, in the technology context the availability of the technology to the company and the characteristics of the technology showing the changes it will bring affect the adoption of that technology. In the organizational context, the resources and the characteristics of the company which are the linking structure between employees, the intra-company communication processes, size, and slack resources of the company are addressed. The environmental context, on the other hand, includes the industry structure, availability of technology service providers, and the regulations affecting the adoption decision. (Baker, 2012)

2.2.5. Technology Acceptance Model (TAM)

One of the most cited acceptance models is the "Technology Acceptance Model" developed by Fred D. Davis. It was derived from TRA and the subjective norm was eliminated from the research as it was found not to have a significant effect on the intention to use technology over and above the factors identified through the study (Davis & Venkatesh, 2000).

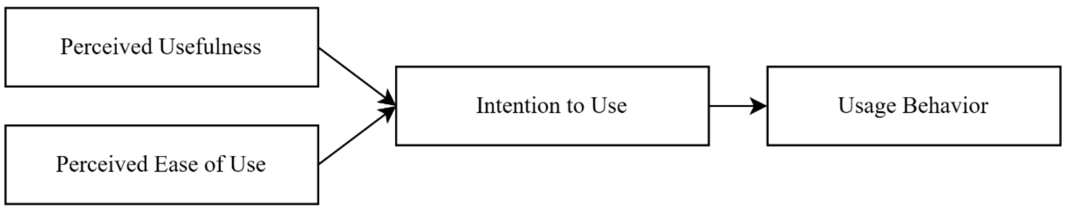


Figure 6: Technology Acceptance Model

As illustrated in Figure 6, the factors in the model are perceived usefulness which is the belief of a person that using a particular system would improve his or her job performance, and perceived ease of use which is the belief of a person that using a particular system would be effortless (Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, 1989). Although perceived usefulness was found to have a stronger relationship with usage behavior, a significant correlation between system uses and both factors was demonstrated by the study (Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, 1989).

2.2.6. Extension of the Technology Acceptance Model (ETAM)

Based on the many empirical tests of TAM, perceived usefulness had been found a strong determinant consistently, with a standardized regression coefficient of 0.6 approximately (Davis & Venkatesh, 2000). Because of this, understanding the determinants of such an important driver of the intention to use technology and how their effects change over time with rising usage experience were studied.

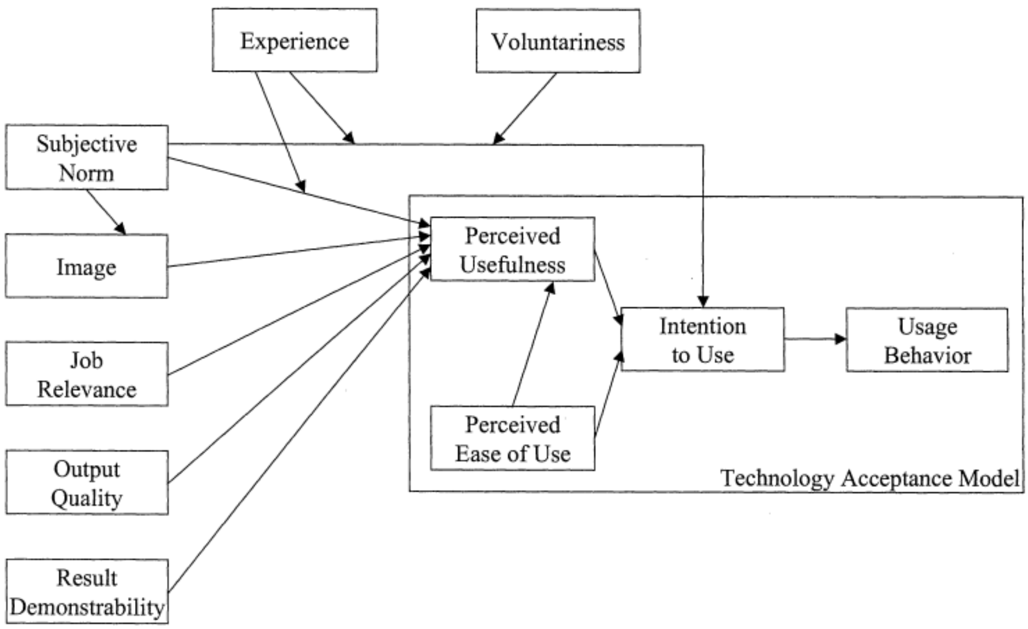


Figure 7: Extension of the Technology Acceptance Model

In this model, additional constructs reflecting social influence are subjective norm, voluntariness, and, image and those reflecting cognitive influence are job relevance, output quality, and result demonstrability integrated into the initial TAM as the factors affecting perceived usefulness. The model is demonstrated in Figure 7. In addition, as it can be figured out from Figure 7, the subjective norm was added to the model again. The factors determined by the study were found to explain 60% of the variance in perceived usefulness. It was also found that in the mandatory settings, subjective norm exerts a significant direct effect on usage intention over and above perceived usefulness. (Davis & Venkatesh, 2000)

2.2.7. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT model was formed by reviewing and integrating factors studied before by eight technology acceptance models. It was confirmed that it outperformed the previous models by providing an adjusted R2 of 69 percent in one data analysis and 70 in another (Venkatesh, Morris, Davis, & Davis, 2003).

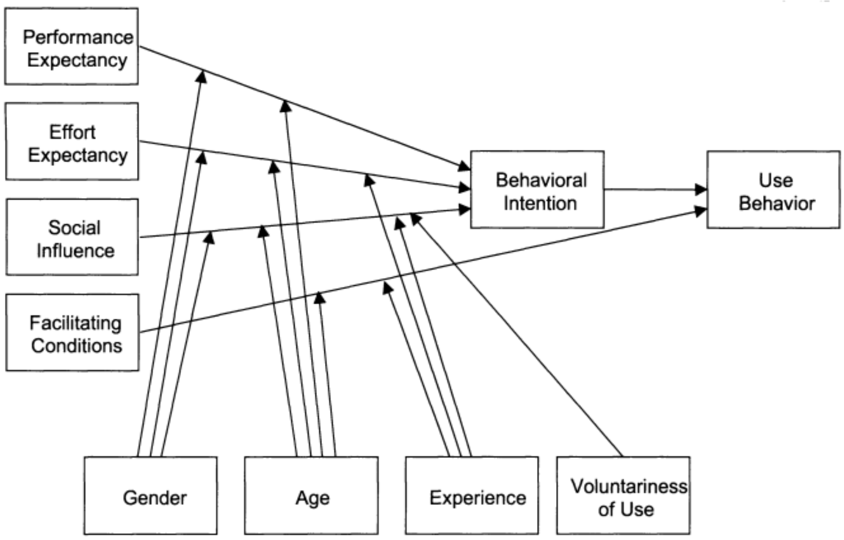
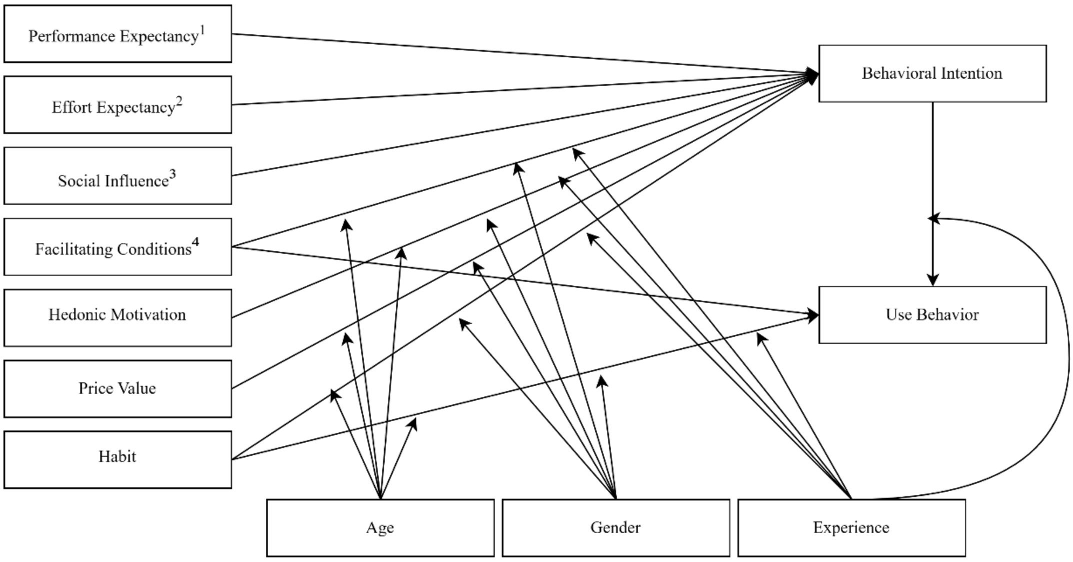


Figure 8: Unified Theory of Acceptance and Use of Technology

Four factors were found to have a direct significant effect on intention or usage behavior. As illustrated in Figure 8, while performance expectancy, effort expectancy, and social influence affect behavioral intention, facilitating conditions affect directly the usage without being fully mediated by intention. In addition; gender, age, experience, and voluntariness of use are the mediating factors influencing the constructs in the model. (Venkatesh, Morris, Davis, & Davis, 2003).

2.2.8. Consumer Acceptance and Use of Information Technology (UTAUT2)

Consumer Acceptance and Use of Information Technology which is known as UTAUT2 is the model developed to study the adoption of technology in the consumer context.



Notes:

1. Moderated by age and gender.
2. Moderated by age, gender, and experience.
3. Moderated by age, gender, and experience.
4. Effect on use behavior is moderated by age and experience.

Figure 9: Consumer Acceptance and Use of Information Technology

Three additional factors which are hedonic motivation, price value, and habit were added to the model to predict the technology usage intention and behavior of the consumers while one of the moderating factors, voluntariness was removed from the model. According to the results of the study, UTAUT2 explained 74 percent of the variance in behavioral intention and 52 percent of that in technology usage while the baseline UTAUT explained 56 and 40 percent respectively in the consumer context. (Venkatesh, Thong, & Xu, 2012) The model is provided in Figure 9 and the details regarding the constructs will be given in Chapter 3.

2.3 Systematic Review of AI Acceptance in Recruitment

In this part of the thesis, the literature on the research topic which is the acceptance of AI tools in the recruitment process is reviewed and the results are assessed.

2.3.1. Databases Used

Scopus, ScienceDirect, and Emerald Insight are used as research databases since they have a large article pool and developed research algorithms enabling easy search by using appropriate keywords. The online databases are reached via METU Library by connecting to the METU network and via METU user name and password.

2.3.2. Identification of Research Criteria

Since AI in recruitment is a relatively new topic, “2000” is selected as the starting point for the research. The research is further limited by language and article type. “English” is selected as the research language while “Review Articles”, “Research Articles”, “Conference Papers” and “Opinion Papers” are selected as article types. In addition, the sources are restricted to being open sources in order not to waste time on the articles which cannot be reached. Keywords “ai”, “adoption”, “acceptance”, “recruitment”, “hr” and “hiring” are used in different combinations with the Boolean operator “AND” to conduct research on the subject. The combinations are as follows:

- “ai” AND “acceptance” AND “hr”,
- “ai” AND “adoption” AND “hr”,
- “ai” AND “adoption” AND “recruitment”,
- “ai” AND “acceptance” AND “recruitment”,
- “ai” AND “acceptance” AND “hiring”,
- “ai” AND “adoption” AND “hiring”.

The literature research has been ended as of 31st May 2023 to progress on the analysis part.

2.3.3. Management of Research Results

The number of papers reached based on the criteria defined in the previous part is presented in Table 3 below.

Table 3: Initial Research Results

Keywords	**Scopus**	**ScienceDirect**	**Emerald Insight**
ai AND acceptance AND hr	5	91	50
ai AND adoption AND hr	32	132	34
ai AND adoption AND recruitment	27	332	19
ai AND acceptance AND recruitment	17	261	35
ai AND acceptance AND hiring	6	110	23
ai AND adoption AND hiring	12	181	54

As seen in Table 3, 1421 papers including duplicates are reached in total. They are revised based on their titles and abstracts and the duplicate ones are reduced to one.

This process led to 87 papers remaining to be examined in content. After those 87 papers were read, 42 of them were found not to be related to the adoption of AI technology. The topics studied in these papers are opportunities and risks of AI, social and ethical issues on AI, marketing, development, or history of AI in HR or recruitment. Therefore, 45 papers are left to be examined further. As a next step, these papers are examined in detail and 12 papers out of 45 are eliminated since either they are the review articles or they have insufficient information to benefit from. The articles remained and analyzed throughout the next sections can be found in Appendix A with references.

2.3.4. Assessment of the Studies

The remaining 33 articles reached from the literature review are analyzed based on the type of the article, source, type, and subject of the source, location, year, characteristics of the sample, size of the sample, research and analysis method, applications used, instrument, dependent variables, independent variables and explanatory power of the model. A database is created by using Microsoft Excel to handle and visualize data. However, some of the articles do not share information regarding the applications used and the overall explanatory power of the model and since some of the studies are theoretical, they do not have any data regarding the sample or research method. The assessment of the articles based on the data available is provided in the subsequent sections.

2.3.4.1. Assessment of the Studies Based on Article Type

The articles assessed in this study are shown based on their type in Figure 10 below.

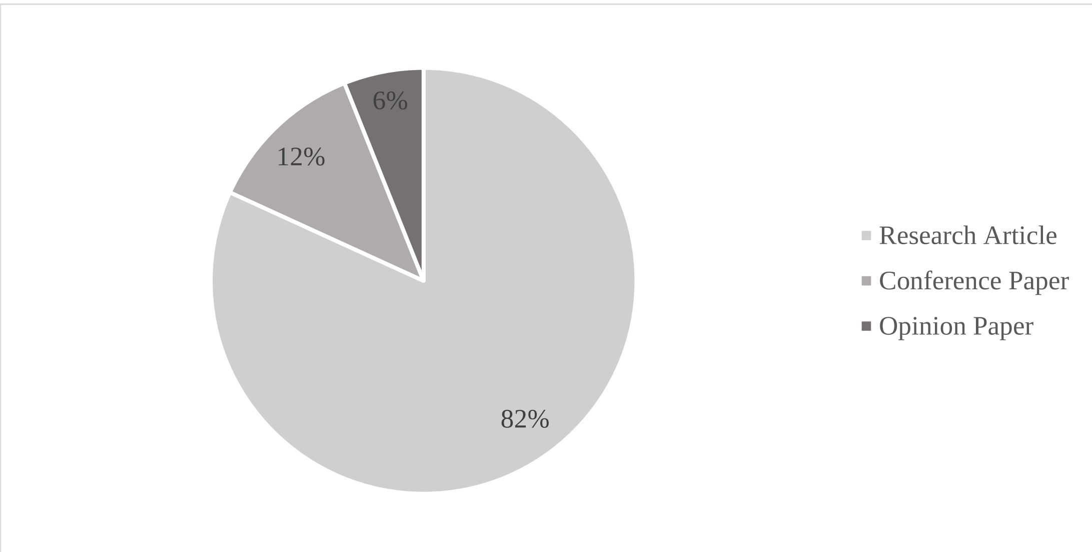


Figure 10: Studies Based on Article Type

As Figure 10 illustrates most of the articles are research articles. Only 4 of them are conference papers while only 2 of them are opinion papers that provide theoretical models to be studied in the future.

2.3.4.2. Assessment of the Studies Based on Year

The articles are investigated based on the year of publication. Figure 11 below shows the distribution of articles with respect to years.

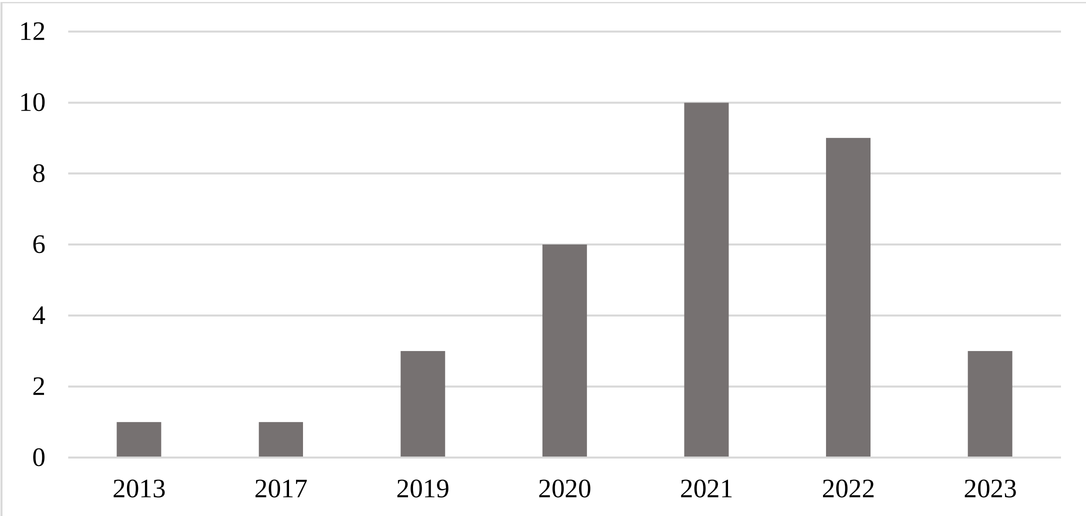


Figure 11: Studies Based on Year

Although "2000" was chosen as the starting year for the research, as can be seen from Figure 11, all of the studies on AI acceptance in recruitment spanned a more recent period, between 2013 and 2023. This proves that the research topic is relatively new. In addition, it can be said that the studies have risen after 2019 and peaked in 2021 due to the COVID-19 pandemic. That’s why remote hiring and accordingly AI usage in recruitment have become prominent issues in these years.

2.3.4.3. Assessment of the Studies Based on Location

The distribution of studies based on country and continent is provided in Figure 12.

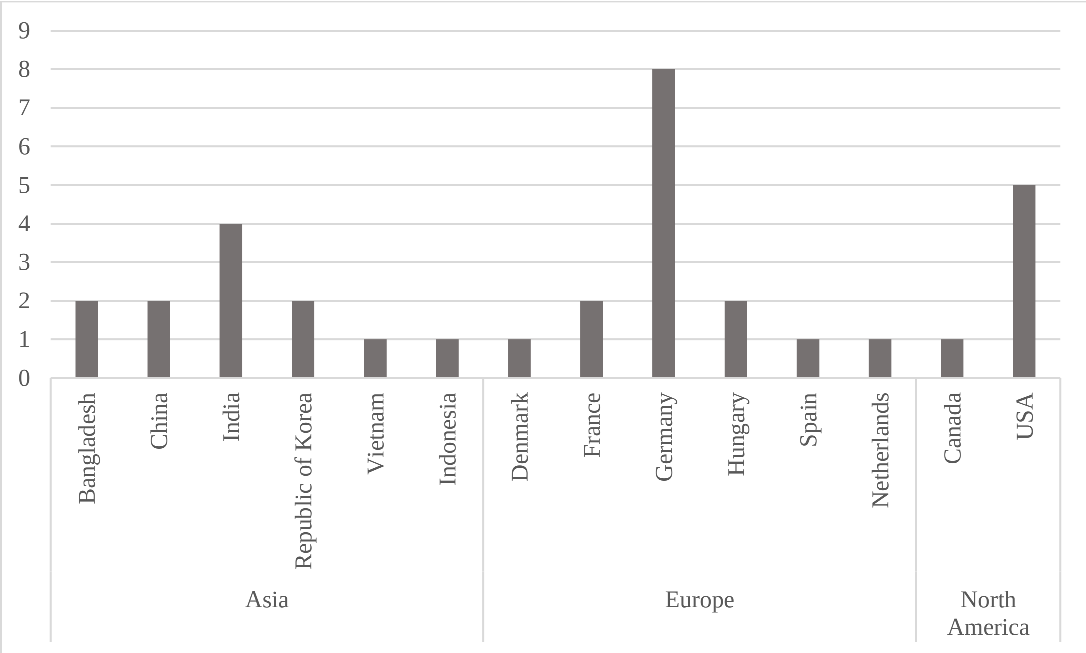


Figure 12: Studies Based on Location

According to Figure 12, most of the research is done in Europe specifically in Germany.

2.3.4.4. Assessment of the Studies Based on Type and Subject of the Source

Of the 33 articles analyzed, 4 were obtained from conference proceedings, and the rest were taken from journals in varying subject areas. The subject areas of the conference proceedings and journals are grouped and these groups are shown in Figure 13 below.

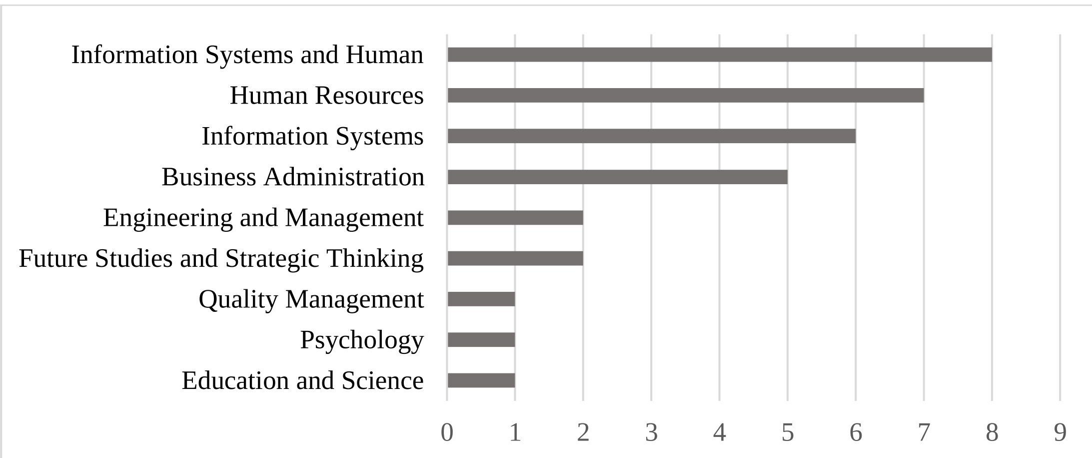


Figure 13: Studies Based on Subject of the Source

The majority of the studies are published in journals on information systems and human, human resources, information systems, and business administration.

2.3.4.5. Assessment of the Studies Based on Instrument

The studies are analyzed according to the instruments they are based on and the distribution is shown in the figure below.

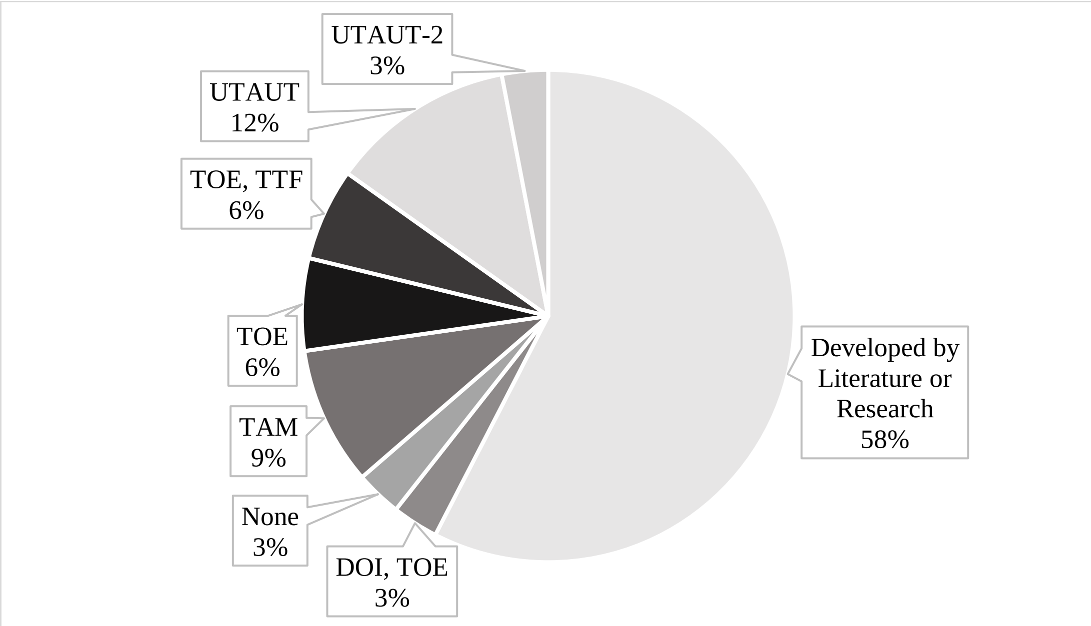


Figure 14: Studies Based on Instrument

As Figure 14 shows, in most of the studies, the models are theorized either based on the literature on technology acceptance, AI, and its usage in HR or based on the qualitative analysis made through experiments or interviews. TOE which is either being used single or in combination with other models, and UTAUT are the other models mostly being basis for the studies.

2.3.4.6. Assessment of the Studies Based on Perspective

The assessment of the studies concerning the perspectives they are based on is a critical issue. Because it changes the direction of the research question and theorized model together with the factors influencing the acceptance of AI in recruitment. While 14 studies examine technology acceptance from the perspective of people who directly use or apply technology such as employees, HR specialists, and HR managers; the remaining 19 studies examine technology acceptance from the perspective of indirect users, in other words, passive users namely candidates. As stated in section 1.3, this study tries to model AI-based recruitment acceptance among job candidates, namely the users who do not have any authority or preference on the usage decision but rather are exposed to it.

Their acceptance of AI-based recruitment is based on their intention to participate in AI-based recruitment rather than their intention to use it. The instruments used in the studies with respect to the perspectives they are based on are provided in Figure 15.

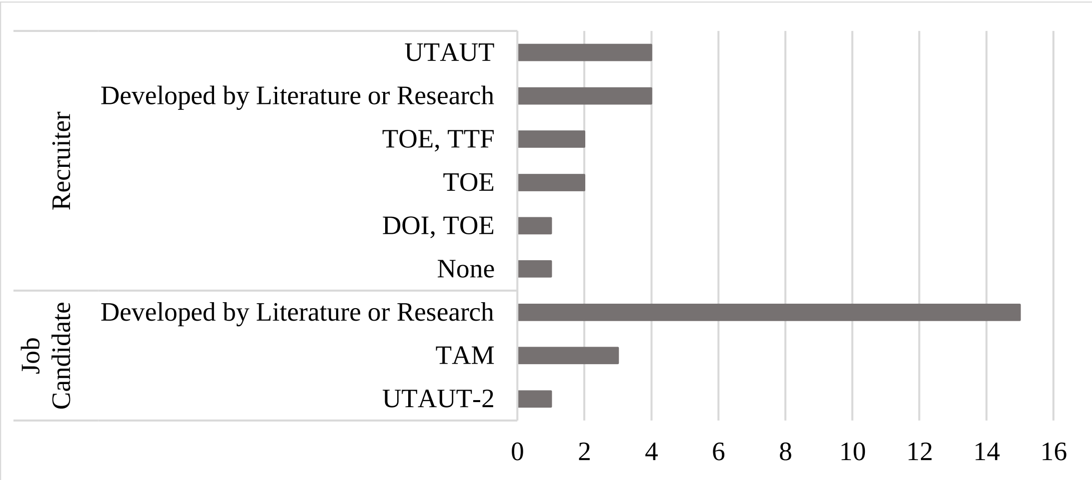


Figure 15: Studies Based on Research Perspective

While models are developed based on literature research or self-analysis in most of the 19 studies, 3 of them use TAM and the last one uses UTAUT-2.

2.3.5. Assessment of the Constructs Used in Selected Articles

19 studies examining technology acceptance from the perspectives of job candidates or job seekers are analyzed in depth for the factors they study. The dependent and independent variables in the studies with paper references can be found in Appendix B. 96 constructs are identified based on these 19 studies. However, since some constructs are either the same or express the same concept with a different naming, they are grouped under 52 common constructs. Out of these 52 constructs, the ones that are used in more than one study are shown in Table 4 below.

Table 4: Constructs Used in Selected Articles

Construct	Frequency	References
Fairness	11	Lukacik, Bourdage, & Roulin, 2022; Wesche & Sonderegger, 2021; Black & van Esch, 2019; Kim & Heo, 2021; Langer, König, & Papathanasiou, 2019; Langer, König, & Krause, 2017; Norskov, et al., 2022; Acikgoz, Davison, Compagnone, & Laske, 2020; Gonzalez, et al., 2022; Mirowska & Mesnet, 2021; Zhang & Yencha, 2022

Table 4 (cont.)

Performance Expectancy	5	Brahmana & Brahmana, 2013; Laurim, Arpaci, Prommegger, & Krcmar, 2021; Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Ochmann & Laumer, 2020; Kim & Heo, 2021
Organizational Attractiveness	5	Langer, König, & Papathanasiou, 2019; Langer, König, & Krause, 2017; van Esch, Black, & Arli, 2021; Mirowska & Mesnet, 2021; Wesche & Sonderegger, 2021
Hedonic Motivation	5	Ochmann & Laumer, 2020; van Esch, Black, & Arli, 2021; Lukacik, Bourdage, & Roulin, 2022; Laurim, Arpaci, Prommegger, & Krcmar, 2021; Brahmana & Brahmana, 2013
Perceived Self-Efficacy	4	Norskov, et al., 2022; Langer, König, & Papathanasiou, 2019; Duong & Thi, 2022; Gonzalez, et al., 2022
Perceived Behavioral Control	4	Langer, König, & Krause, 2017; Gonzalez, et al., 2022; Langer, König, & Papathanasiou, 2019; Laurim, Arpaci, Prommegger, & Krcmar, 2021
Anxiety	4	Laurim, Arpaci, Prommegger, & Krcmar, 2021, van Esch, Black, & Arli, 2021; Lukacik, Bourdage, & Roulin, 2022; Brahmana & Brahmana, 2013
Effort Expectancy	4	Ochmann & Laumer, 2020; Laurim, Arpaci, Prommegger, & Krcmar, 2021; Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Brahmana & Brahmana, 2013
Trust	4	Schick & Fischer, 2021; Laurim, Arpaci, Prommegger, & Krcmar, 2021; Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; van Esch, Black, & Arli, 2021
Perceived Privacy Concerns	3	Langer, König, & Krause, 2017; Langer, König, & Papathanasiou, 2019; Ochmann & Laumer, 2020
Two-way Communication	3	Chen, 2022; Langer, König, & Krause, 2017; Lukacik, Bourdage, & Roulin, 2022
Creepiness	2	Langer, König, & Papathanasiou, 2019; Langer, König, & Krause, 2017
Consistency	2	Lukacik, Bourdage, & Roulin, 2022; Langer, König, & Papathanasiou, 2019
Personal Innovativeness	2	van Esch, Black, & Arli, 2021; Norskov, et al., 2022
Social Presence	2	Lukacik, Bourdage, & Roulin, 2022; Langer, König, & Papathanasiou, 2019
Interpersonal Treatment	2	Langer, König, & Krause, 2017; Langer, König, & Papathanasiou, 2019
Experience	2	Wesche & Sonderegger, 2021; Mirowska & Mesnet, 2021
Resistance	2	Kim & Heo, 2021; Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020
Innovation Expectancy	2	Gonzalez, et al., 2022; Ochmann & Laumer, 2020

Table 4 (cont.)

Satisfaction	2	Duong & Thi, 2022; Gonzalez, et al., 2022
Social Influence	2	Laurim, Arpaci, Prommegger, & Krcmar, 2021; Ochmann & Laumer, 2020
Opportunity to Perform	2	Langer, König, & Krause, 2017; Lukacik, Bourdage, & Roulin, 2022
Attitude	2	Laurim, Arpaci, Prommegger, & Krcmar, 2021; Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020

2.3.6. Assessment of the Applications AI is Exercised in Research Scenarios

19 studies examining the technology acceptance from the perspectives of job candidates or job seekers or namely passive users are analyzed based on the AI application for which the acceptance is researched. The table which shows the categorized summary of the AI applications included in the research scenarios of the selected articles is provided below. The two studies which do not specify the application name are assumed to include all the applications. The detailed applications can be found in Appendix C.

Table 5: Applications AI is Exercised in Research Scenarios

	AI Sourcing and Engagement			**AI Assessment**	
Article No	**AI Advertisement**	**AI Coordination**	**AI Job Search and Application**	**AI Screening**	**AI Interview**
1	Yes	Yes	Yes	Yes	Yes
2	Yes	Yes	Yes	Yes	Yes
3	Yes	Yes	Yes	Yes	Yes
4	Yes	Yes	Yes	Yes	Yes
5	No	No	Yes	Yes	Yes
6	No	No	No	Yes	Yes
7	No	No	No	Yes	Yes
8	No	No	No	Yes	Yes
9	No	No	No	Yes	Yes
10	No	No	No	Yes	Yes
11	No	No	No	Yes	Yes
12	No	No	No	Yes	No
13	No	No	No	Yes	No
14	No	No	No	Yes	No
15	No	No	No	No	Yes
16	No	No	No	No	Yes
17	No	No	No	No	Yes
18	No	No	No	No	Yes
19	No	No	No	No	Yes
Total	**4**	**4**	**5**	**14**	**16**

As Table 5 shows AI interview is the first taken part in the AI-based recruitment scenarios. According to the limited literature review carried out for this study with some constraints and criteria, there are 4 studies which research the acceptance of the recruitment scenario including AI applications in all the phases.

2.3.7. Additional Constructs from Supportive Literature Review

To suggest a model for the acceptance of AI-based recruitment among the candidates, some additional constructs are identified based on the literature review on human-AI interaction, AI acceptance, AI acceptance on HR, service robots such as retail robots or robot instructors, and chatbots as they can be also valid for the acceptance of the use of such AI technologies in the recruitment. These constructs from the studies based on the passive user perspective are also included in the initial model. While the papers with respect to their subject area, benefited from this study can be found in Appendix D, the dependent and independent variables used in them can be found in Appendix E. The independent variables also called constructs in the models are also grouped and named under common constructs and, the ones that are used in more than one study are shown in Table 6 below.

Table 6: Additional Constructs from Supportive Literature Review

Construct	Frequency	References
Performance Expectancy	8	Zhu, Zhang, Wu, & Liu, 2022; Chi, Chi, Gursoy, & Nunkoo, 2023; Pitardi & Marriott, 2021; Brachten, Kissmer, & Stieglitz, 2021; Rasheed, He, Khizar, & Abbas, 2023; Fernandes & Oliveira, 2021; Subero-Navarro, Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2022; Song & Kim, 2022
Effort Expectancy	6	Subero-Navarro, Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2022; Pitardi & Marriott, 2021; Rasheed, He, Khizar, & Abbas, 2023; Fernandes & Oliveira, 2021; Brachten, Kissmer, & Stieglitz, 2021; Chi, Chi, Gursoy, & Nunkoo, 2023
Trust	5	Kim, Jr., Xu, & Kelly, 2022; Rasheed, He, Khizar, & Abbas, 2023; Pitardi & Marriott, 2021; Brachten, Kissmer, & Stieglitz, 2021; Fernandes & Oliveira, 2021
Hedonic Motivation	5	Subero-Navarro, Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2022; Chi, Chi, Gursoy, & Nunkoo, 2023; Ashfaq, Yun, Yu, & Loureiro, 2020; Pitardi & Marriott, 2021; Rasheed, He, Khizar, & Abbas, 2023
Social Presence	3	Pitardi & Marriott, 2021; Fernandes & Oliveira, 2021; Kim, Jr., Xu, & Kelly, 2022

Table 6 (cont.)

Social Influence	2	Chi, Chi, Gursoy, & Nunkoo, 2023; Subero-Navarro, Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2022
Perceived Privacy Concerns	2	Pitardi & Marriott, 2021; Rasheed, He, Khizar, & Abbas, 2023
Anxiety	2	Song & Kim, 2022; Rasheed, He, Khizar, & Abbas, 2023
Subjective Norm	2	Brachten, Kissmer, & Stieglitz, 2021; Fernandes & Oliveira, 2021
Anticipated Service Quality	2	Song & Kim, 2022; Ashfaq, Yun, Yu, & Loureiro, 2020
Social Capability	2	Song & Kim, 2022; Pitardi & Marriott, 2021
Perceived Humanness	2	Chi, Chi, Gursoy, & Nunkoo, 2023; Fernandes & Oliveira, 2021

CHAPTER 3

RESEARCH METHODOLOGY

This study develops a model using UTAUT2 as base model and benefiting from HR expert panel analysis. It is correlational quantitative research applying structural equation modeling for data analysis. This chapter is devoted to explain research methodology of the study.

3.5. Initial Model Proposition

The UTAUT-2 is used as a base model in this study because it is the model explaining the acceptance of the passive users of information technology, consumers. Since the job candidates are also passive users who do not have any authority, decision, or preference on the use of AI technologies in the recruitment process, the model is found to be appropriate to the research context. In addition to constructs proposed by UTAUT-2, some additional constructs are also identified as stated in sections 2.3.5 and 2.3.6. Since some constructs are either the same or express the same concept, they are grouped, evaluated under common constructs, and included in the model in this way. This grouping of the constructs can be found in Appendix F. Therefore, the term “construct” is used for these grouped common constructs from this point on in the study.

The constructs from UTAUT-2 and additional constructs from both the main and supportive literature review are consolidated in the table below with their frequencies. In addition, their definitions are taken from literature and adopted to research context by keeping their meaning. They are also provided in Table 7.

Table 7: Grouped and Consolidated Constructs with Their Frequency of Usage in Literature and Definition

Source	Construct	Frequency	Definition
UTAUT2	Performance Expectancy	13	The degree to which AI technology usage in recruitment will provide benefits to job candidates in performing certain activities (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)

Table 7 (cont.)

UTAUT2	Effort Expectancy	10	The degree of ease associated with the job candidates' experience on the AI technology usage in recruitment (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)
UTAUT2	Hedonic Motivation	10	The fun or pleasure derived from participating in AI-based recruitment (Venkatesh, Thong, & Xu, 2012)
UTAUT2	Social Influence	4	The extent to which job candidates perceive that important others believe they should participate in AI-based recruitment (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)
UTAUT2	Facilitating Conditions	2	The degree to which a job candidate believes that an organizational and technical infrastructure exists to support to participate in AI-based recruitment process (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)
UTAUT2	Habit*	1	The extent to which people tend to perform behaviors automatically because of learning (Venkatesh, Thong, & Xu, 2012; Limayem, Hirt, & Cheung, 2007)
UTAUT2	Price Value*	0	The cognitive tradeoff between the perceived benefits of the technology and the monetary cost for using (Venkatesh, Thong, & Xu, 2012; Dodds, Monroe, & Grewal, 1991)
Additional Literature Review	Fairness	11	Overall perceived fairness on AI-based recruitment including the perceived fairness of the methods used to make organizational decisions and the degree of feeling of outcome to be deserved (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993; Greenberg & Folger, 1985)
Additional Literature Review	Trust	9	Psychological expectation that a trusted party will not behave opportunistically and the willingness of a party to be vulnerable to the actions of other parties (Hmoud & Várallyai, 2020; Kim, Shin, & Lee, 2009)
Additional Literature Review	Anxiety	6	A candidate's pre-existing anxious feeling that elicits uncertainty and discomfort about having a conversation with AI (Song & Kim, 2022; Nomura, Kanda, Suzuki, & Kato, 2008; Chaplin, 1985)
Additional Literature Review	Perceived Privacy Concerns	5	The extent to which job candidates perceive that the use of AI-based recruiting methods is non-transparent and fosters data abuse (Ochmann & Laumer, 2019)

Table 7 (cont.)

Additional Literature Review	Perceived Self-Efficacy	5	Beliefs about a person's ability to learn or behave at a particular level (Duong & Thi, 2022; Schunk & Pajares, 2002)
Additional Literature Review	Social Presence	5	A psychological state in which virtual (para-authentic or artificial) social actors are experienced as actual social actors in either sensory or no sensory ways (Kim, Jr., Xu, & Kelly, 2022; Lee K. , 2004)
Additional Literature Review	Organizational Attractiveness	5	Job candidates' attitude towards the organization (Köchling, Wehner, & Warkocz, 2022; Chapman, Uggerslev, Carroll, Piasentin, & Jones, 2005)
Additional Literature Review	Perceived Behavioral Control	5	The extent to which job candidates believe they can control or influence an outcome with their behavior (Hilliard, Guenole, & Leutner, 2022; Langer, König, & Papathanasiou, 2019)
Additional Literature Review	Two-way Communication	4	Possibility for job candidates to ask questions, and to interact with the recruiter or organization (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993)
Additional Literature Review	Subjective Norm	3	the belief that a substantial group or individual approves or disapproves a given action (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Ajzen, 1991)
Additional Literature Review	Attitude	3	The feelings, thoughts, and favorable or unfavorable assessments about the AI-based recruitment (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, 1989)
Additional Literature Review	Anticipated Service Quality	3	a subjective, forward-looking, individual-centered, cognitive evaluation of a future service delivery (Song & Kim, 2022; Polegato & Bjerke, 2019)
Additional Literature Review	Satisfaction	3	the degree of internal satisfaction of expectations and needs of job candidates in AI-based recruitment (Duong & Thi, 2022)
Additional Literature Review	Personal Innovativeness	3	The degree of willingness of an individual to try out any new information technology (Köchling, Wehner, & Warkocz, 2022; Agarwal & Prasad, 1998)
Additional Literature Review	Creepiness	2	An uncomfortable feeling paired with uncertainty about how to behave or how to judge in AI-based recruitment process (Langer, König, & Krause, 2017; Langer, König, Gebhard, & André, 2016)

Table 7 (cont.)

Additional Literature Review	Resistance	2	the opposition of the individual to the rupture of the status quo produced by the use of AI in recruitment (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Guo, Sun, Wang, Peng, & Yan, 2013)
Additional Literature Review	Perceived Humanness	2	the level of an object's humanlike characteristics both in form and behavior (Fernandes & Oliveira, 2021; Wirtz, et al., 2018)
Additional Literature Review	Innovation Expectancy	2	Perceived degree of innovation associated with organization’s use of new technologies by job candidates (Ochmann & Laumer, 2020)
Additional Literature Review	Complexity	2	The extent to which the functionality of artificial intelligence applications used in recruitment is based on narrow or broad criteria assessment (Schick & Fischer, 2021)
Additional Literature Review	Interpersonal Treatment	2	Job candidates’ feelings of being treated with respect, dignity and human warmth (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993)
Additional Literature Review	Consistency	2	The degree of consistency and being free of bias of decision procedures in AI-based recruitment across people and over time (Langer, König, & Papathanasiou, 2019; Bauer, et al., 2001; Gilliland, 1993)
Additional Literature Review	Opportunity to Perform	2	Job candidates’ feelings of being given enough possibilities to put their best foot forward (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993)
Additional Literature Review	Social Capability	2	The degree of AI-based recruitment robot's social skills to engage in interpersonal relations, such as having interactive communication, being approachable, responding appropriately, and listening without interrupting (Song & Kim, 2022; de Ruyter, Saini, Markopoulos, & van Breemen, 2005; Song & Kim, 2020)

*They are excluded from the model later.

Based on the literature review on AI-based recruitment acceptance and supportive literature review on chatbot, service robot, robot instructor, and voice assistant acceptance, the pool of constructs is formed. All these constructs are used to develop the initial model before they are eliminated based on the HR expert panel analysis to achieve content validity and to form a compact model for the research subject. This initial model is presented in Figure 16.

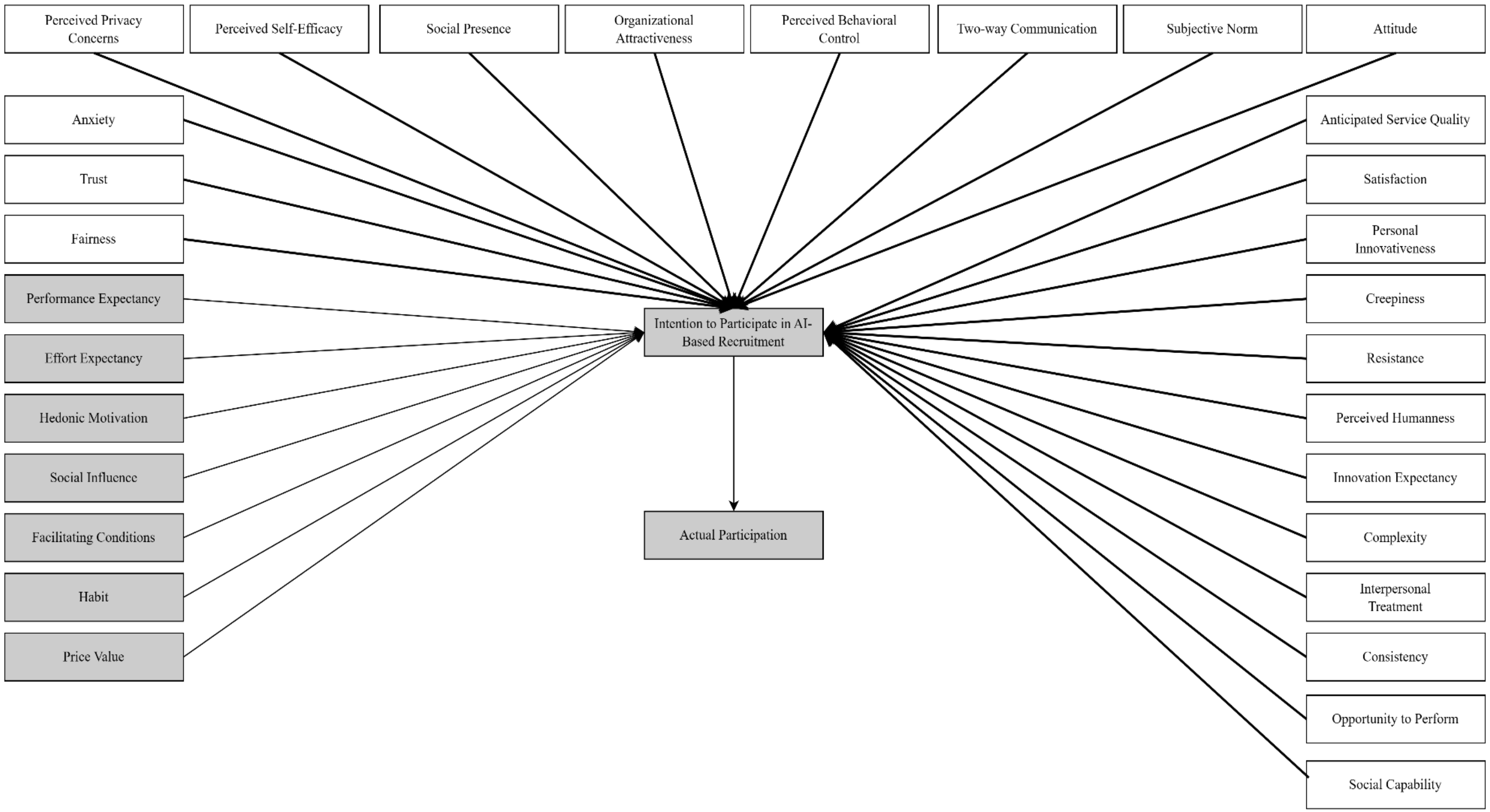


Figure 16: Initial Model Proposed by the Study

3.6. HR Expert Panel Analysis

After the initial model is proposed based on the validated UTAUT-2 model and other constructs are identified with the literature research, an expert panel analysis is conducted to identify the most suitable ones from these additional constructs and to propose a model that is more compact and valid in content for the specific research context of this study. The Delphi method is a structured group communication process to get a collective useful result (Okoli & Pawlowski, 2004). One form of this method is conventional Delphi which includes sharing a questionnaire as a first step and a second questionnaire based on the summarized results of the first (Linstone & Turoff, 2002). Conventional Delphi gives participants a chance to reevaluate their choices at least once and it comprises both pooling and conference processes (Linstone & Turoff, 2002). According to Delphi literature, there should be 10-18 experts for the implementation of this method (Okoli & Pawlowski, 2004). Therefore, to implement conventional Delphi for both model development and achieve content validity at the same time, HR experts whose area of expertise is career and talent management from a self-regulating organization in Turkey in which the researcher works are reached. In particular, 10 HR experts who are familiar with new HR practices, in contact with candidates, and actively involved in the recruitment process were identified for the study. The descriptive information regarding the HR experts is given in Table 8. In addition, %40 of the experts are men while the %60 are women.

Table 8: HR Expert Characteristics

	Age	Years of Experience in HR	Number of Interviews taken part in
Maximum	38	6	100+
Average	31,6	4,2	approximately 55
Minimum	27	1	5

3.2.1. First Round of the HR Expert Panel Analysis

A structured form containing the definitions of constructs and routing instructions for HR experts to make a scored list of 10 constructs picked up from the list of 23 additional constructs identified from the literature is prepared and distributed. The UTAUT-2 model constructs are also provided as information in the form to prevent HR specialists for making gradation without considering the concept of UTAUT-2 constructs. The frequencies of the constructs which are determined based on various research areas such as service robot acceptance are not shared with HR experts so they focus only on the research context and not to be affected by it. Turkish version of the form is distributed since the native language of the HR experts is Turkish. English version of the form can be found in Appendix G while the Turkish version can be found in Appendix H. For the expert panel analysis utilizing conventional Delphi, the Borda count method relying on social choice theory is used as a basis. Social choice theory includes several models and tries to aggregate individual inputs into collective results (List, 2022). Jean-Charles de Borda contributes to the theory by proposing a voting method in which points are assigned based on the rankings done by the voters and the winner is selected based on the sum of these points (Lansdowne & Woodward, 1996). In parallel with the method, each of the experts makes a 10-construct list in which they pick and rank constructs additional to UTAUT-2 constructs, implying that the construct on the top of the list gets 10 points while the construct at the end of the list gets 1. After forms are collected, the lists of constructs and points of them are consolidated in an Excel worksheet and analyzed. The consolidated result of the first round of the expert panel analysis can be found in Appendix I. The preference grades of each construct are summed up and the summarized results of the first round are shown in Table 9 below.

Table 9: Summarized Results of the First Round of the HR Expert Panel Analysis

Construct	**Total Grade**
Fairness	75
Trust	66
Two-way Communication	44
Interpersonal Treatment	38
Creepiness	37
Consistency	35
Perceived Privacy Concerns	34
Anxiety	25
Complexity	23
Perceived Innovativeness	23
Social Capability	17
Anticipated Service Quality	17
Attitude	16
Resistance	15
Innovation Expectancy	13
Opportunity to Perform	11
Perceived Behavioral Control	10
Organizational Attractiveness	9
Perceived Self-Efficacy	7
Perceived Humanness	7
Subjective Norm	7
Social Presence	4

Table 9 (cont.)

Satisfaction	4
AVERAGE GRADE	23

3.2.2. Second Round of the HR Expert Panel Analysis

For the second round of the expert panel analysis, the 10 constructs getting a grade greater than or equal to the average grade given to the constructs are shown to HR experts with their total grades. To reach a common decision themselves, the HR experts are given a chance to discuss those constructs for the research question, the acceptance of AI-based recruitment among job candidates. Again, in this round, the Borda count method is applied to find selected constructs for the final model of the study. That's why, each HR expert is asked to pick 5 constructs and make an ordered list from this 10-construct pool. The consolidated result of the second round of the expert panel analysis can be found in Appendix J. The summarized final result of the expert panel analysis is provided in Table 10.

Table 10: Summarized Final Result of the Expert Panel Analysis

Construct	**Total Grade**
Fairness	35
Trust	25
Two-way Communication	19
Perceived Privacy Concerns	15
Creepiness	15
Interpersonal Treatment	14
Consistency	10
Anxiety	7
Complexity	5
Perceived Innovativeness	4
AVERAGE GRADE	15

According to the results of the expert panel analysis, 5 constructs getting a grade greater than or equal to the average grade emerge as fairness, trust, two-way communication, perceived privacy concerns, and creepiness.

3.3. Modified Model and Formation of Hypothesis

Based on the final results of the expert panel analysis, the 5 constructs that get a grade greater than or equal to the average grade are included in the model in addition to UTAUT-2 constructs. These are fairness, trust, two-way communication, perceived privacy concerns, and creepiness. However, 2 constructs of the UTAUT-2 model which are “habit” and “price value” and moderating factors are excluded from the model. The modified final model is illustrated in Figure 17. The constructs, their inclusion or exclusion reasons, and hypothesis are explained in the subsections.

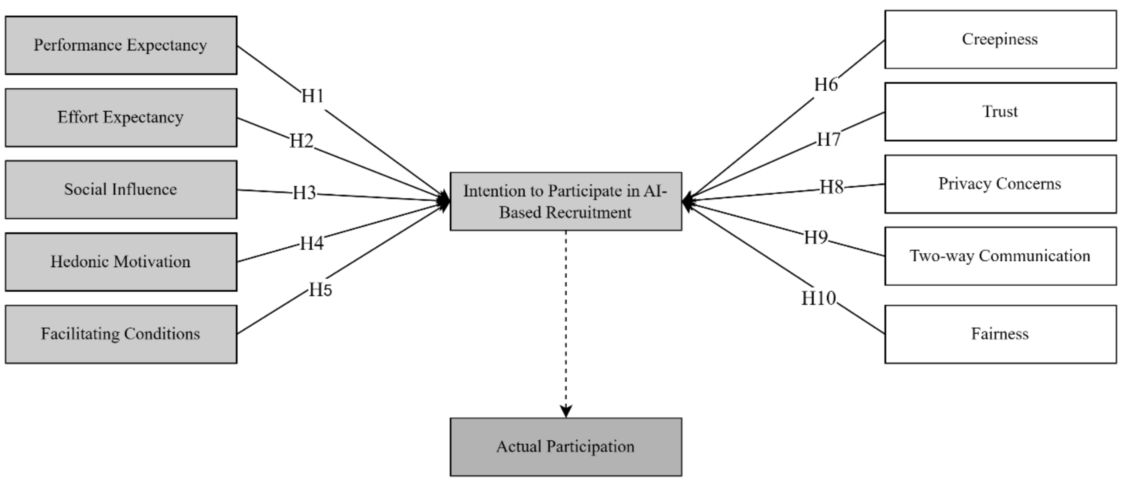


Figure 17: Modified Model

3.3.1. UTAUT-2 Constructs

The definitions, their inclusion or exclusion reasons of constructs proposed by the UTAUT-2 model, and related hypotheses are provided in subsequent sections.

3.3.1.1. Performance Expectancy (PE)

Performance Expectancy is defined in this study as “the degree to which AI technology usage in recruitment will provide benefits to job candidates in performing certain activities” (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003). This construct reflects the perception of job candidates on how useful the usage of AI tools in the recruitment process. Therefore, it is hypothesized that there is a positive relationship with the intention to participate in AI-based recruitment. This construct is used in 13 studies reached by literature review as shown in Table 7. Since it is found relevant to the research context and it has been used in previous studies more than once it is included in the research model. The related hypothesis is:

H1: As job candidates' performance expectancy of usage of AI-tools in recruitment increases, their intention to participate in AI-based recruitment increases.

3.3.1.2. Effort Expectancy (EE)

Effort Expectancy is defined in this study as "the degree of ease associated with the job candidates' experience on the AI technology usage in recruitment (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003). This construct reflects the perception of job candidates on how easy the interaction with AI-based recruitment robot in the recruitment process. Therefore, it is hypothesized that there is a positive relationship with the intention to participate in AI-based recruitment. This construct is used in 10 studies reached by literature review as shown in Table 7. Since it is found relevant for the research context and it is used in previous studies more than once it is included in the research model. The related hypothesis is:

H2: As job candidates' effort expectancy of usage of AI-tools in recruitment increases, their intention to participate in AI-based recruitment increases.

3.3.1.3. Social Influence (SI)

Social influence is defined in this study as "the extent to which job candidates perceive that important others believe they should participate in AI-based recruitment" (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003). This construct reflects the perception of job candidates how people important to them think positive on participating in AI-based recruitment. Therefore, it is hypothesized that there is a positive relationship with the intention to participate in AI-based recruitment. This construct is used in 4 studies reached by literature review as shown in Table 7. Since it is found relevant for the research context and it is used in previous studies more than once it is included in the research model. The related hypothesis is:

H3: As social influence to participate in AI-based recruitment on job candidates increases, their intention to participate in AI-based recruitment increases.

3.3.1.4. Facilitating Conditions (FC)

The construct "facilitating conditions" is defined in this study as "the degree to which a job candidate believes that an organizational and technical infrastructure exists to support to participate in AI-based recruitment process" (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003). This construct reflects the perception of job candidates how organization provides all resources needed in AI-based recruitment. Therefore, it is hypothesized that there is a positive relationship with the intention to participate in AI-based recruitment. This construct is used in 2 studies reached by literature review as shown in Table 7. Since it is found relevant for the research context and it is used in previous studies more than once it is included in the research model. The related hypothesis is:

H4: As the job candidates' perception of facilitating conditions increases, their intention to participate in AI-based recruitment increases.

3.3.1.5. Hedonic Motivation (HM)

Hedonic motivation is defined in this study as "the fun or pleasure derived from participating in AI-based recruitment" (Venkatesh, Thong, & Xu, 2012). This construct reflects the perception of job candidates on how they found AI-based recruitment enjoyable experience. Therefore, it is hypothesized that there is a positive relationship with the intention to participate in AI-based recruitment. This construct is used in 10 studies reached by literature review as shown in Table 7. Since it is found relevant for the research context and it is used in previous studies more than once it is included in the research model. The related hypothesis is:

H5: As job candidates' hedonic motivation to participate in AI-based recruitment increases, their intention to participate in AI-based recruitment increases.

3.3.1.6. Habit

Habit is defined as "the extent to which people tend to perform behaviors automatically because of learning" in the literature (Venkatesh, Thong, & Xu, 2012; Limayem, Hirt, & Cheung, 2007). Although this construct proposed by UTAUT-2 model is valid for consumer acceptance of a technology since the technology usage in consumption context can be a habitual activity, it is found not to be valid for the recruitment context. Because participating in a recruitment cannot be a habitual activity as it is done for a purpose which is either to be hired or get a recruitment experience and, recruitment activities can only be carried out a few times a year by an organization. In support of this argument, "habit" is included in only one of the studies in the literature. Therefore, this construct is excluded from the model.

3.3.1.7. Price Value

Price value is defined as "the cognitive tradeoff between the perceived benefits of the technology and the monetary cost for using" in the literature (Venkatesh, Thong, & Xu, 2012; Dodds, Monroe, & Grewal, 1991). Although this construct proposed by UTAUT-2 model is valid for consumer acceptance of a technology since a good or a service always has a price, it is not valid for the recruitment context. Because most of the time participating in a recruitment is a free activity if a job candidate meets the qualifications and invited to participate in the recruitment process. The only cost for this activity is time and effort and there is no significant monetary cost. Moreover "price" is not included any of the studies in the reviewed literature. Therefore, this construct is excluded from the model.

3.3.1.8. Behavioral Intention to Participate in AI-Based Recruitment (BIP)

In social psychology intentions are used to predict future actual behavior. A person's behavioral intention is defined as this person's subjective probability to actualize the behavior in subject (Fishbein & Ajzen, 1972). In Management Information Systems context Fishbein and Ajzen's TRA forms basis to understand usage behavior in other words usage or rejection decision of the people for a new technology (Dillon & Morris, 1996).While developing TAM, Davis found a significant correlations of 0.35 and 0.63 between intention and self-reported usage respectively at two time periods in time which are one hour and 14 weeks later from the introduction of the new technology (Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, 1989).

Based on this theoretical background “Behavioral Intention” is used in the UTAUT-2 model to predict the technology acceptance of the consumers. In technology acceptance studies, it is seen that the intention may tailored to research context without losing its theoretical basis. “Intention to engage with and complete digital, AI-enabled recruiting processes”, “intention to apply” and "intent to engage in” are examples from the studies on the acceptance of AI-based recruitment (Black & van Esch, 2019; Wesche & Sonderegger, 2021; Black, van Esch, & Arli, Job candidates' reactions to AI-Enabled job application processes, 2021). For this study, the construct proposed by UTAUT-2 called “Behavioral Intention” is adopted to research context as “Behavioral Intention to Participate in AI-Based Recruitment” similar to studies in the literature. Since the job candidates are passive users in the research context their intention to use or expose to AI-enabled applications in recruitment process is determined by their intention to participate in AI-based recruitment process which is than determine the actual participation implying actual use or exposure to related applications. It is the dependent variable in the research model.

3.3.1.9. Moderating Variables

The moderating variables age, gender and experience are also analyzed in UTAUT-2 model. However, moderation analysis is not included in this model in order not to make the model more complex and because of time limitation.

3.3.2. Additional Constructs

The definitions and related hypothesis of constructs selected by the panel results of the HR experts from the pool of constructs gathered by literature review are provided in the subsequent sections.

3.3.2.1. Creepiness (C)

The definition of the "creepiness" is adopted from the literature as "an uncomfortable feeling paired with uncertainty about how to behave or how to judge in AI-based recruitment process" (Langer, König, & Krause, 2017; Langer, König, Gebhard, & André, 2016). It is the last construct which take a grade above the average in the second round of the expert panel analysis although it is included only in 2 studies in literature. Since AI-based recruitment scenario provided first to HR experts in panel analysis and second to job candidates in data collection, consists of AI applications in all stages including interview with an AI-based robot to collect visual and verbal data, the construct has been thought to have a significant effect. The related hypothesis than written as:

H6: As creepiness felt by job candidates in AI-based recruitment process increases, their intention to participate in AI-based recruitment decreases.

3.3.2.2. Trust (T)

The definition of the construct, "Trust" is "psychological expectation that a trusted party will not behave opportunistically and the willingness of a party to be vulnerable to the actions of other parties" in literature (Hmoud & Várallyai, 2020; Kim, Shin, & Lee, 2009). Trust is included as a factor in 9 studies in literature analyzed. It is also second construct getting highest final grade in expert panel analysis. While fairness refers to overall fairness including procedural and outcome fairness (Bauer, et al., 2001), trust refers to the belief that the decisions made are the right ones, free from opportunism or error. The related research hypothesis is:

H7: As trust to AI-based recruitment tools by job candidates increases, their intention to participate in AI-based recruitment increases.

3.3.2.3. Privacy Concerns (PC)

The definition of the "perceived privacy concerns" is adopted from the literature as "the extent to which job candidates perceive that the use of AI-based recruiting methods is non-transparent and fosters data abuse" (Ochmann & Laumer, 2019). While the construct is fourth among the constructs getting highest grade from expert panel analysis, it is included as a factor in 5 studies in literature review. Since a negative relationship is anticipated the hypothesis is written as:

H8: As job candidates' perceived privacy concerns on AI-based recruitment process increases, their intention to participate in AI-based recruitment decreases.

3.3.2.4. Two-way Communication (TC)

The definition of “Two-way communication” is adopted from the literature and it is “possibility for job candidates to ask questions, and to interact with the recruiter or organization” (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993). This construct is third among the constructs getting highest grade from expert panel analysis. It is included as a factor in 4 studies in literature review. How two-way communication is perceived will be an influential factor as more technology is brought into the AI-based recruitment process. Accordingly, a decrease in perceived two-way communication may reduce the intention to participate in AI-based recruitment. Therefore, the related research hypothesis is:

H9: As two-way communication perceived by job candidates in AI-based recruitment process increases, their intention to participate in AI-based recruitment increases.

3.3.2.5. Fairness (F)

The definition of the construct adopted from the literature is “overall perceived fairness on AI-based recruitment including the perceived fairness of the methods used to make organizational decisions and the degree of feeling of outcome to be deserved” (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993; Greenberg & Folger, 1985). Fairness is included as a factor in 11 studies in literature analyzed. It also gets highest final grade in expert panel analysis. Since fairness is associated with the unbiased, fair procedures and decisions, AI-based recruitment may increase perceived fairness as it is understood from the section, "2.1.1. Advantages of Use of Artificial Intelligence". Therefore, the related research hypothesis is:

H10: As fairness perceived by job candidates increases, their intention to participate in AI-based recruitment increases.

3.4. Instrument and Measures

The UTAUT-2 is mainly used as the research instrument and model is developed with additional constructs. The measurement items are taken from pre-validated models in the literature, translated and adopted to research context. The translation is done in two ways, first from English to Turkish, then from Turkish to English and they are checked by the two translators who work in the self-regulating organization in Turkey in which the researcher works. The measurement items for each construct and the references of the resources they are taken provided in Appendix K.

3.5. Sample and Research Method

According to Turkish Statistical Institute, the labor force comprises the working-age population that is willing or able to supply labor for the production of economic goods and services (Labor Force Statistics, 2023). The non-institutional working age population is the population aged 15 and above within the non-institutional population (Labor Force Statistics, 2023). Since the research is grounded on an AI-based recruitment scenario, it is possible for any person in the labor force currently working or not may be faced with such a recruitment scenario. Therefore, the only restriction on sample is specified as the "being 18 years and above" which is defined as the late adolescence in the pediatric research field and deemed to having decisional capacity (Hardin, & Hackell,, 2017; Partridge, 2013).

An online questionnaire consisting of Part A questioning the descriptive data and Part B including the AI-based recruitment scenario, is formed in google forms and the link is shared with participants to collect data for the research. The English version of the questionnaire is provided in Appendix L while the Turkish version is provided in Appendix M. The data from a total of 324 participants 131 male, 193 females above age of 18 years collected with snowball sampling as a form of convenience sampling to access more people (Parker, Scott, & Geddes, 2019).

3.6 Assumptions of the Study

First of all, it is assumed that the sample reached via snowball sampling as a form of convenience sampling reflects the population and has an understanding of the recruitment scenario provided. The second assumption of the study is that all participants answer the questionnaire with honestly and truly because all of them have participated in the study voluntarily without any other motives. The evaluations of the HR experts are also assumed to reflect their opinions correctly.

3.7 Limitations of the Study

The first limitation is that since the sample consists of Turkish participants only, the results may reflect cultural influences.

The second limitation is related to the characteristics of the HR experts. HR experts are from the same organization implying their decisions may be affected by the same organizational culture and their recruitment and selection experiences may be similar.

Furthermore, moderation analysis on gender, age, or recruitment experience and analysis on industry, type, or size of the organization that utilizes AI technologies in recruitment are not carried out in this study.

3.8 Pilot Study

To test the reliability of the measurement model and finalize it to use in data collection, a pilot study is conducted. For the pilot study, the online questionnaire is shared with 68 people over 18 years of age by convenience sampling method and only 3 of them do not return back. Therefore, the data collected from a small sample size of 65 is used in pilot study. The characteristics of the sample consisting of 65 participants is shown in Table 11 below.

Table 11: Sample Characteristics for the Pilot Study

		Number of Participants
Gender	Male	32
	Female	33
Age	28 and below	27
	Between 43 and 28	35
	Between 63 and 43	3
Education	High School	3
	Bachelor's Degree	50
	Master	12

Cronbach’s Alpha is one of the widely used measures of internal reliability of a measurement instrument especially in social sciences which shows how the measures are internally consistent (Bonett & Wright, 2015). As Cronbach's Alpha getting close to 1, the internal consistency of items in a scale increase and a value greater than 0,7 is deemed to be acceptable (Gliem & Gliem, 2003). To test the reliability of the measurement model, Cronbach’s Alpha for each construct and “Cronbach's Alpha if Item Deleted” for each measurement item is calculated by using SPSS as the statistical software tool. The Cronbach's Alpha values and reliability results for each item is provided in Appendix N.

Based on the results, some items are excluded from the measurement model to increase the internal validity of it. The item codes excluded from the model is shown in Table 12 below.

Table 12: Items Excluded from the Model

Construct	**Excluded Item**
Social Influence	SI3
Facilitating Conditions	FC3
Hedonic Motivation	HM1
Trust	T3

The Cronbach's Alpha values of the constructs before and after item exclusion are shown in Table 13.

Table 13: Cronbach's Alpha Values Before and After Item Exclusion

Construct	**Previous Cronbach's Alpha**	**Action**	**New Cronbach's Alpha**
Performance Expectancy	0,830	None	0,830
Effort Expectancy	0,728	None	0,728
Social Influence	0,891	SI3 is excluded.	0,909
Facilitating Conditions	0,701	FC3 is excluded.	0,872
Hedonic Motivation	0,920	HM1 is excluded.	0,962
Creepiness	0,850	None	0,850
Trust	0,802	T3 is excluded.	0,873
Privacy Concerns	0,862	None	0,862
Two-way Communication	0,828	None	0,828
Fairness	0,930	None	0,930
Behavioral Intention to Participate	0,740	None	0,740

Since all of the values are greater than the threshold value of 0,7 in the pilot study, the model is found to be appropriate to use in further data collection and analysis.

3.9 Data Analysis Method

After the measurement model is finalized meaning that items increasing the Cronbach's alpha of the construct if deleted are removed from the measurement model, the data collection is completed. At first, the descriptive statistics regarding the data collected is obtained by using Microsoft Excel. As a second step, normality, reliability analysis of the data and part of the validity analysis mainly explanatory factor analysis are checked by using SPSS version 20. Lastly, other part of the validity analysis which is confirmatory factor analysis and structural equation modelling (SEM) are exercised by using SmartPLS 4.0.

The first reason why the SEM is preferred as the data analysis method is that the research model is complex and it is desired to consider the relative effects of constructs on each other. The SEM is a second-generation multivariate technique involving generalizations and extensions of first-generation techniques such as principal components analysis, factor analysis, or multiple regression and provides a better flexibility to researcher to model relationships between multiple variables, reveal unobservable variables and test a priori theoretical and measurement assumptions against data (Marcoulides, 2013). The second reason to choose SEM as the data analysis method is that it is one of the widely used method both in management information system and HR field of research (Hair, Ringle, & Sarstedt, PLS-SEM: Indeed a Silver Bullet, 2011; Ringle, Sarstedt, Mitchell, & Gudergan, 2020).

There are two approaches used in SEM which are factor-based covariance-fitting and the component-based partial least squares approaches (Marcoulides, 2013). Although both approaches are used in the field of the social sciences, since the covariance-based SEM (CB-SEM) is much stricter on assumptions of normal data distribution, large sample size and correctly specified model, the partial least squares path modeling method of structural equation modelling (PLS-SEM) demanding minimum on measurement scales is embraced (Wong, 2013). There are studies prove the PLS-SEM is more successful in comparison to its covariance-based counterpart when the sample size is relatively small (Hair, Sarstedt, & Ringle, 2012).

SmartPLS is preferred as the software to make analysis because it is user-friendly and the most comprehensive and developed program in the field (Hair J. , Sarstedt, Ringle, & Gudergan, 2023).

CHAPTER 4

DATA ANALYSIS AND RESULTS

In this chapter, the data evaluated based on reliability and validity analysis and PLS-SEM analysis, and the results are presented.

4.1. Sampling Convenience

PLS-SEM is used as the data analysis method in this study as the details regarding the data analysis method is explained in section 3.7. The sample size is evaluated based on the criteria required by this data analysis method. According to Barclay et al, the minimum sample size should be ten times the maximum number of path associations for a construct. (Hair, Sarstedt, & Ringle, 2012; Barclay, Thompson, & Higgins, 1995). This 10-times rule method is the most widely used method when applying PLS-SEM in the field of information systems (Kock & Hadaya, 2018). Since, in this study, the maximum number of path relationships are directed to the construct “Behavioral Intention to Participate” and it is 10, based on the method the minimum sample size should be at least 100. Therefore, the sample size of 324 meets the criteria to be able to analyze data with PLS-SEM.

4.2. Demographics and Descriptive Analysis

Since the data is collected with the online structured questionnaire and skipping any question is not allowed, there is no missing data. Therefore, there is no need for missing value handling.

The characteristics and descriptive analysis of data collected in the first part of the questionnaire are provided in this section. For the analysis of data obtained from 324 participants, Microsoft Excel is used.

Table 14: Sample Characteristics

		Number of Participants	**Percent of Participants**
Gender	Male	131	40,4%
	Female	193	59,6%

Table 14 (cont.)

Age	28 and below	68	21,0%
	Between 43 and 28	163	50,3%
	Between 63 and 43	85	26,2%
	63 and above	8	2,5%
Education	Primary School	1	0,3%
	High School	19	5,9%
	Bachelor's Degree	227	70,1%
	Master	65	20,1%
	Ph.D.	12	3,7%

The recruitment interview experience meaning full participation in a recruitment process of research participants is shown in Figure 18. While 86 of them do not participate in a recruitment interview, 158 participate in 1 to 4 interviews and 80 of them have an interview experience of 4 and above.

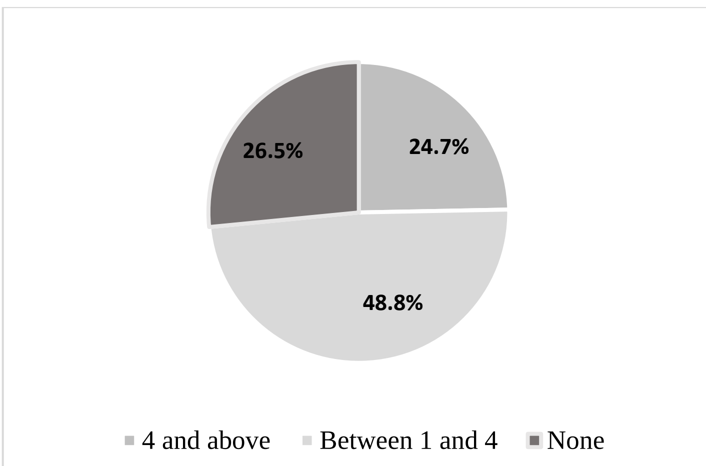


Figure 18: Interview Experience of the Participants

The social media usage of the participants is also investigated to understand their familiarity with the media coverage regarding the AI tools. The majority of the participants spent one hour or more hours on social media. The level of social media usage of the participants is demonstrated in the Figure 19.

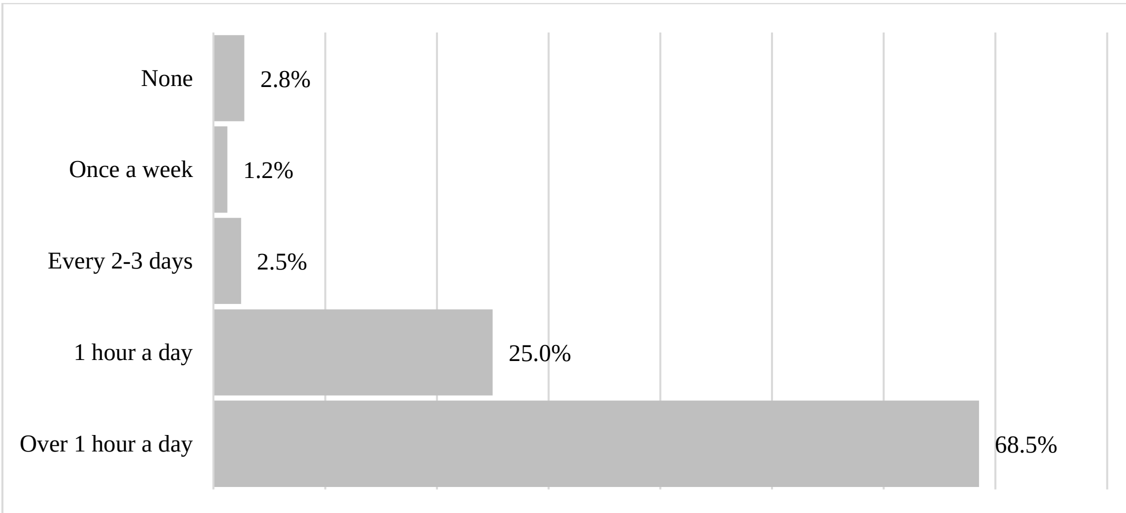


Figure 19: Social Media Usage of the Participants

Besides the social media usage, the participants' interest in technology is analyzed by questioning the way of learning technological developments and news. The frequencies of answers are provided in Figure 20 below.

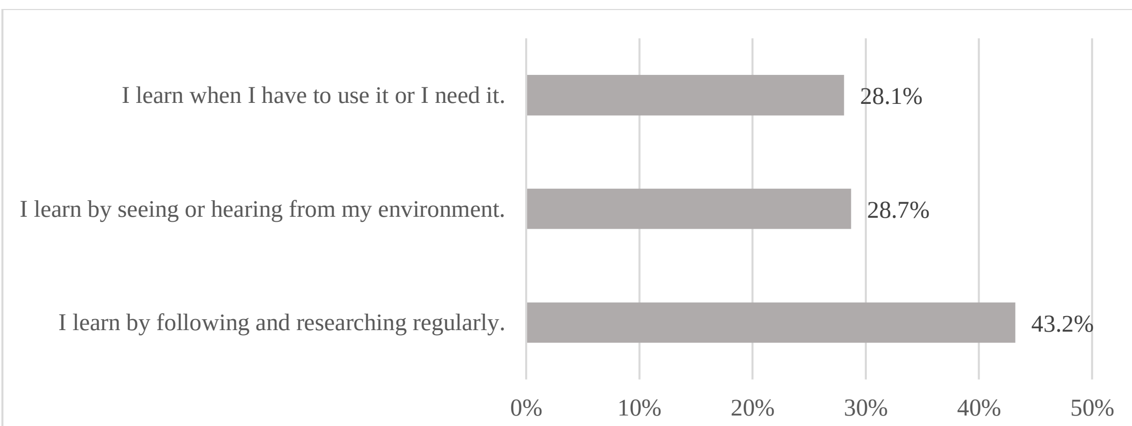


Figure 20: Participants' Way of Learning Technological Developments

Lastly, the familiarity of the participants with AI and AI applications is investigated. While 22 of the participants state they do not know the concept of AI, 302 participants indicated that they know what is AI. The main AI applications are listed for participants to select the terms that they have known. The percentage of participants with respect to number of known terms is shown in Figure 21. Only 5,2% of participants state they do not know any of the terms. The rest of the participants at least know one AI application including the option "other".

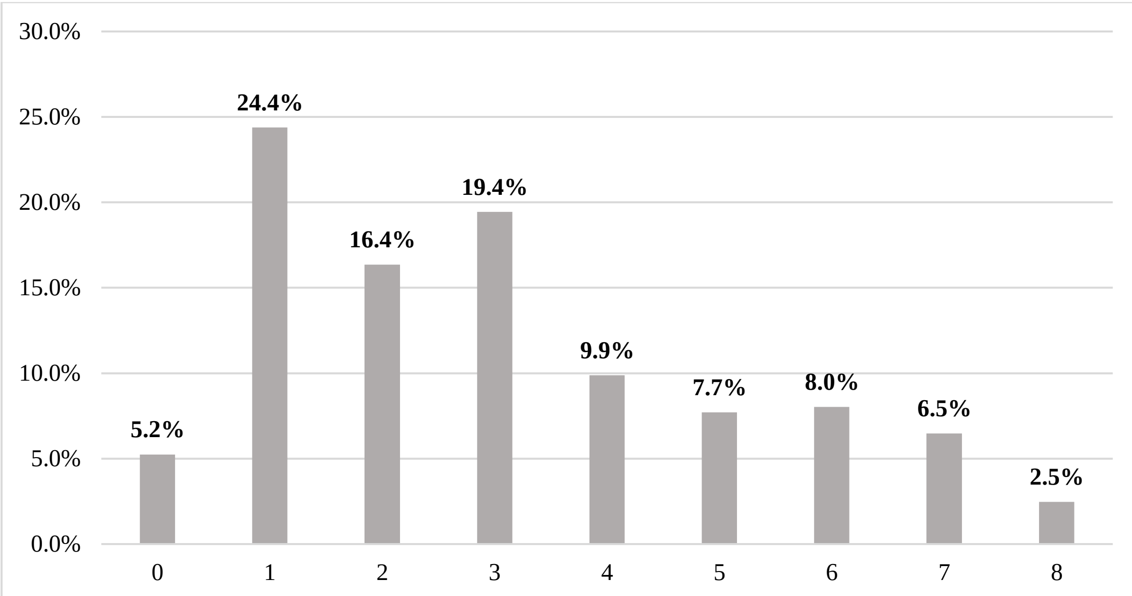


Figure 21: Percentage of Participants with Respect to Number of Known Terms

The AI tools with respect to number of employees to which they are known is provided in Table 15. According to the table, it is seen that face and voice recognition is at the top of the list since it is one of the terms that come across in daily life.

Table 15: AI Tools with Respect to Number of Employees to Which They Are Known

AI Tool	Number of Participants Who Know the AI Tool	% of Recognition of the AI Tool
Face and voice recognition	267	26%
Image processing	171	17%
Machine learning	157	16%
Artificial neural networks	94	9%
Natural language processing	88	9%
Deep learning	88	9%
Expert systems	85	8%
Other	42	4%
None of them	18	2%

4.3. Results of the Preliminary Analysis

In this section data normality, model reliability and validity are analyzed and the results are presented.

4.3.1. Data Normality

The normal distribution also called Gaussian distribution refers to data values spread around the mean and characterized as a bell-shaped curve. Most of the statistical methods such as correlation and regression assume that the sample data is normally distributed (Das & Imon, 2016). To test the data normality, Shapiro-Wilk, and Kolmogorov-Smirnov tests might be used (Das & Imon, 2016; Tabachnick & Fidell, Experimental Designs Using ANOVA, 2020). Kolmogorov-Smirnov and Shapiro-Wilk tests producing non-significant results ($p>0.05$) for the data indicate that data is probably normally distributed while the significant results ($p<0.05$) indicate that the data might not be normal (Field, 2013). However, it is important to note that these tests are meaningful when the sample size is small. According to the central limit theorem which the normality is based on, as sample size increases, the normality matters less since the sampling distribution of the mean is normal, regardless of how the actual values are distributed in the population (Field, 2013).

Descriptive measures which are the skewness showing the symmetry of the data distribution curve and kurtosis indicating the peakedness of this curve might be used as well to test the normality of the data distribution (Das & Imon, 2016; Tabachnick & Fidell, Experimental Designs Using ANOVA, 2020). The skewness and kurtosis values may get positive or negative values. The sign of the skewness value shows whether the pile-up lies on the right or left of the distribution while the that of the kurtosis shows whether distribution is pile-up and light-tailed or pointy and heavy-tailed (Field, 2013). An absolute skewness value of ≤ 2 and an absolute kurtosis value of ≤ 4 might be used as references for determining considerable normality (Mishra, et al., 2019). In support of earlier statements, Kim explains that to assess the data normality, histograms and the absolute values of skewness and kurtosis should be taken into consideration rather than z-values for sample sizes greater than 300. Either an absolute skewness value greater than 2 or an absolute kurtosis greater than 7 may be used as references to assert non-normality (Kim H. , 2013).

In the light of this information, the values of skewness and kurtosis are calculated and provided in Table 16.

Table 16: Values of Skewness and Kurtosis

	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
PE1	324	-,881	,135	,581	,270
PE2	324	-1,133	,135	1,680	,270
PE3	324	-,764	,135	,515	,270
EE1	324	-,240	,135	-,220	,270
EE2	324	-,351	,135	-,324	,270
EE3	324	-,241	,135	-,038	,270
SI1	324	-,129	,135	-,428	,270
SI2	324	-,116	,135	-,552	,270
FC1	324	-1,082	,135	2,062	,270
FC2	324	-1,326	,135	2,940	,270
HM2	324	-,606	,135	,237	,270
HM3	324	-,641	,135	,340	,270
C1	324	,227	,135	-,663	,270
C2	324	,491	,135	-,232	,270
C3	324	,107	,135	-,794	,270
T1	324	-,359	,135	,456	,270
T2	324	-,376	,135	-,176	,270
PC1	324	-,364	,135	-,434	,270
PC2	324	-,377	,135	-,434	,270
PC3	324	-,313	,135	-,698	,270
TC1	324	-,252	,135	-,359	,270
TC2	324	-,064	,135	-,243	,270
TC3	324	-,608	,135	,035	,270
F1	324	-,467	,135	,340	,270
F2	324	-,560	,135	,437	,270
F3	324	-,543	,135	,425	,270
BIP1	324	-,853	,135	1,067	,270
BIP2	324	-,048	,135	-,462	,270
BIP3	324	-,448	,135	-,168	,270
Valid N (listwise)	324				

As it can be seen in the Table 16, while the maximum absolute value of skewness is 1,326, that of kurtosis is 2,940. Therefore, it can be said that sample data distribution is close to normal.

4.3.2. Reliability Analysis of the Measurement Model

As stated earlier in section 3.6, for reliability analysis and internal consistency of the measurement model, Cronbach Alpha values should be considered. When Cronbach's

Alpha gets close to 1, the internal consistency of items in a measurement model increases and a value greater than 0,7 is deemed to be “acceptable” while that of greater than 0,8 is deemed to be “good” and greater than 0,9 is deemed to be “excellent” (Gliem & Gliem, 2003; George & Mallery, 2003). Case processing summary and reliability statistics of the measurement model are provided in Table 17 and Table 18 respectively.

Table 17: Case Processing Summary

		N	%
Cases	Valid	324	100.0
	Excluded[a]	0	0.0
	Total	324	100.0

a. Listwise deletion based on all variables in the procedure.

As Table 17 shows all the data consisting 324 values for each item are valid and included in the analysis.

Table 18: Reliability Statistics of the Measurement Model

Construct	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
PE	.842	.842	3
EE	.834	.834	3
SI	.882	.882	2
FC	.856	.856	2
HM	.898	.899	2
C	.846	.847	3
T	.803	.803	2
PC	.868	.869	3
TC	.820	.820	3
F	.938	.938	3
BIP	.811	.812	3

The Cronbach Alpha of each construct is greater than 0.8 that implies a good internal consistency. However, item-total statistics should also be considered for each item. These statistics are shared in Table 19 below.

Table 19: Item-Total Statistics

Construct	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Item	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PE	.842	.842	PE1	7.31	2.442	.725	.526	.763
			PE2	6.91	2.651	.700	.492	.787
			PE3	7.22	2.647	.697	.487	.790
EE	.834	.834	EE1	6.55	2.929	.685	.511	.780
			EE2	6.50	2.678	.770	.597	.694
			EE3	6.51	3.037	.635	.422	.829
SI	.882	.882	SI1	2.98	1.012	.790	.624	.
			SI2	2.96	0.986	.790	.624	.
FC	.856	.856	FC1	3.86	0.601	.748	.560	.
			FC2	3.80	0.600	.748	.560	.
HM	.898	.899	HM2	3.51	0.919	.816	.666	.
			HM3	3.59	0.844	.816	.666	.
C	.846	.847	C1	5.40	3.473	.689	.490	.808
			C2	5.76	3.397	.762	.581	.739
			C3	5.33	3.435	.689	.490	.808
T	.803	.803	T1	3.19	0.766	.671	.450	.
			T2	3.23	0.692	.671	.450	.
PC	.868	.869	PC1	6.68	3.513	.709	.517	.849
			PC2	6.62	3.289	.799	.640	.768
			PC3	6.64	3.204	.739	.568	.824
TC	.820	.820	TC1	6.48	2.795	.665	.455	.761
			TC2	6.67	2.717	.717	.515	.708
			TC3	6.27	2.929	.640	.417	.786
F	.938	.938	F1	7.02	3.027	.821	.687	.949
			F2	7.02	2.857	.918	.855	.873
			F3	7.03	2.894	.878	.818	.905
BIP	.811	.812	BIP1	6.58	2.827	.654	.437	.751
			BIP2	7.14	2.634	.633	.404	.770
			BIP3	6.80	2.417	.702	.495	.698

As can be observed from Table 19, the removal of the item F1 results in a slight increase in Cronbach alpha of the “fairness”. At this point, it is kept in the model to be considered after validation analysis.

4.3.3. Validity Analysis of the Measurement Model

Validity of the model implies whether the model accurately measures the thing which is wanted to be measured or not (Fitzner, 2007). Construct validity which is analyzed throughout this section shows the compliance between specific measurement model and the theoretical concept (Fitzner, 2007). To test the construct validity of the research model exploratory factor analysis, confirmatory factor analysis including convergent and discriminant validity analysis are done.

4.3.3.1. Exploratory Factor Analysis (EFA)

The goal of the factor analysis is to understand the structure of the associations between measures for a large data set. It determines the number of distinct constructs explaining the model of the correlations among the measures. These unnamed constructs are referred as “factors” or “common factors” while the values showing constructs’ strength and direction of influence on each other is called as “factor loading” (Fabrigar & Wegener, 2012). EFA is mostly used to understand the factor model structure when there is no theoretical foundation for the measures. Although the measures in this study are gathered from validated research in the literature, it is used as a pre-test to see whether they are loaded to factors that are predicted to be loaded. After EFA, confirmatory factor analysis (CFA) is done as a primary method to test the validity of the theorized model.

Before starting EFA, sampling adequacy should be checked. For EFA, Gorsuch and Hatcher suggest a minimum subject to item ratio of at least 5:1, but they both emphasize that higher ratios are better (Osborne & Costello, 2004). On the other hand, there is a widely-cited rule of thumb proposed by Nunnally that the subject to item ratio for exploratory factor analysis should be at least 10:1 (Osborne & Costello, 2004). Since item number in this study is 29 after the removal of the 4 items in pilot study, 290 is a minimum required sample size for the factor analysis. Therefore, it can be said that the sample size of 324 is suitable for the EFA. In addition to sample size, correlation matrix, anti-image correlation (AIC) matrix, Kaiser-Meyer-Olkin Measure (KMO) of sampling adequacy and Bartlett’s test of sphericity is used to test the data set to carry out EFA (Yong & Pearce, 2013). The values in the correlation matrix should be minimum of 0.3, the KMO index should be minimum of 0.5 and the Bartlett’s test of sphericity should be significant ($p<.05$) to proceed in EFA (Williams, Onsman, & Brown, 2010; Tabachnick & Fidell, 2007; Hair, Black, Babin, & Anderson, 2010). Anti-image correlation matrix shows the inverse of partial pairwise correlations between items disregarded from another item’s influence (Guvendir & Ozkan, 2022). Therefore, the values on the diagonal of the matrix also called as measures of sample adequacy (MSA) values should be greater than 0.5 and that is associated low values on off-diagonal measures (Guvendir & Ozkan, 2022).

The values on the diagonal of the anti-image correlation matrix are shared in Table 20.

Table 20: Measures of Sample Adequacy (MSA) Values

Item	MSA Values on the Diagonal of the AIC Matrix
PE1	.951
PE2	.937
PE3	.956
EE1	.941
EE2	.934
EE3	.945
SI1	.875
SI2	.871
FC1	.733
FC2	.782
HM2	.921
HM3	.905
C1	.904
C2	.813
C3	.811
T1	.903
T2	.885
PC1	.824
PC2	.712
PC3	.804
TC1	.930
TC2	.940
TC3	.949
F1	.940
F2	.892
F3	.907
BIP1	.949
BIP2	.958
BIP3	.952

As shown in Table 20, the minimum MSA value is 0.712 which is above the threshold. After correlation and AIC matrixes are examined, KMO and Bartlett's test values are found. As Table 21 shows the KMO value is 0,908 while the p value of Bartlett's test is 0.000 meaning the data is suitable for EFA.

Table 21: KMO and Bartlett's Test Results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,908
Bartlett's Test of Sphericity	Approx. Chi-Square	6443,097
	df	406
	Sig.	0,000

After the suitability of the data set for the EFA is checked, EFA is exercised. The rotated factor matrix is acquired with principal axis factoring based on a threshold eigenvalue of 1 applying the rotation method of varimax with Kaiser Normalization. The table showing the total variance explained for the factors with the eigenvalues greater than 1 is provided in Table 22 while the rotated factor matrix is provided in Table 23 below.

Table 22: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.086	38.229	38.229	10.729	36.997	36.997	4.743	16.355	16.355
2	3.047	10.507	48.736	2.736	9.434	46.431	3.909	13.478	29.833
3	1.851	6.381	55.117	1.489	5.135	51.565	2.289	7.893	37.726
4	1.468	5.061	60.178	1.160	3.999	55.564	2.207	7.611	45.336
5	1.366	4.710	64.888	1.066	3.675	59.239	2.179	7.512	52.849
6	1.110	3.827	68.715	.771	2.660	61.899	1.728	5.959	58.808
7	1.059	3.651	72.366	.680	2.344	64.244	1.576	5.436	64.244

Table 23: Rotated Factor Matrix

	Factor						
	1	2	3	4	5	6	7
EE2	.663						
PE3	.661						
PE1	.649						
EE1	.646						
PE2	.638						
EE3	.598						
HM2	.581						
HM3	.551						
BIP3		.470					
F2		.820					
F1		.781					
F3		.762					
BIP1		.545					
T1		.485					
T2		.420					
PC2			.890				
PC3			.780				
PC1			.746				
C2				.835			
C3				.756			
C1				.707			

Table 23 (cont.)

SI1					.765		
SI2					.703		
BIP2					**.418**		
FC2						.796	
FC1						.741	
TC2							.634
TC1							.573
TC3							.409

"Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization."

a. Rotation converged in 9 iterations.

As it is shown in Table 23, items are loaded into 7 different factors meaning that it is the most compact form of the model to measure what is wanted to be measured correctly. These 7 components explain the %64.244 variance in the model.

The factor loadings of all the items shown in the rotated component matrix are restricted to being greater than 0.4 to show the meaningful factor placement of the items. According to Tabachnick and Fidell, 0.32 is a good rule of thumb for the minimum loading of an item (Tabachnick & Fidell, 2007). Items used to measure FC, C, PC, and TC are loaded to the separate factors as predicted. The items used to measure PE, EE, and HM are loaded to the same factor while those used to measure T, F, and BIP are loaded to the same factor. Although items used to measure different constructs are loaded to the same factors, it can be said that the same construct items are together with close factor loading values. The most problematic item is BIP2 as it is loaded to a factor with the items of SI. Therefore, BIP2 is removed from the model, and other issues identified in the EFA are left to be examined after the CFA.

4.3.3.2. Confirmatory Factor Analysis (CFA)

CFA tests the pre-defined measurement model which has grounds in literature research and explains the interrelations among the observed measures and factors. In EFA, measurement errors are specified to be random meaning that the relationships observed between measures in the same factor are solely due to shared influence (Brown, 2023). However, in CFA two measures may covary for reasons such as method effects rather than shared influence of the factor (Brown, 2023). Therefore, CFA as a method to test the theory is required to confirm the findings of the EFA (Harrington, 2009).

CFA includes convergent validity and discriminant validity checking.

Convergent validity shows how closely the items used to measure the same construct are related. For a study to have convergent validity, standardized factor loadings should be greater than 0.5 while composite reliability (CR) and average variance extracted (AVE) which are calculated based on these standardized weights should be greater than 0.7 and 0.5 respectively (Panahi, Bazrafshani, & Mirzaie, 2023). Table 24 illustrates the standardized factor loadings of the items to their related constructs while Table 25 shows CR and AVE values for each construct.

Table 24: Standardized Factor Loadings

	PE	**EE**	**SI**	**FC**	**HM**	**C**	**T**	**PC**	**TC**	**F**	**BIP**
PE1	0.807										
PE2	0.775										
PE3	0.817										
EE1		0.838									
EE2		0.846									
EE3		0.694									
SI1			0.903								
SI2			0.874								
FC1				0.817							
FC2				0.916							
HM2					0.956						
HM3					0.854						
C1						0.798					
C2						0.861					
C3						0.761					
T1							0.884				
T2							0.760				
PC1								0.786			
PC2								0.876			
PC3								0.834			
TC1									0.724		
TC2									0.876		
TC3									0.726		
F1										0.853	
F2										0.968	
F3										0.930	
BIP1											0.802
BIP3											0.787

As seen in Table 24, 0.694 is the smallest factor loading value but still greater than the threshold value of 0.5.

Table 25: CR and AVE Values

	Composite Reliability (CR)	Average Variance Extracted (AVE)
PE	0.842	0.640
EE	0.838	0.634
SI	0.882	0.79
FC	0.859	0.753
HM	0.899	0.822
C	0.847	0.652
T	0.805	0.679
PC	0.871	0.694
TC	0.821	0.606
F	0.941	0.843
BIP	0.772	0.631

Table 25 shows composite reliability (CR) values which are another reliability measure for the internal consistency of the model are all greater than the threshold value of 0.7 and average variance extracted (AVE) values showing how well the items explain the variance in the construct is greater than the threshold value of 0.5 for each construct. As a result, it can be said that convergent validity is achieved.

Discriminant validity measures how well the constructs are differentiated from each other in the model. According to Fornell & Larcker Criterion which is a popular method used to test the discriminant validity, the square root of the construct's AVE must be greater than the correlation between that construct and others (Panahi, Bazrafshani, & Mirzaie, 2023; Hair, Sarstedt, & Ringle, 2012). Table 26 shows the square root of the constructs' AVE values on the diagonal while showing the correlation between constructs on the other cells.

Table 26: Discriminant Validity Results

	PE	**EE**	**SI**	**FC**	**HM**	**C**	**T**	**PC**	**TC**	**F**	**BIP**
PE	**0.800**										
EE	**0.848**	**0.796**									
SI	0.520	0.616	**0.889**								
FC	0.452	0.327	0.315	**0.868**							
HM	0.713	0.688	0.565	0.446	**0.906**						
C	-0.305	-0.391	-0.213	0.027	-0.373	**0.808**				"	

Table 26 (cont.)

T	0.574	0.559	0.409	0.158	0.457	-0.204	**0.824**				
PC	-0.207	-0.220	-0.098	0.189	-0.105	0.375	-0.361	**0.833**			
TC	0.651	0.759	0.607	0.357	0.651	-0.291	0.589	-0.169	**0.779**		
F	0.641	0.572	0.470	0.374	0.565	-0.316	0.591	-0.183	0.665	**0.918**	
BIP	0.740	0.683	0.608	0.323	0.740	-0.357	0.642	-0.234	0.650	0.740	**0.795**

As seen in Table 26, all of the values on the diagonal are higher than the related construct's correlations with other constructs except for the correlation between PE and EE. The correlation between the constructs PE and EE, 0.848, is higher than the square root of AVE values of PE and EE which are 0.8 and 0.796 respectively. This result matches the findings of EFA. However, there is no other construct which is not differentiated from any other construct. Since EFA does not consider the theory and the study the model is based on while determining the factor loadings and number of factors, the results of the discriminant validity are used as a road map for the study. Therefore, PE and EE are merged as a single construct as "Performance and Effort Expectancy (PEE)" to achieve discriminant validity.

4.3.4. Reevaluation of Reliability and Validity After Model Modification

In EFA, since item BIP2 is loaded to a different factor with items BIP1 and BIP3, it is removed from the model. In CFA, since the correlation between the constructs PE and EE, is found to be higher than the square root of AVE values of PE and EE implying that they cannot be differentiated, these constructs are merged. Because of these modifications, the reliability and validity of the model are checked again.

While Table 27 shows the CA values for the model, Table 28 shows standardized factor loadings, Table 29 shows CR and AVE values and lastly Table 30 shows the square root of the AVE values on the diagonal and correlations among constructs on the other cells.

Table 27: Recalculated Reliability Statistics

Construct	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
PEE	.889	.889	6
SI	.882	.882	2
FC	.856	.856	2
HM	.898	.899	2
C	.846	.847	3
T	.803	.803	2
PC	.868	.869	3

Table 27 (cont.)

TC	.820	.820	3
F	.938	.938	3
BIP	.770	.774	2

The CA values are greater than 0.7 which is deemed to be acceptable (Gliem & Gliem, 2003; George & Mallery, 2003).

Table 28: Recalculated Standardized Factor Loadings

	PEE	**SI**	**FC**	**HM**	**C**	**T**	**PC**	**TC**	**F**	**BIP**
PEE1	0.756									
PEE2	0.729									
PEE3	0.790									
PEE4	0.811									
PEE5	0.804									
PEE6	0.657									
SI1		0.895								
SI2		0.882								
FC1			0.810							
FC2			0.924							
HM2				0.954						
HM3				0.856						
C1					0.797					
C2					0.863					
C3					0.760					
T1						0.882				
T2						0.761				
PC1							0.786			
PC2							0.876			
PC3							0.834			
TC1								0.727		
TC2								0.872		
TC3								0.728		
F1									0.852	
F2									0.969	
F3									0.929	
BIP1										0.797
BIP3										0.791

As seen in Table 28, all factor loadings are greater than 0.5.

Table 29: Recalculated CR and AVE Values

	Composite Reliability	AVE
PEE	0.891	0.577
SI	0.882	0.790
FC	0.860	0.755
HM	0.899	0.821
C	0.847	0.652
T	0.804	0.678
PC	0.871	0.694
TC	0.821	0.606
F	0.941	0.843
BIP	0.773	0.631

The CR values are greater than the threshold value of 0.7 and AVE values are greater than the threshold value of 0.5.

Table 30: Recalculated Discriminant Validity Results

	PEE	SI	FC	HM	C	T	PC	TC	F	BIP
PEE	0.760									
SI	0.599	0.889								
FC	0.403	0.312	0.869							
HM	0.735	0.566	0.444	0.906						
C	-0.366	-0.212	0.024	-0.373	0.808					
T	0.596	0.410	0.157	0.460	-0.203	0.824				
PC	-0.225	-0.097	0.187	-0.106	0.375	-0.361	0.833			
TC	0.745	0.608	0.356	0.653	-0.291	0.591	-0.169	0.779		
F	0.635	0.471	0.374	0.566	-0.316	0.591	-0.183	0.666	0.918	
BIP	0.746	0.610	0.322	0.742	-0.356	0.644	-0.234	0.652	0.739	0.794

Lastly, the square root of the AVE values calculated for each construct are all greater than the correlations among the constructs.

4.4. Results of the Structural Equation Modeling (SEM)

In this section of the thesis, PLS-SEM analysis is exercised to understand the path relationships among the constructs and test the hypotheses of the research proposed in section 3.3. At first, the constructs proposed by the UTAUT-2 model are used to show their exploratory power on the research topic. Second, the model proposed by this study is used in SEM analysis to show relationships and the effects of independent variables on the dependent variable which is job candidates' behavioral intention to participate in AI-based recruitment. The exploratory power of the model is also investigated to compare it with that of the model solely based on UTAUT-2 constructs.

4.4.1. SEM with UTAUT-2 Constructs

In this section of the thesis, at first preliminary analysis of the UTAUT-2 model with the research data is made. After that, SEM is exercised for UTAUT-2 and the results are shared.

4.4.1.1. Validity Analysis of the UTAUT-2 Model

To do SEM with the UTAUT-2 model, constructs added based on expert panel analysis are removed from the analysis. At first, since the reliability of the measures is tested before, the model with UTAUT-2 constructs is tested only for validity.

Table 31 demonstrates how the items are loaded to each factor and Table 32 shows the CR and AVE values.

Table 31: Standardized Factor Loadings for UTAUT2 Model Constructs

	PE	**EE**	**SI**	**FC**	**HM**	**BIP**
PE1	0.809					
PE2	0.784					
PE3	0.807					
EE1		0.819				
EE2		0.858				
EE3		0.711				
SI1			0.905			
SI2			0.873			
FC1				0.823		
FC2				0.909		
HM2					0.947	
HM3					0.862	
BIP1						0.761
BIP2						0.735
BIP3						0.815

As seen from Table 31, all of the factor loadings are greater than 0.7 which implies a good item-construct fit.

Table 32: CR and AVE Values for UTAUT2 Model Constructs

	CR	AVE
PE	0.843	0.641
EE	0.840	0.637
SI	0.883	0.790
FC	0.858	0.752
HM	0.899	0.820
BIP	0.815	0.594

As Table 32 shows CR values for all the constructs are greater than 0.8 implying a good internal consistency between measures and AVE values are greater than the threshold value of 0.5 corresponds to acceptable exploratory power of the measures. Therefore, it can be said that the model has convergent validity.

To examine the discriminant validity, the square root of AVE values is compared with correlations among the constructs as illustrated in Table 33.

Table 33: Discriminant Validity Results for UTAUT2 Model Constructs

	PE	EE	SI	FC	HM	BIP
PEE	**0.800**					
EE	**0.842**	**0.798**				
SI	0.519	0.617	**0.889**			
FC	0.455	0.329	0.316	**0.867**		
HM	0.717	0.695	0.569	0.444	**0.905**	
BIP	0.710	0.712	0.636	0.282	0.750	**0.771**

The correlation between PE and EE is higher than the square root of the AVE values of these constructs which is the same with the results for the proposed model. Therefore, they are merged as a single construct to continue with SEM. The reliability and validity statistics after the modification are shared in Appendix O.

4.4.1.2. Results of the SEM with UTAUT-2 Constructs

The PLS-SEM does not assume that the data follows a normal distribution as stated earlier in section 3.7. Therefore, to handle non-normality issues, bootstrapping including the generation of multiple random samples from the original data to calculate standard errors for hypothesis testing is utilized and this allows the assessment of the significance of estimated coefficients in PLS-SEM (Hair, Ringle, & Sarstedt, 2011). The recommended minimum number of bootstrap samples is 5,000 and the number of cases should be equal to the number of observations (Hair, Ringle, & Sarstedt, 2011). Therefore, the maximum likelihood method is used to calculate path coefficients as well as R^2 value, and bootstrapping algorithm for 5,000 bootstrap samples with 324 cases is run to find the significance of the relationships. The model with the results of the analysis is visualized in Figure 22.

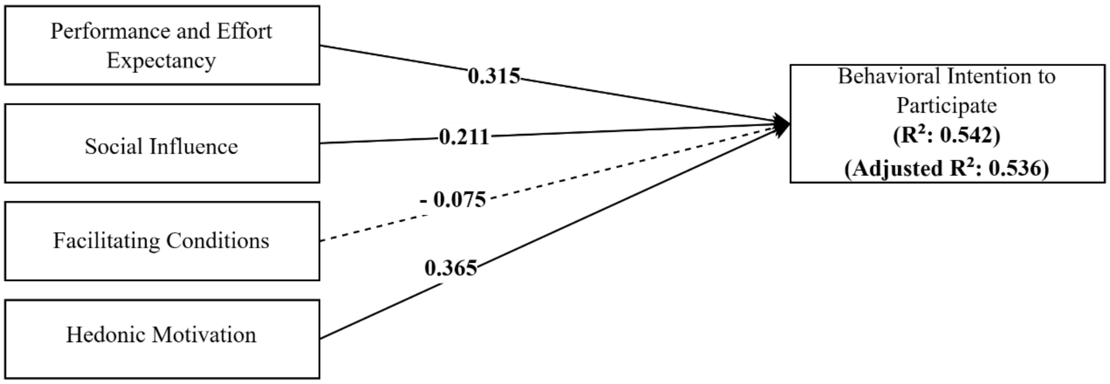


Figure 22: SEM Analysis with UTAUT2 Constructs

As seen in Figure 22, the R^2 value is 0.542 implying that this model explains the 54.2 % of the variance in the job candidates' behavioral intention to participate in AI-based recruitment. The standardized path coefficients, t, and p values are shared in Table 34 below.

Table 34: Path Analysis of the Model with UTAUT2 Factors

Relation	**Path Coefficient**	**T Statistics**	**P Values**	**Significance**
PEE → BIP	0.315	5.002	0.000	Significant at p<0.01 level
SI → BIP	0.211	4.623	0.000	Significant at p<0.01 level
FC → BIP	-0.075	1.409	0.159	Not significant
HM → BIP	0.365	6.630	0.000	Significant at p<0.01 level

The absolute value of a critical t-value for a two-tailed test should be above 1.65 for a significance level of 10 percent, above 1.96 for a significance level of 5 percent, and above 2.58 for a significance level of 1 percent for path coefficients to be significant (Hair, Ringle, & Sarstedt, 2011). When the t-table is investigated the three-digit rounded values are 1.645, 1.960, and 2.576 respectively. According to Table 37, while the relation between PEE, SI, HM, and BIP are significant at $p<0.01$ level, the one between FC and BIP is not significant.

4.4.2. SEM with Proposed Model

The proposed model including the constructs of the UTAUT-2 model and the constructs added with literature research and expert panel analysis analyzed with PLS-SEM to present the path coefficients and exploratory power of the model. Bootstrapping algorithm for 5,000 bootstrap samples is run to find the significance of the relationships. The output of the analysis consisting of key measures which are standardized path coefficients, t values, and p values are provided in Table 35 below.

Table 35: Path Analysis of the Proposed Model

Relation	**Path Coefficient**	**T Statistics**	**P Values**	**Significance**
PEE → BIP	0.159	2.554	0.011	Significant at p<0.05 level
SI → BIP	0.125	2.407	0.016	Significant at p<0.05 level
FC → BIP	-0.036	0.766	0.444	Not significant
HM → BIP	0.263	4.145	0.000	Significant at p<0.01 level
C → BIP	-0.018	0.389	0.697	Not significant
T → BIP	0.122	1.922	0.055	Significant at p<0.1 level
PC → BIP	-0.035	0.704	0.482	Not significant
TC → BIP	-0.026	0.438	0.662	Not significant
F → BIP	0.311	4.672	0.000	Significant at p<0.01 level

As seen from the Table 35, while the relations of performance and effort expectancy, social influence, hedonic motivation, trust, and fairness with behavioral intention are found to be significant, that of facilitating conditions, creepiness, privacy concerns, and two-way communication are found to be non-significant. The model with path coefficients and R^2 value is visualized in Figure 23 below. The non-significant relationships are demonstrated as dashed lines.

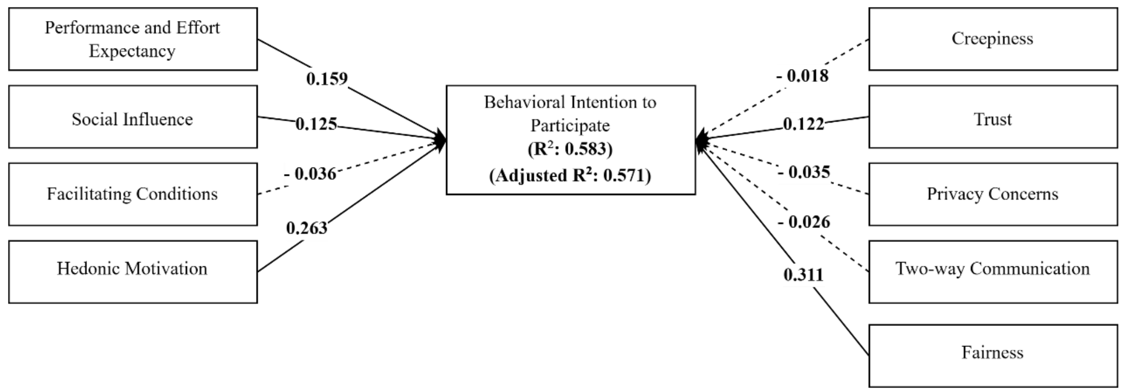


Figure 23: Proposed Path Model by the Study

The R^2 of the model is found as 58.3 % which is a good exploratory power since predicting human behavior in social sciences is difficult as it is prone to be affected by self-interest, group dynamics, feelings at a point in time (Ozili, 2023). It is slightly higher than that of the model solely consisting of UTAUT2 constructs.

4.4.2.1. Model Modification

According to the literature "honesty" or "openness" and two-way communication" are two predictors of perceived fairness (Gilliland, 1993; Bauer, et al., 2001). Because of this, two relationships between "trust" and "fairness" and "two-way communication" and "fairness" are added to the model.

Based on the study of Levin, Cross, and Abrams, for one person called a "knowledge-seeker" to trust another party called a "knowledge source", the source should be discreet meaning that it should not reveal confidential information (Levin, Cross, & Abrams, 2002). Therefore, another additional relationship between privacy concerns and trust is also added to the model.

In addition to these relationships, two others are hypothesized and tested. Since creepiness is defined as "an uncomfortable feeling paired with uncertainty about how to behave or how to judge a situation", it is thought that there would be a negative relationship between creepiness and hedonic motivation (Langer, König, & Krause, 2017; Langer, König, Gebhard, & André, 2016). Moreover, as perceived organizational and technical support increase, it is thought that the usefulness and easiness associated with AI-based recruitment will increase. Therefore, another relationship between facilitating conditions and performance and effort expectancy is added to the model.

Table 36: Recalculated Path Analysis of the Proposed Model

Relation	Path Coefficient	T Statistics	P Values	Significance
PEE → BIP	0.160	2.540	0.011	Significant at p<0.05 level
SI → BIP	0.127	2.454	0.014	Significant at p<0.05 level
FC → BIP	-0.037	0.787	0.431	Not significant
HM → BIP	0.264	4.171	0.000	Significant at p<0.01 level
C → BIP	-0.018	0.384	0.701	Not significant
T → BIP	0.123	1.918	0.055	Significant at p<0.1 level
PC → BIP	-0.033	0.639	0.523	Not significant
TC → BIP	-0.033	0.544	0.587	Not significant
F → BIP	0.312	4.656	0.000	Significant at p<0.01 level
FC → PEE	**0.361**	**4.903**	**0.000**	**Significant at p<0.01 level**
C → HM	**-0.347**	**5.104**	**0.000**	**Significant at p<0.01 level**
T → F	**0.315**	**5.622**	**0.000**	**Significant at p<0.01 level**
PC → T	**-0.322**	**5.313**	**0.000**	**Significant at p<0.01 level**
TC → F	**0.447**	**7.673**	**0.000**	**Significant at p<0.01 level**

According to the results shared in Table 36, all of the path coefficients belonging to the new relationships are found statistically significant. In addition, although facilitating conditions (FC), trust (T), privacy concerns (PC) and two-way communication (TC) do not have a statistically significant relationship with the behavioral intention to participate, their indirect effects on the behavioral intention to participate are found out due to relationships newly identified in the model. The specific indirect effects and their p values are presented in the Table 37 below.

Table 37: Specific Indirect Effects in Proposed Model

	T statistics	P values	Significance
PC -> T -> F -> BIP	3.038	0.002	Significant at p<0.01 level
PC -> T -> F	3.863	0.000	Significant at p<0.01 level
FC -> PEE -> BIP	2.272	0.023	Significant at p<0.05 level
T -> F -> BIP	3.719	0.000	Significant at p<0.01 level
PC -> T -> BIP	1.652	0.099	Not significant
TC -> F -> BIP	3.729	0.000	Significant at p<0.01 level
C -> HM -> BIP	3.225	0.001	Significant at p<0.01 level

4.5. Final Model Proposition

The final model with added relationships, path coefficients, and R^2 values is visualized in Figure 24 below.

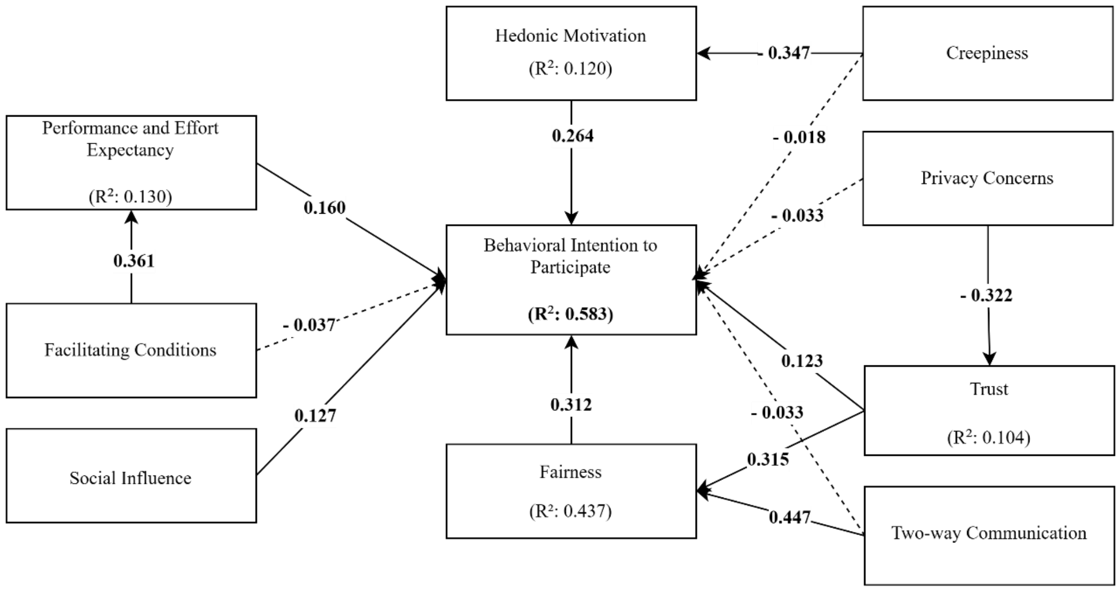


Figure 24: Final Path Model Proposed by the Study

As seen in Figure 24, although R^2 is still 58.3 %, it shows more relationships. While trust and two-way communication directly affect fairness, privacy concerns affect trust, creepiness affects hedonic motivation and facilitating conditions affect performance and effort expectancy. The R^2 and adjusted R-square values are provided in Table 38 below.

Table 38: R-square Values for the Final Model

Construct	**R-square**	**R-square adjusted**
BIP	0.583	0.571
F	0.437	0.433
HM	0.120	0.118
PEE	0.130	0.128
T	0.104	0.101

CHAPTER 5

DISCUSSION AND CONCLUSION

In this chapter, at first, the results of the data analysis based on proposed model and hypothesis testing are summarized and explained. After that, the findings of the study are discussed within the scope of literature on AI-based recruitment acceptance. Lastly, the limitations of the study are identified and suggestions for future studies are made.

5.1. Discussion

In this study, the acceptance of AI-based recruitment among job candidates is investigated by using consumer acceptance and use of information technology known as UTAUT2, developed by Venkatesh, Thong, and Xu in 2012. At first, the descriptive data is investigated to define the characteristics of the sample.

When the participants' recruitment experiences including interview are analyzed, it is seen that 73,5 % of them participate in at least one. It is inferred from that most of the candidates have a pre-determined opinion regarding a recruitment experience to compare it with the scenario provided in the questionnaire.

While 93,5 % of the participants state that they spend time in social media at least one hour in a day, consistent with that information 94,8 % of them state they know at least one term related with AI. This implies that, majority of the participants have a pre-learnt information to grasp the concept of AI-based recruitment scenario. Face and voice recognition, image processing and machine learning are respectively the top three terms known by the participants.

The participants' interest in technology is analyzed based on the information on how they learn technological developments and news. 43,2 % of the participants state that they are regularly follow technological developments implying an interest on the technology and innovation. While 28.7 % of them learn a new technology from others implying that although they do not have any interest on technology they are influenced by others, 28,1 % of the participants learn a new technology only if they have to use it.

For the investigation of the factors influencing job candidates' behavioral intention to participate in an AI-based recruitment, data is analyzed with the partial least squares path modeling method of structural equation modelling (PLS-SEM). To analyze the data, a model is developed. While UTAUT-2 is used as a base model, a pool of constructs attained by literature review is used in expert panel analysis to add new constructs to the model specifically proposed for this research context. Following model development, 10 hypotheses are proposed in section 3.3 to test the model. The validation analysis of the model is done for the data collected and based on the results, the items belong to two constructs “performance expectancy” (PE) and “effort expectancy” (EE) are found highly correlated in measurement instrument. Therefore, they are merged to be a single construct called “performance and effort expectancy” (PEE). As a result, the hypothesis 1 and hypothesis 2 are evaluated together since they are both hypothesized to have a positive relationship with the dependent variable, behavioral intention to participate in AI-based recruitment. In addition to relationships hypothesized in section 3.3., new relationships are identified through data analysis and literature. The relations in the proposed model, related hypotheses and the results showing whether they are supported or not provided in the Table 39 below.

Table 39: Hypotheses and Results

Relation	**Code**	**Hypothesis**	**Result**
PEE → BIP	H1 & H2	As job candidates’ performance expectancy and effort expectancy of usage of AI tools in recruitment increases, their intention to participate in AI-based recruitment increases.	Supported
SI → BIP	H3	As social influence to participate in AI-based recruitment on job candidates increases, their intention to participate in AI-based recruitment increases	Supported
FC → BIP	H4	As the job candidates’ perception of facilitating conditions increases, their intention to participate in AI-based recruitment increases.	Not supported
HM → BIP	H5	As job candidates’ hedonic motivation to participate in AI-based recruitment increases, their intention to participate in AI-based recruitment increases.	Supported
C → BIP	H6	As creepiness felt by job candidates in the AI-based recruitment process increases, their intention to participate in AI-based recruitment decreases.	Not supported
T → BIP	H7	As trust in AI-based recruitment tools by job candidates increases, their intention to participate in AI-based recruitment increases.	Supported
PC → BIP	H8	As job candidates’ perceived privacy concerns about AI-based recruitment process increases, their intention to participate in AI-based recruitment decreases.	Not supported
TC → BIP	H9	As two-way communication perceived by job candidates in the AI-based recruitment process increases, their intention to participate in AI-based recruitment increases.	Not supported
F → BIP	H10	As fairness perceived by job candidates increases, their intention to participate in AI-based recruitment increases.	Supported

Table 39 (cont.)

FC → PEE	New	As the job candidates' perception of facilitating conditions increases, their performance expectancy and effort expectancy of usage of AI tools in recruitment increase.	Supported
C → HM	New	As creepiness felt by job candidates in the AI-based recruitment process increases, their hedonic motivation to participate in AI-based recruitment decreases.	Supported
T → F	New	As trust in AI-based recruitment tools by job candidates increases, fairness perceived by job candidates increases.	Supported
PC → T	New	As job candidates' perceived privacy concerns about the AI-based recruitment process increases, trust in AI-based recruitment tools by job candidates decreases.	Supported
TC → F	New	As two-way communication perceived by job candidates in an AI-based recruitment process increases, fairness perceived by job candidates increases,	Supported

Hypotheses 1 and 2 suggesting that performance and effort expectancy (PEE) have a positive effect on job candidates' behavioral intention to participate in AI-based recruitment (BIP), are supported by the study. With a p value of 0.011, the relationship is found to be statistically significant at %95 confidence interval. This implies that as perceived benefit meaning the effectiveness and easiness associated with AI tools used in a recruitment process increases behavioral intention to participate in such a recruitment process increases. As provided in section 2.3.5, when the studies in the literature are examined, they are also found to be determinants of intention (Brahmana & Brahmana, 2013; Ochmann & Laumer, 2020; Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Laurim, Arpaci, Prommegger, & Krcmar, 2021; Kim & Heo, 2021). Therefore, this result is consistent with the literature. Since the performance and effort expectancy is a direct determinant of acceptance of AI in recruitment, the recruiters can benefit AI for flexible interview scheduling, pre-recorded video assessment or chatbots providing information 24/7 to make AI-based recruitment more efficient and easier for job candidates (Albert, 2019; Saad, Nugro, Thinakaran, & Baijed, 2021).

Hypothesis 3 suggesting that social influence (SI) has a positive effect on job candidates' behavioral intention to participate in AI-based recruitment (BIP), is supported by the study. With a p value of 0.014, the relationship is found to be statistically significant at %95 confidence interval. This implies that when people important to job candidates think they should participate in a recruitment process implementing AI tools, candidates' intention to participate increase. This result is compatible with the literature (Ochmann & Laumer, 2020; Laurim, Arpaci, Prommegger, & Krcmar, 2021). That's why, recruiters can enhance the recruitment experience of candidates and employer branding by benefiting from AI in order candidates to refer the company to others (Rezzani, Caputo, & Cortese, 2021; Black, & van Esch, 2020).

Hypothesis 4 suggests that as perceived facilitating conditions (FC) increase job candidates' behavioral intention to participate in AI-based recruitment (BIP) increase. However, this hypothesis is not supported by the study with a p value of 0.431. When turned back to the literature review, it is seen that it is used as a factor in one study on AI acceptance in recruitment and one study on the acceptance of chatbots (Ochmann & Laumer, 2020; Brachten, Kissmer, & Stieglitz, 2021). Therefore, it can be said that the results of this study do not compatible with these of two studies for this factor. However, in the data analysis process the new relationship between facilitating conditions (FC) and performance and effort expectancy (PEE) is tested and found to be statistically significant at %95 confidence interval. When the indirect effect of facilitating conditions (FC) on behavioral intention to participate in AI-based recruitment (BIP) with this path is analyzed, the indirect effect is also found significant. This implies that facilitating conditions (FC) only indirectly affects behavioral intention through performance and effort expectancy (PEE). In the light of this information, it can be said that facilitating conditions (FC) may affect the actual participation decision rather than behavioral intention which is similar with the results of original UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003). It can be also added that since in this research, a hypothetical scenario is provided to participants, facilitating conditions (FC) directly affects only perceived performance and effort expectancy (PEE) rather than intention to participate.

Hypothesis 5 suggests that as job candidates' hedonic motivation (HM) to participate in AI-based recruitment increases, their intention to participate in AI-based recruitment (BIP) increases. This hypothesis is supported by the study with a p value of 0 meaning that the relationship is found to be statistically significant at %99 confidence interval. As shared in section 3.1, hedonic motivation (HM) is included in 5 studies based on literature review on AI-based recruitment acceptance (Ochmann & Laumer, 2020; van Esch, Black, & Arli, 2021; Lukacik, Bourdage, & Roulin, 2022; Laurim, Arpaci, Prommegger, & Krcmar, 2021; Brahmana & Brahmana, 2013). Therefore, the result of the study is consistent with the literature. Moreover, hedonic motivation (HM) is second most effective determinant of the behavioral intention to participate in AI-based recruitment (BIP) with a path coefficient of 0.264. For this reason, recruiters can make recruitment process more interesting by adding games or simulations in assessment stages (Allal-Chérif & Makhlouf, 2016; Yannakakis & Togelius, 2015).

Although hypothesis 6 suggests that as creepiness (C) felt by job candidates in the AI-based recruitment process increases, their intention to participate in AI-based recruitment (BIP) decreases, it is rejected by the study with a p value of 0.701. This means that creepiness (C) does not have a direct negative effect on the behavioral intention to participate in AI-based recruitment (BIP). While this factor is found as a determinant influencing candidates' acceptance of an automated recruitment in 2 studies in the literature, this study shows the opposite (Langer, König, & Papathanasiou, 2019; Langer, König, & Krause, 2017). This can be explained by the sample characteristics as investigated previously in this section. Since 94,8 % of the participants state they know at least one term related with AI and therefore they have a pre-learnt information to grasp the concept of AI-based recruitment scenario, the feeling of uncertainty may not affect their behavioral intention to participate in AI-based recruitment directly. On the other, the effect of creepiness (C) on hedonic motivation hypothesized in data analysis process and it is found that crepiness (C) negatively affects hedonic motivation (HM) with a p value of 0 and indirectly affects the behavioral intention to participate in AI-based recruitment (BIP) with a p value of 0.001. This means that although crepiness (C) do not directly affects behavioral intention to participate in AI-based recruitment (BIP), it affects the fun or pleasure derived from participating in AI-based recruitment.

According to hypothesis 7 proposed in section 3.3, as trust (T) in AI-based recruitment tools by job candidates increases, their intention to participate in AI-based recruitment (BIP) increases. This hypothesis is accepted by the study with a p value of 0.055 implying that the relationship is statistically significant at 90% confidence interval. This result is compatible with the results of the literature (Schick & Fischer, 2021; Laurim, Arpaci, Prommegger, & Krcmar, 2021; Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; van Esch, Black, & Arli, 2021). As long as the job candidates believe that the AI tools produce accurate and correct results which may be negative for themselves but not wrong or opportunist, they can be open to these results and accept them and their behavioral intention to participate in AI-based recruitment increase. According to the literature “honesty” or “openness” are two predictors of perceived fairness (Gilliland, 1993; Bauer, et al., 2001). That’s why, the relation between trust (T) and fairness (F) is also investigated and a significant relationship is found. It means that trust (T) not only affects the behavioral intention to participate in AI-based recruitment (BIP) directly but also affects it indirectly through fairness (F). Because of this, recruiters should ensure the accuracy of the results, by testing the AI technologies in order them not to produce any biased decision and the regulations and ethical codes should be defined beforehand.

Based on the hypothesis 8, as job candidates’ perceived privacy concerns about AI-based recruitment process increases, their intention to participate in AI-based recruitment decreases. This hypothesis is not supported by the study as understood from the p value of 0.523, contrary to literature (Langer, König, & Krause, 2017; Langer, König, & Papathanasiou, 2019; Ochmann & Laumer, 2020). According to Levin, Cross, and Abrams, for one person to trust another party, this party should not reveal confidential information (Levin, Cross, & Abrams, 2002). Therefore, the relationship between privacy concerns (PC) and trust (T) is also analyzed and it is found statistically significant with a p value of 0. However, it also does not affect the behavioral intention to participate in AI-based recruitment (BIP) through trust (T), because this specific indirect effect is found non-significant with a p value of 0.099. It only has an effect on BIP through the path from trust to fairness and fairness to behavioral intention.

Hypothesis 9 suggests that as two-way communication (TC) perceived by job candidates in the AI-based recruitment process increases, their intention to participate in AI-based recruitment (BIP) increases. This hypothesis is also rejected by the study with a p value of 0.662. Although some of the studies in the literature found two-way communication (TC) as a determinant in the context of AI-based recruitment acceptance, this study does not reach same results with them (Chen, 2022; Langer, König, & Krause, 2017; Lukacik, Bourdage, & Roulin, 2022). However, since two-way communication (TC) is a predictor of perceived fairness in the literature, the relation between two-way communication (TC) and fairness (F) is tested for this model (Gilliland, 1993; Bauer, et al., 2001). The relationship is found statistically significant with a p value of 0 in %99 confidence interval and also the indirect effect of two-way communication (TC) on behavioral intention to participate in AI-based recruitment (BIP) is identified with a p value of 0.

The last hypothesis, hypothesis 10, suggests that as fairness (F) perceived by job candidates increases, their intention to participate in AI-based recruitment (BIP) increases. This hypothesis is supported by the study with a p value of 0 in a 99% confidence interval that is consistent with the results of the literature (Lukacik, Bourdage, & Roulin, 2022; Wesche & Sonderegger, 2021; Black & van Esch, 2019; Kim & Heo, 2021; Langer, König, & Papathanasiou, 2019; Langer, König, & Krause, 2017; Norskov, et al., 2022; Acikgoz, Davison, Compagnone, & Laske, 2020; Gonzalez, et al., 2022; Mirowska & Mesnet, 2021; Zhang & Yencha, 2022). This proves that as the perceived fairness of the AI methods used to make organizational decisions and the degree of feeling of outcome to be deserved increases, job candidates' behavioral intention to participate in AI-based recruitment increases. "Fairness" is the strongest determinant of the behavioral intention to participate in AI-based recruitment with a path coefficient of 0.312. For this reason, the rules of the evaluation stages in AI-based recruitment should be clear and transparent, and it should be emphasized that it eliminates subjective evaluations that may arise with human influence factors as stated in the literature (Rezzani, Caputo, & Cortese, 2021; Black, van Esch, & Ferolie, 2019; Hemalatha, Nawaz, Kumari, & Gajenderan, 2021).

5.2. Conclusion

Artificial intelligence technologies such as machine learning, natural language processing, expert systems, voice and image recognition, take part in people's lives increasingly. Although their origin dates back to over 50 years from now, its utilization in human resources (HR) is relatively new. Although there are companies using such technologies, they are not common. However, it is expected to expand in the near future (Rao & Greenstein, 2022). Recruitment is an important function in HR which AI utilization may bring several benefits. As a result, it is important to understand how AI-based recruitment is welcomed by job candidates and which factors influence their behavioral intention to participate in such a recruitment process. This study aims to investigate this subject and tries to model factors affecting job candidates' behavioral intention to participate in AI-based recruitment.

According to the results and discussion of the findings of the study, performance and effort expectancy (HM), social influence (SI), hedonic motivation (HM), trust (T), and fairness (F) are found to have positive effect on job candidates' behavioral intention to participate in AI-based recruitment (BIP). On the other hand, facilitating conditions (FC), creepiness (C), privacy concerns (PC) and two-way communication (TC) do not have direct effect on job candidates' behavioral intention to participate in AI-based recruitment (BIP). They just indirectly affect it. The model from which the non-significant paths are removed is presented in Figure 25. The model has a R square value of 58.3 % that is slightly higher than the that of the model only UTAUT2 factors are utilized which is 54.2 %.

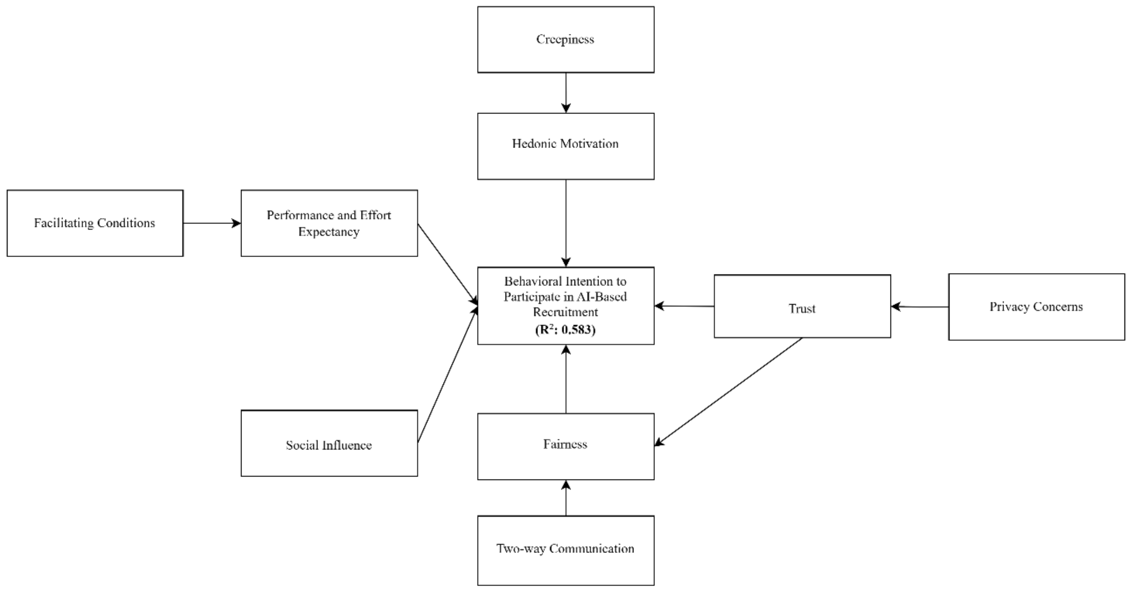


Figure 25: Final Model

5.3. Contribution of the Study

This study contributes to literature in several ways. First of all, by examining the factors influencing Turkish job candidates' behavioral intention to participate in AI-based recruitment, it contributes to the literature.

Secondly, according to the limited literature review carried out for this study with some constraints and criteria, most of the studies either use a pre-prosed model or develop a model with qualitative analysis. This study, on the other hand, reviews literature not only on AI-acceptance in recruitment but also similar concepts namely acceptance of chatbots, service robots, robot instructors and voice assistants, to get a large diverse pool of constructs to be utilized later in expert panel analysis. Then, HR experts' opinions are used as both ensure content validity and develop model in this study. These are how the study contributes to the literature.

Moreover, according to the limited literature review carried out for this study with some constraints and criteria, there is limited research studying a recruitment scenario utilizing AI technologies in all the phases. By studying the acceptance of AI-based recruitment scenario in which AI technologies are utilized as a whole this study contributes to the literature in this field.

As well as the results of the study, the systematic literature review, the pool of constructs and the findings of HR expert panel analysis can be beneficial for researchers. The results or the model proposed by the study, on the other hand, can be used as a roadmap for HR functions or decision makers in the companies in which an investment to AI technologies in the recruitment are planned to make.

5.4 Implications for Further Research

Since the results may reflect country culture, the study can be repeated for other countries to see results in different cultures.

Secondly, the study can be carried out by expanding the pool of HR experts to reflect more diverse expert opinions.

Furthermore, moderation analysis on gender, age, generation, or recruitment experience can be carried out by future studies.

In addition, factors identified through the literature review but eliminated after panel analysis such as “Organizational Attractiveness”, “Perceived Self-Efficacy”, “Perceived Behavioral Control”, or “Anxiety” can be tested for model development to reach a higher exploratory power.

Lastly, the study can be carried out based on sector, type or size of the organization that utilizes AI technologies in recruitment with a sample having a grasp of that specific sector, organization type, or size.

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APPENDICES

APPENDIX A

STUDIES FROM MAIN LITERATURE REVIEW

Title	Reference
Justice perceptions of artificial intelligence in selection	Acikgoz, Davison, Compagnone, & Laske, 2020
AI adoption by human resource management: a study of its antecedents and impact on HR system effectiveness	Agarwal A. , 2022
HR Professionals’ Intention to Adopt and Use of Artificial Intelligence in Recruiting Talents	Alam, Khan, Dhar, & Munira, 2020
AI adoption in the hiring process – important criteria and extent of AI adoption	Bhatt, 2021
Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting	Black & van Esch, 2019
Job candidates' reactions to AI-enabled job application processes	Black, van Esch, & Arli, 2021
What Factor s Drive Job Seekers Attitude in Using E-Recruitment	Brahmana & Brahmana, 2013
Collaboration among recruiters and artificial intelligence: removing human prejudices in employment	Chen, 2022
How Does AI Recruitment Influence Satisfaction Among Student Job-Seekers? The Role of Self-Efficacy as A Moderator and Mediator	Duong & Thi, 2022
OK computer: Worker perceptions of algorithmic recruitment	Fumagalli, Rezaei, & Salomons, 2022
Allying with AI? Reactions toward human-based, AI/ML-based, and augmented hiring processes	Gonzalez, et al., 2022
Artificial Intelligence in Human Resources Information Systems: Investigating its Trust and Adoption Determinants	Hmoud & Várallyai, 2020
Assessing HR Leaders' Attitude Toward the Adoption of Artificial Intelligence in Recruitment	Hmoud B. , 2021

Recruiter's perception of artificial intelligence (AI)-based tools in recruitment	Horodyski, 2023
Technology Adoption and Human Resource Management Practices: The Use of Artificial Intelligence for Recruitment in Bangladesh	Islam, Al Mamun, Afrin, Quaosar, & Uddin, 2022
Artificial intelligence video interviewing for employment: perspectives from applicants, companies, developer and academicians	Kim & Heo, 2021
Can I show my skills? Affective responses to artificial intelligence in the recruitment process	Köchling, Wehner, & Warkocz, 2022
Examining digital interviews for personnel selection: Applicant reactions and interviewer ratings	Langer, König, & Krause, 2017
Highly automated job interviews: Acceptance under the influence of stakes	Langer, König, & Papathanasiou, 2019
Computer, Whom Should I Hire? – Acceptance Criteria for Artificial Intelligence in the Recruitment Process	Laurim, Arpaci, Prommegger, & Krcmar, 2021
FAT-CAT—Explainability and augmentation for an AI system: A case study on AI recruitment-system adoption	Lee & Cha, 2023
Into the void: A conceptual model and research agenda for the design and use of asynchronous video interviews	Lukacik, Bourdage, & Roulin, 2022
Preferring the devil, you know: Potential applicant reactions to artificial intelligence evaluation of interviews	Mirowska & Mesnet, 2021
Employers' and applicants' fairness perceptions in job interviews: using a teleoperated robot as a fair proxy	Norskov, et al., 2022
Fairness as a Determinant of AI Adoption in Recruiting: An Interview-based Study	Ochmann & Laumer, 2019
AI Recruitment: Explaining job seekers' acceptance of automation in human resource management	Ochmann & Laumer, 2020
The adoption of artificial intelligence in employee recruitment: The influence of contextual factors	Pan, Froese, Liu, Hu, & Ye, 2021
Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations	Pillai & Sivathanu, 2020
Assessed by Machines: Development of a TAM-Based Tool to Measure AI-based Assessment Acceptance Among Students	Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020
Dear Computer on My Desk, Which Candidate Fits Best? An Assessment of Candidates' Perception of Assessment Quality When Using AI in Personnel Selection	Schick & Fischer, 2021
Artificial Intelligence and Talent Acquisition-Role of HR leaders in Adoption	Tiwari, Rajput, & Garg, 2022
Repelled at first sight? Expectations and intentions of job-seekers reading about AI selection in job advertisements	Wesche & Sonderegger, 2021
Examining perceptions towards hiring algorithms	Zhang & Yencha, 2022

APPENDIX B

DEPENDENT AND INDEPENDENT VARIABLES IN THE STUDIES FROM MAIN LITERATURE REVIEW

Dependent Variable	**Independent Variables**	**Reference**
Organizational Attraction Pursuit Intentions Litigation Intentions	Procedural Justice Interactional Justice	Acikgoz, Davison, Compagnone, & Laske, 2020
Intention to engage with and complete digital, AI-enabled recruiting processes	Social Media Use Intrinsic Rewards Fair Treatment Trendy	Black & van Esch, 2019
Intent to Engage (Job Application Process)	Organizational Attractiveness Intrinsic Motivation Novelty Trust Anxiety	Black, van Esch, & Arli, 2021
Intention to Use	Perceived Ease of Use Perceived Enjoyment Perceived Usefulness Perceived Stress	Brahmana & Brahmana, 2013
Acceptance of AI recruitment	The accuracy of the job description and increased performance (Job Advertisement-Recruiter) Convenience and efficiency (Job Search-Applicant) Accuracy (Application-Applicant) AI reliability (Selection-Recruiter) Fairness and impartiality (Assessment-Manager) Natural communication (Coordination-Applicant) Accuracy (Coordination-Recruiter)	Chen, 2022
Job seeker satisfaction on AI recruitment	Perception of AI recruitment expected value Self-efficacy	Duong & Thi, 2022
Participants' reactions toward the hiring process	Procedural justice (process-directed reactions) Interpersonal justice (process-directed reactions) Perceived fit (company-directed reactions) Perceived supportive culture (company-directed reactions) Perceived recognition culture (company-directed reactions)	Gonzalez, et al., 2022

	Perceived innovation climate (company-directed reactions) Perceived control (self-directed reactions) Self-efficacy (self-directed reactions) Need satisfaction (autonomy, competence, relatedness) (self-directed reactions)	
Adoption of AI assessment	Efficiency Fairness Bias and accountability Emotions and psychological resistance Social and cultural issues	Kim & Heo, 2021
It is a comparison of two methods of interviews.	Emotional Creepiness Creepy Ambiguity Privacy Concerns Perceived Behavioral Control Two-way Communication Interpersonal treatment Chance to perform Global Fairness Overall organizational attractiveness	Langer, König, & Krause, 2017
Attractiveness of highly automated interviews Attractiveness of videoconference interviews	Social presence Perceived behavior control Creepiness Privacy concerns Consistency Interpersonal treatment Fairness	Langer, König, & Papathanasiou, 2019
Technology acceptance	Perceived usefulness (Job relevance, Complexity, Social influence) Perceived Ease of Use (Attitude, Perceived enjoyment, Anxiety, Trialability) Technology Readiness (Sense of Control, Trust)	Laurim, Arpaci, Prommegger, & Krcmar, 2021
Interview Performance Organizational Attraction Job Offer Acceptance	Procedural Justice Perceptions (Opportunity to Perform, Reconsideration Opportunity, Consistency, Two-way Communication, Explanation) Distributive Justice Perceptions (Eqity, Equality, Needs) Reactions During Interview (Reaction to Technology, Motivation to Perform) Social Presence Perception Interview Anxiety Impression Management	Lukacik, Bourdage, & Roulin, 2022
Preference to involve in AI evaluation process	Exposure to AIE (personality, socio-economic background, demographic characteristics, previous awareness of and experience with AI and AIE) -> Justice perceptions of AIE (distributive, procedural, interpersonal, informational)	Mirowska & Mesnet, 2021

	Company type, job type, and job level -> Signaling reactions (positive signals, negative signals)	
Adoption of robot-mediated job interview	Perceived interactional fairness Personal innovativeness Core self-evaluations	Norskov, et al., 2022
Attitude towards AI Intention to apply	Performance expectancy Effort expectancy Social influence Habit Privacy risk expectation (newly identified) Innovation expectancy (newly identified)	Ochmann & Laumer, 2020
Behavioral Intention	Perceived usefulness Perceived ease of use Attitude towards use Subjective norm (Newly added) Resistance to change (Newly added) Trust (Newly added)	Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020
Assessment quality perceptions	AI Complexity AI Intangibility AI Reliability	Schick & Fischer, 2021
Intention to apply	Perceived organizational attractiveness and prestige Expected procedural justice	Wesche & Sonderegger, 2021
Adoption of hiring algorithms	Perception of Fairness Perception of Effectiveness Perception of Acceptability	Zhang & Yencha, 2022

APPENDIX C

AI APPLICATIONS STUDIED IN SELECTED PAPERS

AI Application	Reference
Resume Screening Digital Interview Scored by an Algorithm	Acikgoz, Davison, Compagnone, & Laske, 2020
Job application through social media via a Mobile Device AI Tools Analyzing Behavioral and Physiological Characteristics	Black & van Esch, 2019
AI-Recruitment (No details)	Black, van Esch, & Arli, 2021
E-Recruitment Website Which is Applying Test and Collecting Biodata	Brahmana & Brahmana, 2013
AI-Based Job Advertisement Chatbot in Job Search Resume Parsing and Data Transmission AI Algorithm in Selection Video Interviewing Automated Calls, Tests, and Scheduling	Chen, 2022
AI-Recruitment (No details)	Duong & Thi, 2022
AI-Based Assessment Asynchronous Video Interview	Gonzalez, et al., 2022
AI-Based Interview	Kim & Heo, 2021
Digital Interview	Langer, König, & Krause, 2017
Virtual Interview	Langer, König, & Papathanasiou, 2019
Automated Job Advertisement Analysis Search Query Personalization Conversational Agents (Chatbots) AI Video Analysis Automated Pre-Screening Reports	Laurim, Arpaci, Prommegger, & Krcmar, 2021
Digital Interview	Lukacik, Bourdage, & Roulin, 2022
Artificial Intelligence Evaluation	Mirowska & Mesnet, 2021

Robot-Mediated Interview	Norskov, et al., 2022
Web-based Information Extraction CV Parsing Analysis of Biometrics	Ochmann & Laumer, 2020
AI-Based Student Assessment	Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020
Algorithm Speech Analysis Robotic Interview	Schick & Fischer, 2021
AI Screening AI Interview	Wesche & Sonderegger, 2021
Resume Screening Video Interview Screening	Zhang & Yencha, 2022

APPENDIX D

STUDIES FROM SUPPORTIVE LITERATURE REVIEW

Subject Area	Title	Reference
Acceptance of chatbots	I, Chatbot: Modeling the determinants of users’ satisfaction and continuance intention of AI-powered service agents	Ashfaq, Yun, Yu, & Loureiro, 2020
Acceptance of chatbots	The acceptance of chatbots in an enterprise context – A survey study	Brachten, Kissmer, & Stieglitz, 2021
Acceptance of chatbots	AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots	Zhu, Zhang, Wu, & Liu, 2022
Acceptance of robot instructors	Perceived credibility of an AI instructor in online education: The role of social presence and voice features	Kim, Jr., Xu, & Kelly, 2022
Acceptance of service robots	Customers’ acceptance of artificially intelligent service robots: The influence of trust and culture	Chi, Chi, Gursoy, & Nunkoo, 2023
Acceptance of service robots	Research on service robot adoption under different service scenarios	Liu, Wang, & Wang, 2022
Acceptance of service robots	Exploring Consumer-Robot interaction in the hospitality sector: Unpacking the reasons for adoption (or resistance) to artificial intelligence	Rasheed, He, Khizar, & Abbas, 2023
Acceptance of service robots	The role of the human-robot interaction in consumers’ acceptance of humanoid retail service robots	Song & Kim, 2022
Acceptance of service robots	Proposal for modeling social robot acceptance by retail customers: CAN model	Subero-Navarro, Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2022
Acceptance of voice assistants	Understanding consumers’ acceptance of automated technologies in service encounters: Drivers of digital voice assistants’ adoption	Fernandes & Oliveira, 2021
Acceptance of voice assistants	Alexa, she's not human but… Unveiling the drivers of consumers' trust in voice-based artificial intelligence	Pitardi & Marriott, 2021

APPENDIX E

DEPENDENT AND INDEPENDENT VARIABLES IN THE STUDIES FROM SUPPORTIVE LITERATURE REVIEW

Dependent Variable	Independent Variables	Reference
Continuance intention	Perceived enjoyment Service quality Satisfaction Information quality Perceived usefulness Perceived ease of use	Ashfaq, Yun, Yu, & Loureiro, 2020
Intention to use enterprise bots	Perceived usefulness Perceived ease-of-use Trust Perceived behavioral control Efficacy Attitude towards using Peer influence Subjective norm Superior influence Facilitating conditions	Brachten, Kissmer, & Stieglitz, 2021
Acceptance of AI chatbots	Perceived effectiveness Certainty of consumer needs Product type	Zhu, Zhang, Wu, & Liu, 2022
Intention to take an AI instructor-based online course	Voice of AI Expertise of AI Credibility Social presence	Kim, Jr., Xu, & Kelly, 2022
Willingness to use AI robots Objection to use AI robots	Perceived Performance Expectancy Perceived Effort Expectancy Hedonic Motivation Perceived social influence Anthropomorphism Emotion Trust in interaction with AI robots	Chi, Chi, Gursoy, & Nunkoo, 2023
Service robot adoption intention	Perceived uncertainty Service component Service type	Liu, Wang, & Wang, 2022

Adoption of AI and robot service in the hospitality	Perceived usefulness Perceived ease of use Perceived enjoyment Perceived safety Technological anxiety Privacy concern Perceived innovativeness Technological complexity	Rasheed, He, Khizar, & Abbas, 2023
Retail service robot (RSR) acceptance	Usefulness Anxiety toward robots Anticipated service quality Social capability Appearance	Song & Kim, 2022
Intention to use social robots	Performance expectancy Effort expectancy Arousal Pleasure Social influence Technophobia	Subero-Navarro, Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2022
Acceptance of digital voice assistants	Perceived usefulness Perceived ease of use Trust Perceived social presence Perceived social interactivity Experience Subjective social norms Perceived humanness Rapport Preference on technology-based interaction	Fernandes & Oliveira, 2021
Intention to use	Perceived usefulness Perceived ease of use Perceived enjoyment Trust Perceived privacy concerns Social presence Attitude Social cognition	Pitardi & Marriott, 2021

APPENDIX F

GROUPING OF THE CONSTRUCTS REACHED FROM LITERATURE

Performance Expectancy	Perceived Effectiveness
	Perceived Performance Expectancy
	Perceived Usefulness
	Performance Expectancy
	Usefulness
	Perceived Usefulness
	Perception of Effectiveness
	Efficiency
Fairness	Distributive justice perceptions
	Expected Procedural Justice
	Fair Treatment
	Fairness
	Fairness perceptions
	Global Fairness
	Interactional Fairness
	Interactional Justice
	Interpersonal Justice
	Justice Perceptions
	Perception of Fairness
	Procedural Justice
	Procedural justice perceptions
Effort Expectancy	Effort Expectancy
	Perceived Ease of Use
	Perceived ease-of-use
	Perceived Effort Expectancy
	Effort Expectancy
Hedonic Motivation	Arousal
	Hedonic Motivation
	Perceived Enjoyment
	Pleasure
	Hedonic motivations
	Intrinsic Motivation
	Motivation to Perform

Trust	Credibility
	Perceived Safety
	Trust
	AI Reliability
Anxiety	Anxiety toward robots
	Technological Anxiety
	Anxiety
	Interview anxiety
	Perceived Stress
Organizational Attractiveness	Attractiveness
	Organizational Attractiveness
	Perceived negative signals regarding company
	Perceived Organizational Attractiveness and Prestige
	Perceived positive signals regarding company
Perceived Behavioral Control	Perceived behavioral control
	Perceived Behavioral Control
	Perceived Control
	Perceived Controllability
	Sense of Control
Perceived Privacy Concerns	Perceived Privacy Concerns
	Privacy Concern
	Privacy Concerns
	Privacy Risk Expectancy
Perceived Self-efficacy	Efficacy
	Core self-evaluations
	Perceived Self-efficacy
	Self-efficacy
Social Presence	Perceived Social Presence
	Social Presence
	Social presence perception
Social Influence	Perceived Social Influence
	Social Influence
Two-way Communication	Perceived Social Interactivity
	Natural communication
	Two-way Communication
Anticipated service quality	Anticipated service quality
	Service Quality
	Convenience and efficiency
Attitude	Attitude towards using
	Attitude
	Attitude towards use

Experience	Experience
	Exposure to AIE
Perceived Innovativeness	Perceived Innovativeness
	Novelty
	Personal innovativeness
Satisfaction	Satisfaction
	Job seeker satisfaction
	Need Satisfaction (autonomy, competence, relatedness)
Subjective Norm	Peer influence
	Subjective Norm
	Subjective Social Norms
	Superior influence
Complexity	Technological Complexity
	AI Complexity
Consistency	Consistency
Creepiness	Creepiness (Emotional Creepiness / Creepy Ambiguity)
	Creepy Ambiguity
	Emotional Creepiness
Facilitation Conditions	Facilitating conditions
Innovation Expectancy	Perceived Innovation Climate
	Innovation Expectancy
Interpersonal Treatment	Interpersonal Treatment
Opportunity to Perform	Chance to Perform
	Opportunity to Perform
Perceived Humanness	Anthropomorphism
	Perceived Humanness
Resistance	Emotions and psychological resistance
	Resistance to change
Social capability	Social capability
	Warmth
Acceptability	Perception of Acceptability
Accountability	Bias and accountability
Accuracy	Accuracy
AI Intangibility	AI Intangibility
Appearance	Appearance
Certainty of Consumer Needs	Certainty of Consumer Needs
Compatibility	Rapport
Culture	Social and cultural issues
Emotion	Emotion
Eqity	Eqity
Equality	Equality

Explanation	Explanation
Habit	Habit
Impression management	Impression management
Information Quality	Information Quality
Intrinsic Rewards	Intrinsic Rewards
Perceived Fit	Perceived Fit
Perceived Supportive Culture	Perceived Supportive Culture
Needs	Needs
Outcome Favorability	Outcome Favorability
Social Cognition	Social Cognition
Perceived Experience of the AI-Based Tool	Perceived Experience of the Machine
Perceived Recognition Culture	Perceived Recognition Culture
Perceived Uncertainty	Perceived Uncertainty
Perception of expected value	Perception of AI recruitment expected value
Preference on Technology-Based Interaction	Preference on Technology-Based Interaction
Product Type	Product Type
Reaction to Technology	Reaction to Technology
Reconsideration Opportunity	Reconsideration Opportunity
Service Component	Service Component
Service Type	Service Type
Social Media Use	Social Media Use
Technological Affinity	Technological Affinity
Technological Readiness	Technology Readiness
Technophobia	Technophobia
Trendy	Trendy
Trialability	Trialability

APPENDIX G

DETERMINATION OF THE FACTORS TO BE INCLUDED IN THE MODEL OF ACCEPTANCE OF ARTIFICIAL INTELLIGENCE-BASED RECRUITMENT AMONG CANDIDATES BY DELPHI METHOD - ROUND 1

This form was created to build consensus based on expert opinions in order to identify the factors and effects affecting the acceptance of AI-based recruitment among candidates and to integrate them into the existing technology acceptance model. In the recruitment scenario within the scope of the research, artificial intelligence technologies are utilized in the stages of creating a candidate pool, screening candidates, matching them with the positions sought; interviews are conducted with virtual recruitment robots. The information obtained will only be used in this scientific research and will not be shared with anyone. Thank you for your participation.

Factors in the UTAUT2 Model	**Definition**
Performance Expectancy	The degree to which AI technology usage in recruitment will provide benefits to job candidates in performing certain activities (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)
Effort Expectancy	The degree of ease associated with the job candidates' experience on the AI technology usage in recruitment (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)
Hedonic Motivation	The fun or pleasure derived from participating in AI-based recruitment (Venkatesh, Thong, & Xu, 2012)
Social Influence	The extent to which job candidates perceive that important others believe they should participate in AI-based recruitment (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)
Facilitating Conditions	The degree to which a job candidate believes that an organizational and technical infrastructure exists to support to participate in AI-based recruitment process (Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003)
Habit	The extent to which people tend to perform behaviors automatically because of learning (Venkatesh, Thong, & Xu, 2012; Limayem, Hirt, & Cheung, 2007)
Price Value	The cognitive tradeoff between the perceived benefits of the technology and the monetary cost for using (Venkatesh, Thong, & Xu, 2012; Dodds, Monroe, & Grewal, 1991)

A. Please fill in the descriptive information.

Year of birth:

Gender:

Experience in HR (years):

Approximate number of interviews attended as a recruiter:

B. Of the factors below, please list the 10 factors that you think will most influence candidates' intentions to participate in AI-based recruitment and their adoption of this technology in the table below. Factor 1 in the table will receive 10 points, while the score for the other factors will decrease by one, and factors that are not ranked will be assumed to be given 0 points.

Number	Factor
1	
2	
3	
4	
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6	
7	
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9	
10	

Factor	Definition
Fairness	Overall perceived fairness on AI-based recruitment including the perceived fairness of the methods used to make organizational decisions and the degree of feeling of outcome to be deserved (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993; Greenberg & Folger, 1985)
Trust	Psychological expectation that a trusted party will not behave opportunistically and the willingness of a party to be vulnerable to the actions of other parties (Hmoud & Várallyai, 2020; Kim, Shin, & Lee, 2009)
Anxiety	A candidate's pre-existing anxious feeling that elicits uncertainty and discomfort about having a conversation with AI (Song & Kim, 2022; Nomura, Kanda, Suzuki, & Kato, 2008; Chaplin, 1985)
Perceived Privacy Concerns	The extent to which job candidates perceive that the use of AI-based recruiting methods is non-transparent and fosters data abuse (Ochmann & Laumer, 2019)
Perceived Self-Efficacy	Beliefs about a person's ability to learn or behave at a particular level (Duong & Thi, 2022; Schunk & Pajares, 2002)
Social Presence	A psychological state in which virtual (para-authentic or artificial) social actors are experienced as actual social actors in either sensory or no sensory ways (Kim, Jr., Xu, & Kelly, 2022; Lee K. , 2004)
Organizational Attractiveness	Job candidates' attitude towards the organization (Köchling, Wehner, & Warkocz, 2022; Chapman, Uggerslev, Carroll, Piasentin, & Jones, 2005)

Perceived Behavioral Control	The extent to which job candidates believe they can control or influence an outcome with their behavior (Hilliard, Guenole, & Leutner, 2022; Langer, König, & Papathanasiou, 2019)
Two-way Communication	Possibility for job candidates to ask questions, and to interact with the recruiter or organization (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993)
Subjective Norm	the belief that a substantial group or individual approves or disapproves a given action (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Ajzen, 1991)
Attitude	The feelings, thoughts, and favorable or unfavorable assessments about the AI-based recruitment (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, 1989)
Anticipated Service Quality	a subjective, forward-looking, individual-centered, cognitive evaluation of a future service delivery (Song & Kim, 2022; Polegato & Bjerke, 2019)
Satisfaction	the degree of internal satisfaction of expectations and needs of job candidates in AI-based recruitment (Duong & Thi, 2022)
Personal Innovativeness	The degree of willingness of an individual to try out any new information technology (Köchling, Wehner, & Warkocz, 2022; Agarwal & Prasad, 1998)
Creepiness	An uncomfortable feeling paired with uncertainty about how to behave or how to judge in AI-based recruitment process (Langer, König, & Krause, 2017; Langer, König, Gebhard, & André, 2016)
Resistance	the opposition of the individual to the rupture of the status quo produced by the use of AI in recruitment (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Guo, Sun, Wang, Peng, & Yan, 2013)
Perceived Humanness	the level of an object's humanlike characteristics both in form and behavior (Fernandes & Oliveira, 2021; Wirtz, et al., 2018)
Innovation Expectancy	Perceived degree of innovation associated with organization’s use of new technologies by job candidates (Ochmann & Laumer, 2020)
Complexity	The extent to which the functionality of artificial intelligence applications used in recruitment is based on narrow or broad criteria assessment (Schick & Fischer, 2021)
Interpersonal Treatment	Job candidates’ feelings of being treated with respect, dignity and human warmth (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993)
Consistency	The degree of consistency and being free of bias of decision procedures in AI-based recruitment across people and over time (Langer, König, & Papathanasiou, 2019; Bauer, et al., 2001; Gilliland, 1993)
Opportunity to Perform	Job candidates’ feelings of being given enough possibilities to put their best foot forward (Langer, König, & Krause, 2017; Bauer, et al., 2001; Gilliland, 1993)
Social Capability	The degree of AI-based recruitment robot's social skills to engage in interpersonal relations, such as having interactive communication, being approachable, responding appropriately, and listening without interrupting

	(Song & Kim, 2022; de Ruyter, Saini, Markopoulos, & van Breemen, 2005; Song & Kim, 2020)

APPENDIX H

YAPAY ZEKÂ TEMELLİ İŞE ALIMIN ADAYLAR ARASINDA KABULÜ MODELİNE DAHİL EDİLECEK FAKTÖRLERİN DELPHI YÖNTEMİ İLE BELİRLENMESİ - 1. TUR

Bu form, yapay zeka tabanlı işe alımın adaylar arasında kabulünü etkileyen faktörlerin ve etkilerinin tespit edilerek mevcut teknoloji kabulü modeline entegre edilmesi amacıyla uzman görüşlerine dayanarak fikir birliği sağlanması için oluşturulmuştur. Araştırma kapsamındaki işe alım senaryosunda aday havuzu oluşturulması, adayların taranması, aranan pozisyonlarla eşleşmesi aşamalarında yapay zeka teknolojilerinden faydalanılmakta; mülakat sanal işe alım robotları ile gerçekleştirilmektedir. Elde edilen bilgiler sadece bu bilimsel araştırmada kullanılacak ve kimseyle paylaşılmayacaktır. Katılımınız için teşekkürler.

Factors in the UTAUT2 Model	Definition
Performans Beklentisi	İşe alımda yapay zeka teknolojisi kullanımının iş adaylarına belirli faaliyetleri gerçekleştirmede ne derece fayda sağlayacağı (Venkatesh, Thong ve Xu, 2012; Venkatesh, Morris, Davis ve Davis, 2003)
Çaba Beklentisi	İş adaylarının işe alımda yapay zeka teknolojisi kullanımı konusundaki deneyimleriyle ilişkili kolaylık derecesi (Venkatesh, Thong ve Xu, 2012; Venkatesh, Morris, Davis ve Davis, 2003)
Hedonik Motivasyon	YZ tabanlı işe alımlara katılmaktan elde edilen eğlence veya zevk (Venkatesh, Thong, & Xu, 2012)
Sosyal Etki	İş adaylarının, önemli diğer kişilerin YZ tabanlı işe alımlara katılmaları gerektiğine inandıklarını algılama derecesi (Venkatesh, Thong ve Xu, 2012; Venkatesh, Morris, Davis ve Davis, 2003)
Kolaylaştırıcı Koşullar	Bir iş adayının YZ tabanlı işe alım sürecine katılmayı destekleyecek kurumsal ve teknik altyapının var olduğuna inanma derecesi (Venkatesh, Thong ve Xu, 2012; Venkatesh, Morris, Davis ve Davis, 2003)
Alışkanlık	İnsanların öğrenme nedeniyle davranışları otomatik olarak gerçekleştirme eğiliminde olma derecesi (Venkatesh, Thong ve Xu, 2012; Limayem, Hirt ve Cheung, 2007)
Fiyat Değeri	Teknolojinin algılanan faydaları ile kullanımın parasal maliyeti arasındaki bilişsel değiş tokuş (Venkatesh, Thong, & Xu, 2012; Dodds, Monroe, & Grewal, 1991)

A. Lütfen açıklayıcı bilgileri doldurunuz.

Doğum yılı

Cinsiyet

İK alanındaki deneyim (yıl):

İşe alım uzmanı olarak katıldığınız yaklaşık mülakat sayısı:

C. Aşağıdaki faktörlerden, adayların yapay zeka tabanlı işe alımlara katılma niyetlerini ve bu teknolojiyi benimsemelerini en çok etkileyeceğini düşündüğünüz 10 faktörü lütfen aşağıdaki tabloda listeleyiniz. Tablodaki 1. faktör 10 puan alırken, diğer faktörlerin puanı bir azalacak ve sıralanmayan faktörlere 0 puan verileceği varsayılacaktır.

Sıra	Faktör
1	
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Faktör	Tanım
Adalet	Örgütsel kararlar almak için kullanılan yöntemlerin algılanan adaleti ve sonucun hak edildiği hissinin derecesi de dahil olmak üzere YZ tabanlı işe alımda genel olarak algılanan adalet (Langer, König ve Krause, 2017; Bauer, vd., 2001; Gilliland, 1993; Greenberg ve Folger, 1985)
Güven	Güvenilen bir tarafın fırsatçı davranmayacağına dair psikolojik beklenti ve bir tarafın diğer tarafların eylemlerine karşı savunmasız olma isteği (Hmoud ve Várallyai, 2020; Kim, Shin ve Lee, 2009)
Anksiyete	Adayın önceden var olan ve yapay zeka ile konuşma konusunda belirsizlik ve rahatsızlık uyandıran endişeli hissi (Song ve Kim, 2022; Nomura, Kanda, Suzuki ve Kato, 2008; Chaplin, 1985)
Algılanan Gizlilik Endişeleri	İş adaylarının yapay zeka tabanlı işe alım yöntemlerinin kullanımının şeffaf olmadığını ve veri istismarını teşvik ettiğini algılama derecesi (Ochmann & Laumer, 2019)
Algılanan Öz Yeterlilik	Bir kişinin belirli bir düzeyde öğrenme veya davranma yeteneğine ilişkin inançlar (Duong & Thi, 2022; Schunk & Pajares, 2002)
Sosyal Varlık	Sanal (para-otantik veya yapay) sosyal aktörlerin duyusal veya duyusal olmayan yollarla gerçek sosyal aktörler olarak deneyimlendiği psikolojik bir durum (Kim, Jr., Xu ve Kelly, 2022; Lee K. , 2004)

Organizasyonel Çekicilik	İş adaylarının kuruma yönelik tutumu (Köchling, Wehner ve Warkocz, 2022; Chapman, Uggerslev, Carroll, Piasentin ve Jones, 2005)
Algılanan Davranışsal Kontrol	İş adaylarının davranışlarıyla bir sonucu kontrol edebileceklerine veya etkileyebileceklerine ne ölçüde inandıkları (Hilliard, Guenole ve Leutner, 2022; Langer, König ve Papathanasiou, 2019)
Çift Yönlü İletişim	İş adaylarının soru sorma ve işe alan kişi veya kurumla etkileşime geçme imkanı (Langer, König ve Krause, 2017; Bauer, vd., 2001; Gilliland, 1993)
Öznel Norm	Önemli bir grup veya bireyin belirli bir eylemi onayladığı veya onaylamadığı inancı (Sánchez-Prieto, Cruz-Benito, Therón ve García-Peñalvo, 2020; Ajzen, 1991)
Tutum	YZ tabanlı işe alımla ilgili duygular, düşünceler ve olumlu ya da olumsuz değerlendirmeler (Sánchez-Prieto, Cruz-Benito, Therón ve García-Peñalvo, 2020; Davis, 1989)
Beklenen Hizmet Kalitesi	Gelecekteki bir hizmet sunumunun öznel, ileriye dönük, birey merkezli, bilişsel bir değerlendirmesi (Song ve Kim, 2022; Polegato ve Bjerke, 2019)
Memnuniyet	YZ tabanlı işe alımlarda iş adaylarının beklenti ve ihtiyaçlarının içsel tatmin derecesi (Duong ve Thi, 2022)
Kişisel Yenilikçilik	Bireyin yeni bir bilgi teknolojisini denemeye isteklilik derecesi (Köchling, Wehner ve Warkocz, 2022; Agarwal ve Prasad, 1998)
Ürkütücülük	Yapay zeka tabanlı işe alım sürecinde nasıl davranılacağı veya nasıl karar verileceği konusunda belirsizlikle eşleştirilmiş rahatsız edici bir duygu (Langer, König ve Krause, 2017; Langer, König, Gebhard ve André, 2016)
Direnç	işe alımda yapay zeka kullanımının ürettiği statükonun kırılmasına bireyin muhalefeti (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Guo, Sun, Wang, Peng, & Yan, 2013)
Algılanan İnsanlık	Bir nesnenin hem biçim hem de davranış olarak insana benzer özelliklerinin seviyesi (Fernandes & Oliveira, 2021; Wirtz, vd., 2018)
İnovasyon Beklentisi	İş adayları tarafından kurumun yeni teknolojileri kullanmasıyla ilişkili algılanan yenilik derecesi (Ochmann & Laumer, 2020)
Karmaşıklık	İşe alımda kullanılan yapay zeka uygulamalarının işlevselliğinin ne ölçüde dar veya geniş kriter değerlendirmesine dayandığı (Schick & Fischer, 2021)
Kişilerarası Tedavi	İş adaylarının saygı, haysiyet ve insani sıcaklıkla muamele görme duyguları (Langer, König ve Krause, 2017; Bauer, vd., 2001; Gilliland, 1993)
Tutarlılık	İnsanlar arasında ve zaman içinde YZ tabanlı işe alımlarda karar prosedürlerinin tutarlılık derecesi ve önyargısız olması (Langer, König ve Papathanasiou, 2019; Bauer, vd., 2001; Gilliland, 1993)
Performans Gösterme Fırsatı	İş adaylarının ellerinden gelenin en iyisini yapabilmeleri için kendilerine yeterli imkanın sunulduğuna dair duyguları (Langer, König ve Krause, 2017; Bauer ve diğerleri, 2001; Gilliland, 1993)
Sosyal Yetenek	Yapay zeka tabanlı işe alım robotunun etkileşimli iletişim kurma, cana yakın olma, uygun şekilde yanıt verme ve sözünü kesmeden dinleme gibi kişilerarası ilişkilere girme konusundaki sosyal becerilerinin derecesi (Song ve Kim, 2022; de Ruyter, Saini, Markopoulos ve van Breemen, 2005; Song ve Kim, 2020)

APPENDIX I

THE CONSOLIDATED RESULT OF THE FIRST ROUND OF THE EXPERT PANEL ANALYSIS

	Participants										
Factor	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Fairness	10	8	8	0	10	10	0	9	10	10	75
Trust	8	3	10	4	9	7	8	2	9	6	66
Two-way Communication	9	0	9	0	0	9	0	5	5	7	44
Interpersonal Treatment	0	10	7	0	6	0	7	0	8	0	38
Creepiness	0	6	5	9	2	8	6	0	0	1	37
Consistency	7	9	0	8	0	4	1	0	4	2	35
Privacy Concerns	3	0	3	6	8	1	9	0	0	4	34
Anxiety	0	7	0	10	0	0	0	0	0	8	25
Complexity	5	1	1	2	0	5	4	3	2	0	23
Perceived Innovativeness	0	0	0	5	5	0	3	1	0	9	23
Social Capability	2	2	0	7	1	0	0	0	0	5	17
Anticipated Service Quality	0	0	6	0	3	0	0	8	0	0	17
Attitude	0	0	0	0	0	0	10	0	6	0	16
Resistance	6	5	4	0	0	0	0	0	0	0	15
Innovation Expectancy	0	0	0	0	0	6	0	6	1	0	13
Opportunity to Perform	4	0	0	0	0	0	0	0	7	0	11
Perceived Behavioral Control	0	0	0	1	4	3	2	0	0	0	10
Organizational Attractiveness	0	0	2	0	0	0	0	4	3	0	9
Perceived Self-Efficacy	0	0	0	0	7	0	0	0	0	0	7
Perceived Humanness	0	0	0	0	0	0	0	7	0	0	7
Subjective Norm	0	0	0	0	0	2	5	0	0	0	7
Social Presence	0	4	0	0	0	0	0	0	0	0	4
Satisfaction	1	0	0	3	0	0	0	0	0	0	4
											AVR:23

APPENDIX J

THE CONSOLIDATED RESULT OF THE SECOND ROUND OF THE EXPERT PANEL ANALYSIS

	Participants										
Factor	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Fairness	5	3	3	0	5	5	0	4	5	5	35
Trust	3	0	5	0	4	2	4	2	4	1	25
Two-way Communication	4	0	4	0	0	4	0	5	0	2	19
Privacy Concerns	0	0	0	2	3	0	5	0	2	3	15
Creepiness	0	1	0	4	2	3	1	3	1	0	15
Interpersonal Treatment	0	5	2	0	1	0	3	0	3	0	14
Consistency	2	4	1	3	0	0	0	0	0	0	10
Anxiety	0	2	0	5	0	0	0	0	0	0	7
Complexity	0	0	0	1	0	0	0	0	0	4	5
Perceived Innovativeness	0	0	0	0	0	1	2	1	0	0	4
											AVR:15

APPENDIX K

MEASUREMENT ITEMS FOR EACH CONSTRUCT WITH REFERENCES

Construct	Item Code	Item	Reference
Performance Expectancy	PE1	I find AI tools useful in the recruitment process.	(Venkatesh, Thong, & Xu, 2012)
	PE2	AI tools will speed up the recruitment process.	(Venkatesh, Thong, & Xu, 2012)
	PE3	AI tools will increase the efficiency of the recruitment process.	(Venkatesh, Thong, & Xu, 2012)
Effort Expectancy	EE1	My interaction with the AI-powered recruitment robot would be clear and understandable.	(Venkatesh, Thong, & Xu, 2012)
	EE2	I would find it easy to interact with the AI-assisted recruitment robot.	(Venkatesh, Thong, & Xu, 2012)
	EE3	It is very easy for me to become skilled in interacting with the AI-powered recruitment robot.	(Venkatesh, Thong, & Xu, 2012)
Social Influence	SI1	People who are important to me would think that I should apply for a job position practicing AI-based recruitment.	(Venkatesh, Thong, & Xu, 2012)
	SI2	People who have influence over my behavior would think I should apply for a job position with AI-based recruitment.	(Venkatesh, Thong, & Xu, 2012)
	SI3	People whose opinions I value would prefer that I apply for a job position with AI-based recruitment.	(Venkatesh, Thong, & Xu, 2012)
Facilitating Conditions	FC1	I need to have the necessary resources to take part in AI-based recruitment.	(Venkatesh, Thong, & Xu, 2012)
	FC2	I need to have the necessary knowledge to take part in AI-based recruitment.	(Venkatesh, Thong, & Xu, 2012)
	FC3	When I struggle in an AI-based interview, I feel the need to seek help from others.	(Venkatesh, Thong, & Xu, 2012)
Hedonic Motivation	HM1	It would be fun to be involved in an AI-based recruitment process.	(Venkatesh, Thong, & Xu, 2012)
	HM2	It would be enjoyable to be involved in an AI-based recruitment process.	(Venkatesh, Thong, & Xu, 2012)

	HM3	It would be very entertaining to be involved in an AI-based recruitment process.	(Venkatesh, Thong, & Xu, 2012)
Creepiness	C1	I would feel uneasy during an AI-based interview.	(Langer, König, & Krause, 2017)
	C2	I would have unspeakable fear during an AI-based interview.	(Langer, König, & Krause, 2017)
	C3	I would not know exactly how to behave during an AI-based interview.	(Langer, König, & Krause, 2017)
Trust	T1	AI tools are trustworthy.	(Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Gefen, Karahanna, & Straub, 2003)
	T2	I trust AI tools even though I know very little about them.	(Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Gefen, Karahanna, & Straub, 2003)
	T3	AI tools can provide an accurate assessment of candidates for hire.	(Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020; Gefen, Karahanna, & Straub, 2003)
Privacy Concerns	PC1	I would have doubts over the confidentiality of my interactions with an AI-powered recruitment robot.	(Pitardi & Marriott, 2021; McLean & Osei-Frimpong, 2019)
	PC2	I am concerned that my personal information stored in the AI-based recruitment process could be stolen.	(Pitardi & Marriott, 2021; McLean & Osei-Frimpong, 2019)
	PC3	I would be concerned that the AI-driven recruitment robot would collect too much information about me.	(Pitardi & Marriott, 2021; McLean & Osei-Frimpong, 2019)
Two-way Communication	TC1	The AI-based recruitment process would make it possible for me to ask all my questions about the process.	(Langer, König, & Krause, 2017; Bauer, et al., 2001)
	TC2	There will be enough communication in the AI-based recruitment process.	(Langer, König, & Krause, 2017; Bauer, et al., 2001)

	TC3	I would feel comfortable asking questions about the AI-based recruitment process if I had any.	(Langer, König, & Krause, 2017; Bauer, et al., 2001)
Fairness	F1	All things considered; this AI-based recruitment procedure would be fair.	(Langer, König, & Krause, 2017)
	F2	I think this AI-based recruitment is a fair procedure to select someone for the job.	(Langer, König, & Krause, 2017)
	F3	I think the AI-based recruitment procedure would be fair.	(Langer, König, & Krause, 2017)
Behavioral Intention to Participate	BIP1	I would participate in AI-based recruitment.	(Venkatesh, Thong, & Xu, 2012)
	BIP2	I would like to participate in AI-based recruitment often.	(Venkatesh, Thong, & Xu, 2012)
	BIP3	I hope to participate in AI-based recruitment in the future.	(Venkatesh, Thong, & Xu, 2012)

APPENDIX L

THE ENGLISH VERSION OF THE QUESTIONNAIRE

Dear participant,

This questionnaire form is designed to provide data for the master's thesis on "Acceptance of Artificial Intelligence Based Recruitment Among Candidates", which is conducted under the supervision of Prof. Dr. Sevgi Özkan Yıldırım within the scope of Information Systems Master's Program offered by Middle East Technical University, Department of Information Systems.

The data to be obtained in the research will be used entirely for academic purposes and will not be shared with any person or organization other than the researchers.

This questionnaire does not include any personal or organizational identifying questions. The questionnaire consists of two parts and takes approximately 10 minutes. Answering the questions in the questionnaire completely and accurately is extremely important for the validity of the research.

Thank you for your contribution to the research.
Researcher Büşra Aydemir
E-mail:

I have read the above information and agree to participate in this study voluntarily. ☐

A. Write the information requested below correctly in the relevant fields.

Birth Year: ____

Gender:

Female ☐

Male ☐

Education Status:

High School ☐

University ☐

Master’s Degree ☐

PhD ☐

Number of recruitments you have participated in before:

0 ☐

Between 1 and 4 ☐

4 and above ☐

Have you ever had a job application experience where you had an interview with a robot, conducted with artificial intelligence applications from start to finish?

Yes ☐

No ☐

Your level of social media use

Never ☐

Once a week ☐

Every 2-3 days ☐

1 hour a day ☐

Over 1 hour a day ☐

Your level of following technology news and technological innovations:

I learn when I have to use it, when I need it. ☐

I learn by seeing or hearing from my environment. ☐

I learn by following and researching regularly. ☐

Are you familiar with the concept of artificial intelligence?

Yes ☐

No ☐

Which of the following terms related to artificial intelligence do you know?

Machine learning ☐

Natural language processing ☐

Artificial neural networks ☐

Expert systems ☐

Image processing ☐

Face and voice recognition ☐

Deep learning ☐

Other ☐

None ☐

B. Read the recruitment scenario carefully and indicate whether you agree or disagree with the following statements according to your own opinion by marking a score between 1 and 5.

Recruitment scenario: In the recruitment scenario within the scope of this research, the job advertisement is announced to candidates via social media and the organization's website, and resume information is collected through the format provided in the link. The resumes are scanned by untouched artificial intelligence and the candidates are sent an online exam link and a personality inventory test after being matched based on the criteria previously determined for the job position. After the tests are completed, interview invitations are automatically sent to a certain number of candidates based on personality matches and exam scores. Candidates can schedule the interview date and time from the calendar application on the organization's website. In the final stage, artificial recruitment robots interview candidates, calculate the percentage of accuracy of their answers to questions based on predefined answers, and analyze their tone of voice and facial expressions. At the end of the interviews, candidates are notified of their hiring results by human resources employees by phone.

Factor	**Question**	**1. Strongly Disagree**	**2.Disagree**	**3. Neither Agree nor Disagree**	**4. Agree**	**5. Strongly Agree**
Performance Expectation	I find AI tools useful in the recruitment process.					
	AI tools will speed up the recruitment process.					
	AI tools will increase the efficiency of the recruitment process.					
Effort Expectation	My interaction with the AI-powered recruitment robot would be clear and understandable.					
	I would find it easy to interact with the AI-assisted recruitment robot.					
	It is very easy for me to become skilled in interacting with the AI-powered recruitment robot.					
Social Impact	People who are important to me would think that I should apply for a job position practicing AI-based recruitment.					
	People who have influence over my behavior would think I should apply for a job position with AI-based recruitment.					
	People whose opinions I value would prefer that I apply for a job position with AI-based recruitment.					

Facilitating Conditions	I need to have the necessary resources to take part in AI-based recruitment.					
	I need to have the necessary knowledge to take part in AI-based recruitment.					
	When I have difficulty in an AI-based interview, I feel the need to seek help from others.					
Hedonic Motivation	It would be fun to be involved in AI-based recruitment.					
	It would be enjoyable to be involved in an AI-based recruitment process.					
	It would be fun to be involved in an AI-based recruitment process.					
Creepiness	I would feel uneasy during an AI-based interview.					
	I would have unspeakable fear during an AI-based interview.					
	I would not know exactly how to behave during an AI-based interview.					
Trust	AI tools are reliable.					
	I trust AI tools, even though I know very little about them.					
	AI tools can provide an accurate assessment of candidates for hire.					
Privacy Concerns	I would have doubts about the confidentiality of my interactions with an AI-powered recruitment robot.					
	I would be concerned that my personal information stored in the AI-based recruitment process could be stolen.					
	I would be concerned that the AI-driven recruitment robot would collect too much information about me.					
Two-Way Communication	The AI-based recruitment process would make it possible for me to ask all my questions about the process.					
	There will be satisfactory communication in the AI-based recruitment process.					
	If I had a question, I would feel comfortable asking about the AI-based recruitment process.					

Fairness	All things considered; this AI-based recruitment procedure would be fair.					
	I think this AI-based recruitment is a fair procedure to select someone for the job.					
	I think the AI-based recruitment procedure would be fair.					
Behavioral Intention to Participate	I would participate in AI-based recruitment.					
	I would like to participate in AI-based recruitment often.					
	I hope to participate in AI-based recruitment in the future.					

APPENDIX M

THE TURKISH VERSION OF THE QUESTIONNAIRE

Sayın katılımcı,

Bu anket formu; Orta Doğu Teknik Üniversitesi Bilişim Sistemleri Ana Bilim Dalı tarafından sunulan Bilişim Sistemleri Yüksek Lisans Programı kapsamında Prof. Dr. Sevgi Özkan Yıldırım danışmanlığı ile yürütülen "Adaylar Arasında Yapay Zeka Tabanlı İşe Alımın Kabulü" konulu yüksek lisans tezine veri sağlamak amacıyla oluşturulmuştur.

Araştırmada elde edilecek olan veriler tamamen akademik amaçla kullanılacak olup araştırmacılar dışında hiçbir kişi ya da kurum ile paylaşılmayacaktır.

Bu ankette kişisel veya kurumsal tanımlayıcı hiçbir soru yer almamaktadır. İki bölümden oluşan anket yaklaşık 10 dakika sürmektedir. Ankette yer alan soruların eksiksiz ve doğru bir şekilde yanıtlanması araştırmanın geçerliliği açısından son derece önemlidir.

Araştırmaya sağlayacağınız katkı için teşekkürler.
Araştırmacı: Büşra Aydemir
E-posta:

Yukarıdaki bilgileri okudum ve bu araştırmaya gönüllü olarak katılmayı kabul ediyorum. ☐

C. Aşağıda istenen bilgileri doğru bir şekilde ilgili alanlara yazınız.

Doğum yılınız: ____

Cinsiyetiniz:

Kadın ☐

Erkek ☐

Eğitim Durumunuz

Lise ☐

Üniversite ☐

Yüksek Lisans ☐

Doktora ☐

Daha önce katıldığınız işe alım mülakat sayısı:

0 ☐

1 le 4 arası ☐

4 ve üzeri ☐

Daha önce robotla mülakat gerçekleştirdiğiniz, baştan sona yapay zeka uygulamaları ile yürütülen bir iş başvurusu tecrübeniz oldu mu?

Evet ☐

Hayır ☐

Sosyal medya kullanım düzeyiniz:

Hiç ☐

Haftada bir ☐

2-3 günde bir ☐

Günde 1 saat ☐

Günde 1 saat üzeri ☐

Teknoloji haberlerini ve teknolojik yenilikleri takip etme düzeyiniz:

Kullanmak zorunda kaldığımda, ihtiyacım olduğunda öğrenirim. ☐

Çevremden görerek veya duyarak öğrenirim. ☐

Düzenli olarak takip ederek ve araştırarak öğrenirim. ☐

Yapay zeka kavramını biliyor musunuz?

Evet ☐

Hayır ☐

Yapay zekaya ilişkin aşağıdaki terimlerden hangilerini biliyorsunuz?

Makine öğrenmesi ☐

Doğal dil işleme ☐

Yapay sinir ağları ☐

Uzman sistemler ☐

Görüntü işleme ☐

Yüz ve ses tanıma ☐

Derin öğrenme ☐

Diğer ☐

Hiçbiri ☐

D. **Araştırma konusu işe alım senaryosunu dikkatli bir şekilde okuyarak aşağıda verilen ifadelere kendi düşüncenize göre katılıp katılmadığınızı 1 ile 5 arasında bir puan işaretleyerek belirtiniz.**

İşe alım senaryosu: Bu araştırma kapsamındaki işe alım senaryosunda iş ilanı sosyal medya ve kurum websitesi aracılığıyla adaylara duyurulmakta, sağlanan linkteki format üzerinden özgeçmiş bilgileri toplanmaktadır. Özgeçmişler el değmeden yapay zeka aracılığıyla taranmakta ve daha önce iş pozisyonu için belirlenmiş kriterler üzerinden eşleştirme yapılarak adaylara çevrim içi sınav linki ve kişilik envanteri testi gönderilmektedir. Testlerin tamamlanmasının ardından kişilik eşleşmeleri ve sınav skoru üzerinden belli sayıda adaya mülakat daveti otomatik olarak gönderilmektedir. Adaylar kurum websitesindeki takvim uygulamasından mülakat tarih ve saatini planlayabilmektedir. Son aşamada yapay işe alım robotları, adaylarla mülakat yaparak daha önce tanımlanmış cevaplar üzerinden adayların sorulara verdikleri cevapların doğruluk yüzdesini hesaplamakta ve ses tonu ile mimik analizi yapmaktadır. Mülakatlar sona erdiğinde adayların işe alım sonuçları kendilerine insan kaynakları çalışanları tarafından telefonla bildirilmektedir.

Faktör	**Soru**	**1. Hiç Katılmıyorum**	**2. Katılmıyorum**	**3. Kararsızım**	**4. Katılıyorum**	**5. Tamamen Katılıyorum**
Performans Beklentisi	Yapay zeka araçlarını işe alım sürecinde faydalı bulurum.					
	Yapay zeka araçları işe alım sürecini hızlandıracaktır.					
	Yapay zeka araçları, işe alım sürecinin verimliliğini artıracaktır.					
Çaba Beklentisi	Yapay zeka destekli işe alım robotu ile etkileşimim açık ve anlaşılır olacaktır.					
	Yapay zeka destekli işe alım robotuyla etkileşimi kolay bulurdum.					
	Yapay zeka destekli işe alım robotuyla etkileşim kurma konusunda beceri sahibi olmak benim için çok kolay.					
Sosyal Etki	Benim için önemli olan insanlar, yapay zeka tabanlı işe alım uygulayan bir iş pozisyonuna başvurmam gerektiğini düşünür.					
	Davranışlarım üzerinde etkisi olan insanlar, yapay zeka tabanlı işe alım uygulayan bir iş pozisyonuna başvurmam gerektiğini düşünürler.					
	Fikirlerine değer verdiğim insanlar, yapay zeka tabanlı işe alım uygulayan bir iş pozisyonuna başvurmamı tercih ederler.					

Kolaylaştırıcı Koşullar	Yapay zeka tabanlı işe alımda yer almak için gerekli kaynaklara sahip olmam gerekiyor.					
	Yapay zeka tabanlı işe alımda yer almak için gerekli bilgiye sahip olmam gerekiyor.					
	Yapay zeka tabanlı mülakatta zorlandığım zaman başkalarından yardım alma ihtiyacı duyarım.					
Hedonik Motivasyon	Yapay zeka tabanlı işe alım sürecine dahil olmak eğlenceli olacaktır.					
	Yapay zeka tabanlı işe alım sürecine dahil olmak keyifli olacaktır.					
	Yapay zeka tabanlı işe alım sürecine dahil olmak çok eğlenceli olurdu.					
Ürperticilik	Yapay zeka tabanlı görüşme sırasında kendimi huzursuz hissederdim.					
	Yapay zeka tabanlı görüşme sırasında tarifsiz bir korkum olur.					
	Yapay zeka tabanlı görüşmede tam olarak nasıl davranacağımı bilemezdim.					
Güven	Yapay zeka araçları güvenilirdir.					
	Onlar hakkında çok az bilgim olsa da yapay zeka araçlarına güvenirim.					
	Yapay zeka araçları, işe alınacak adayların doğru bir şekilde değerlendirilmesini sağlayabilir.					
Gizlilik Endişesi	Yapay zeka destekli işe alım robotuyla etkileşimlerimin gizliliği konusunda şüphelerim olurdu.					
	Yapay zeka tabanlı işe alım sürecinde saklanan kişisel bilgilerimin çalınabileceğinden endişe duyarım.					
	Yapay zeka destekli işe alım robotunun benim hakkımda çok fazla bilgi toplamasından endişe duyarım.					
İki Yönlü İletişim	Yapay zeka tabanlı işe alım süreci, süreçle ilgili tüm sorularımı sormamı mümkün kılardı.					
	Yapay zeka tabanlı işe alım sürecinde tatmin edici bir iletişim olacaktır.					
	Bir sorum varsa, yapay zeka tabanlı işe alım süreci hakkında soru sormak konusunda rahat hissederdim.					

Adillik	Her şey düşünüldüğünde, bu yapay zeka tabanlı işe alım prosedürü adil olacaktır.					
	Bence bu yapay zeka tabanlı işe alım, işe birilerini seçmek için adil bir prosedür.					
	Yapay zeka tabanlı işe alım prosedürünün adil olacağını düşünüyorum.					
Davranışsal Katılım Niyeti	Yapay zeka tabanlı işe alım sürecine katılırdım.					
	Yapay zeka tabanlı işe alım sürecine sık sık katılmak isterim.					
	Gelecekte yapay zeka tabanlı işe alım sürecine katılmayı umuyorum.					

APPENDIX N

PILOT STUDY CRONBACH'S ALPHA VALUES AND THE RELIABILITY RESULTS FOR EACH ITEM

Construct	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Item	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PE	.830	.830	PE1	7.66	2.384	.711	.515	.743
			PE2	7.18	2.497	.718	.522	.736
			PE3	7.55	2.813	.642	.413	.810
EE	.728	.725	EE1	7.00	2.563	.497	.325	.704
			EE2	6.97	1.999	.698	.487	.442
			EE3	6.71	2.835	.475	.303	.725
SI	.891	.893	SI1	6.57	3.749	.777	.697	.854
			SI2	6.42	3.340	.874	.780	.765
			SI3	6.25	3.532	.716	.557	.909
FC	.701	.742	FC1	7.11	2.191	.652	.612	.480
			FC2	7.14	2.152	.618	.604	.505
			FC3	7.78	1.953	.367	.137	.872
HM	.920	.920	HM1	7.431	3.624	.737	.557	.962
			HM2	7.508	3.066	.915	.882	.822
			HM3	7.554	2.845	.877	.866	.854
C	.850	.850	C1	5.523	4.160	.664	.444	.841
			C2	5.785	3.922	.762	.590	.749
			C3	5.308	3.966	.732	.559	.777
T	.802	.808	T1	6.91	2.366	.749	.632	.634
			T2	6.98	2.234	.703	.611	.671
			T3	6.69	2.529	.515	.271	.873
PC	.862	.865	PC1	6.62	4.209	.748	.560	.800
			PC2	6.62	4.240	.738	.546	.809
			PC3	6.58	3.653	.740	.549	.812
TC	.828	.829	TC1	6.88	2.953	.742	.552	.703
			TC2	6.95	3.107	.688	.488	.761
			TC3	6.48	3.816	.641	.420	.809
F	.930	.930	F1	7.323	2.566	.834	.704	.915
			F2	7.415	2.465	.847	.730	.905
			F3	7.446	2.376	.887	.787	.872
BIP	.740	.743	BIP1	7.25	2.720	.593	.365	.631
			BIP2	7.82	2.215	.607	.384	.605
			BIP3	7.28	2.672	.508	.258	.720

APPENDIX O

THE RELIABILITY AND VALIDITY RESULTS AFTER THE MODIFICATION OF THE MODEL INCLUDING ONLY UTAUT2 CONSTRUCTS

Standardized Factor Loadings					
	PEE	SI	HM	FC	BIP
PE1	0.762				
PE2	0.737				
PE3	0.784				
EE1	0.798				
EE2	0.804				
EE3	0.667				
SI1		0.894			
SI2		0.883			
HM2			0.946		
HM3			0.863		
FC1				0.814	
FC2				0.920	
BIP1					0.759
BIP2					0.736
BIP3					0.815
Reliability Results and AVE Values					
	Cronbach's alpha (standardized)	Cronbach's alpha (unstandardized)	Composite Reliability	Average Variance Extracted (AVE)	
BIP	0.812	0.811	0.815	0.594	
FC	0.856	0.856	0.859	0.754	
HM	0.899	0.898	0.899	0.820	
PEE	0.889	0.889	0.891	0.578	
SI	0.882	0.882	0.882	0.790	
Discriminant Validity (Fornell-Larcker Criterion)					
	BIP	FC	HM	PE	SI
BIP	**0.771**				
FC	0.282	**0.868**			
HM	0.751	0.442	**0.905**		
PEE	0.748	0.406	0.741	**0.760**	
SI	0.639	0.313	0.569	0.600	**0.889**