

T.R.
GEBZE TECHNICAL UNIVERSITY
GRADUATE SCHOOL

**THE EFFECTS OF ARTIFICIAL INTELLIGENCE AND
ROBOTICS ON WORKING ENVIRONMENT**



GÖZDE DÖVEN

A THESIS OF DOCTORATE
DEPARTMENT OF BUSINESS ADMINISTRATION

ADVISOR: PROF. DR. BÜLENT SEZEN

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LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

YAPAY ZEKA VE ROBOTLARIN ÇALIŞMA ORTAMI
ÜZERİNDEKİ ETKİLERİ

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ABSTRACT

This research aims to determine how prepared office professionals are to accept robots as co-workers and offer guidance to organisations and robot developers on promoting robot acceptance in the near future of the Industry 5.0 era. Using the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT), the study explores how professionals accept robots in office environments, focusing on perceived sociability as an extension of this framework. Participants from Türkiye and the United Kingdom participated in the study to examine differences in robot adoption. A structured questionnaire, focused on working professionals in office settings, was used to gather data. It asked about demographics, robot usage or intention to use, and preferences for robot appearance. Two studies are derived from this data. Study one analysed robot co-worker preferences in the office environment by professionals. The results of this study verified the Theory of Uncanny Valley. In Study 2, a comparative method was used between the two countries, utilising three datasets. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse the data using the UTAUT framework. The results show that Performance Expectancy, Effort Expectancy, Social Influence, and Perceived Sociability are key factors that influence Behavioural Intentions to use robots. According to the findings of this study, robots may be allowed to work in offices in the future, and human-robot co-working may lead to renewed workflows in organisations. The findings provide practical guidance for designing socially engaging robots and implementing them in various work environments. Future research directions include broadening the cultural focus and applying qualitative techniques to examine further elements that may enhance our understanding of robot acceptance.

Keywords: Industry 5.0, Human-Robot Co-working, UTAUT, Robot Acceptance, Perceived Sociability, Office Environment

ÖZET

Bu çalışmanın amacı, Endüstri 5.0'a yakın olduğumuz bu dönemde, ofis çalışanlarının robotları iş arkadaşları olarak kabul etmeye ne kadar hazır olduklarını belirlemektir. Ayrıca, robot geliştiricilere ve organizasyonlara robotları işe alma konusunda rehberlik sağlamak olacaktır. Çalışma, Birleşik Teknoloji Kabul ve Kullanım Teorisi (UTAUT) çerçevesini kullanarak, çalışma profesyonellerin ofis ortamlarında robotları nasıl kabul ettiklerini, bu çerçevenin bir uzantısı olarak algılanan sosyallik üzerine odaklanarak araştırmaktadır. Türkiye ve Birleşik Krallık'tan katılımcılar, robot benimsemedeki farklılıkları incelemek için çalışmaya katıldılar. Ofis ortamlarındaki çalışan profesyonellere odaklanan yapılandırılmış bir anket, veri toplamak için kullanıldı. Demografik bilgiler, robot kullanımı veya kullanma niyeti ve robot görünümüne yönelik tercihleri sordu. Bu verilerden iki çalışma türetilmiştir. Birinci çalışma, profesyoneller tarafından ofis ortamında robot iş arkadaşları tercihlerini analiz etti. İlk çalışmanın bulguları, Tekinsiz Vadi Teorisi'ni destekledi. İkinci çalışmada üç veri seti kullanılarak iki ülke arasında karşılaştırmalı bir yöntem kullanıldı. Verileri UTAUT çerçevesini kullanarak analiz etmek için Kısmi En Küçük Kareler Yapısal Eşitlik Modellemesi (PLS-SEM) kullanıldı. Sonuçlar, Performans Beklentisi, Çaba Beklentisi, Sosyal Etki ve Algılanan Sosyallik gibi faktörlerin robotları kullanma davranışsal niyetlerini etkileyen anahtar faktörler olduğunu göstermektedir. Bu çalışmanın sonuçlarına göre, robotlar gelecekte ofislerde çalışabilir ve organizasyonlarda insan-robot ortak çalışması, iş akışlarının yenilenmesine neden olabilir. Bulgular, sosyal olarak etkileşimli robotlar tasarlamak ve bunları çeşitli çalışma ortamlarında uygulamak için pratik rehberlik sağlamaktadır. Gelecek araştırmalar, kültürel odaklanmayı artırmayı ve robot kabulünü daha iyi anlamak için nitel yöntemler kullanmayı içerebilir.

Anahtar Kelimeler: Endüstri 5.0, Robot İş Arkadaşı, UTAUT, Robot Kabulü, Algılanan Sosyallik, Ofis Ortamı

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	: Artificial Intelligence
AVE	: Average variance extracted
CASA	: Computers Are Social Agents
CFA	: Confirmatory Factor Analysis
GTU	: Gebze Technical University
HRI	: Human-Robot Interaction
HTMT	: HeteroTrait-Monotrait Ratio of Correlations
SEM	: Structural Equation Modelling
SIoT	: Social Internet of Things
SMC	: Squared Multiple Correlation
SRMR	: Standardised Root-Mean-square Residual
TAM	: Technology Acceptance Model
TR	: Türkiye
TRA	: Theory of Reasoned Action
UK	: United Kingdom
UTAUT	: Unified Theory of Acceptance and Use of Technology
WoS	: Web of Science
USA	: United States of America
U.S.C.	: United States Codes

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1. INTRODUCTION

1.1. Background

Although there was a century-long time gap between the first three Industrial Revolutions, the duration between 3.0 and 4.0 was around half of the previous revolutions. Figure 1.1 illustrates the Industrial Revolutions from 1.0 to 5.0, highlighting important inventions and subjects. Given technological improvements, we are quite close to Industry 5.0 (Demir et al., 2019). One of the main goals of Industry 5.0 is to have a Human-Centric working environment (Liao et al., 2023). The others are sustainability and resilience (Ivanov, 2023). It could be achieved when the 3D tasks, which are Dirty, Dangerous, and Dull, are given to the robots (Demir et al., 2019). The economy and working environments in many sectors are already being significantly impacted by the ongoing artificial intelligence (AI) revolution, which is being driven by advancements in large language models (LLMs) and generative AI programs (Thormundsson, 2024). To prevent humans from performing no-added-value tasks, Generative AI technology should improve the skills and abilities of the robots (Wirtz and Stock-Homburg, 2025).

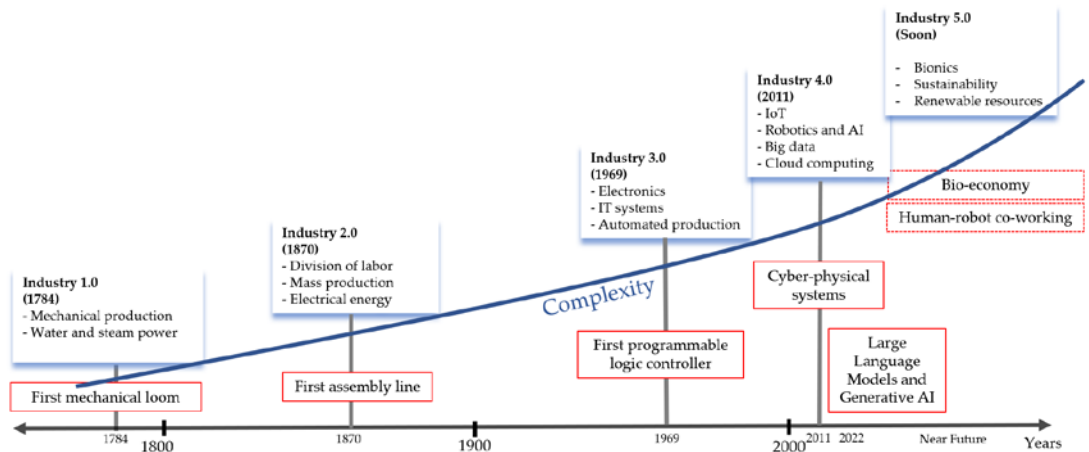


Figure 1.1: Industrial Revolutions from 1.0 to 5.0, Adapted and Improved from (Demir et al., 2019)

Industry 5.0 has received significant attention and has been the focus of numerous studies in recent years (Maddikunta et al., 2022). Industry 5.0 emphasises more resilient, sustainable, and human-centric organisations, while Industry 4.0's main objective is to be technology-centric (X. Xu et al., 2021). Industry 5.0 is a paradigm that "places the well-being of the worker at the centre of the production process and uses new technologies to provide prosperity beyond jobs and growth while respecting the production limits of the planet," according to the European Commission (Web 3, 2024). There are the core distinctions between the principles of Industry 4.0 (I4.0) and Industry 5.0 (I5.0) below (Dhanda et al., 2025; Maddikunta et al., 2022; Wang et al., 2023):

- In I4.0, the "Information" has transformed to the "Intelligence" in I5.0,
- In I4.0, "Communication" has transformed to "Connectivity" in I5.0,
- In I4.0, the "System" has transformed to the "Social System" in I5.0.

Co-working and human-robot interaction at the organisational level can reduce non-added-value tasks and put people at the centre of the work organisation, which will increase their creativity (X. Xu et al., 2021). There is an illustrative human bias example that when a robot interviewer did the face-to-face job interview, the interview was perceived as fairer by both introverted and extraverted applicants (Nørskov et al., 2020).

A previous study in 2020 investigated the use of a greeting robot with limited abilities in an office environment among professionals, examining the reactions and perceptions of office workers towards the robot (Okafuji et al., 2020). It concluded that social influence was important, in particular, an individual's attention to the robot prompted group interaction. The sociability of the robot, such as greetings, increased worker attention, and facilitated the initiation of human-human conversation.

The European Commission has been researching into the possibilities and implications of Industry 5.0 in the 27 European Union member states (Web 3, 2024). Their investigation, which was named the Special Eurobarometer 554, Artificial Intelligence and the Future of Work, found that more than 60% of respondents had a positive opinion of the use of robots and artificial intelligence in the workplace as co-workers, and they thought that robots and Artificial Intelligence tools are helpful to do the jobs that are considered as boring or repetitive (Web 1, 2025). Moreover, robots have

recently undergone a metamorphosis, following the progress in Generative AI and Large Language Models (LLMs). Before 2022, robots were programmed to think and move using machine learning, which involves algorithms learning patterns from data, and/or deep learning, which simulates human brain processing in neural networks. Nowadays, they can think and act using generative AI, which creates new, individual content. With these technological improvements, robots have produced non-code programming (Wirtz and Stock-Homburg, 2025). Due to these recent technological advancements, the development of robots in various areas of human life is expected to grow more rapidly (Demir et al., 2019).

1.2. Contributions of this Research

This research contributes to the literature on robots in the office environment and responds to investigations of professionals' behavioural intentions regarding working with robot co-workers in an office environment. As one of the first studies to examine robot acceptance in an office environment, this research is important because it will guide similar studies, particularly in light of the technological advancements in robotics and the evolving paradigm as we approach Industry 5.0. According to this study, office environments across various locations may be open to accepting robots. Naturally, the study needs to be expanded to other nations with diverse cultures to ascertain whether robot acceptance will be universal.

1.3. Overview of the Dissertation

The research includes two studies.

The first study aims to provide an understanding of the perception of which robot appearance is preferred as a co-worker.

The second study aims to understand the intention to use the robot (Named ADA7) as a co-worker in an office environment.

1.4. Statement of the Problem

During COVID-19, the application of robots in front-office services was limited as managers lacked knowledge concerning the level of development of robots' artificial

intelligence systems, and therefore lacked the necessary expertise to properly implement robots successfully (Forgas-Coll et al., 2022). Despite the successful implementation of robots in easily automatable jobs in healthcare, education, and hospitality environments, as mentioned in Chapter 2, robots in front-office settings require more advanced social intelligence skills for Human-Robot Interaction (Andriella et al., 2020).

The problem is that the acceptance of robots as co-workers in an office environment is not considered in the literature.

1.5. Significance of the Problem

This research is significant as it is one of the early studies investigating robot acceptance in an office work environment, and it will guide similar future studies.

1.6. Research Hypotheses

This research comprises four main hypotheses. Hypothesis 2 consists of two hypotheses, H2a and H2b, which aim to understand how Effort Expectancy influences Performance Expectancy and Behavioural Intention to use the robot in office environments.

These are shown below.

H1: Performance Expectancy (PE) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

H2a: Effort Expectancy (EE) is significantly related to Performance Expectancy (PE) in an office environment.

H2b: Effort Expectancy (EE) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

H3: Social Influence (SI) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

H4: Perceived Sociability (PS) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

1.7. Research Overview

1.7.1. Research Questions

In this context, the research questions (RQs) were formed as follows:

RQ1: Are office professionals accepting robots for human-robot co-working in the near future?

RQ2: Are the robot acceptance statistics similar in different locations for human-robot co-working in office environments?

1.7.2. Research Strategy

Due to the research questions, the study 2 is conceptualised as a structural equation model (SEM) that aims to measure the relationship between Performance Expectancy, Effort Expectancy, Social Influence, and Perceived Sociability and the Behavioral Intention to use humanoid service robots as co-workers with Unified Technology Acceptance and Use Theory (UTAUT), which is one of the well-investigated technology acceptance models. It was conducted in the United Kingdom and Türkiye. These countries were chosen from the OECD Better Life Index. Instead of focusing on present emotions, life satisfaction monitors how individuals assess their lives overall. On a scale of 0 to 10, people in the OECD gave their general score of life satisfaction an average score of 6.7 in 2024. In the OECD Better Life Index 2024, Türkiye has a score of 0.0, ranking it among the lowest among OECD countries. The United Kingdom has a score of 6.4, which is in the middle of the scale from 41 countries (Web 4, 2024). Additionally, Türkiye and the UK are not part of the European Union. Therefore, they are not measured under the Special Eurobarometer 554, Artificial Intelligence and the Future of Work.

1.7.3. Research Scope

The scope of this research includes Study 1 (Robot Appearance Preferences) and Study 2 (Testing the Theoretical Model). Study 1 involves understanding the perception of robot colleagues' appearance, and Study 2 aims to determine whether professionals are ready to work with robots in office environments. Additionally, Perceived Sociability

was employed as an extension to the UTAUT framework to investigate the relationship with robot acceptance. Although previous robot acceptance studies have shown no evidence of a relationship with intention to use as a construct of UTAUT (Conti et al., 2017; Forgas-Coll et al., 2022; Han and Conti, 2020; Heerink et al., 2010; Shin and Choo, 2011).

1.8. Assumptions

The assumptions of the measurement activity are given below.

Assumption 1: In this research, it is assumed that robots work as colleagues in an office environment.

Assumption 2: The literature review examined articles that utilised service robots, as described in ISO 7383:2021, and employed the Structural Equation Modelling (SEM) statistical method using Partial Least Squares (PLS).

Assumption 3: Three separate datasets, namely UK, TR, and Complete, have been created from data collected at two different locations, specifically the United Kingdom and Türkiye. These datasets have been tested independently to identify differences in the statistical model, with the assumption that the sample accurately represents the entire demographic of office workers in each country.

Assumption 4: In this research, most survey participants had no experience working with robots, as current office environments lack widespread robot use. Their responses are based on their intentions to use robots, as visualised through the video demonstrating potential robot interactions in the workplace.

1.9. Key Definitions: Artificial Intelligence, Generative AI, Large Language Models, Robot and Robot Types

Artificial Intelligence: According to the United States Code 15 (2023), the term "artificial intelligence" refers to a machine-based system that, for a given set of human-defined goals, can make predictions, recommendations, or decisions that impact real or virtual environments. Particularly, the artificial intelligence (AI) researchers focus on the development of machine-based intelligence as opposed to biologically based intellect (McCarthy, 2007).

Artificial intelligence systems utilise both machine and human-based inputs to;

(A) perceive real and virtual environments;

(B) abstract those perceptions into models through automated analysis; and

(C) use model inference to formulate options for information or action (Web 6, 2023).

Generative Artificial Intelligence (Gen AI): Generative artificial intelligence refers to computational methods able to create apparently new, meaningful content from training data such as text, images, or audio (Feuerriegel et al., 2024). Before the Generative AI and robot integration, robots were mainly used for simple and repetitive tasks, and they had not produced the expected returns in several applications (Knof et al., 2024). As generative artificial intelligence (GenAI) is included in physical service robots, this is expected to change (Wirtz and Stock-Homburg, 2025).

Large Language Models (LLMs): Large Language Models are advanced language models with large parameter sizes and exceptional learning capabilities (M. Chen et al., 2021; Kasneci et al., 2023; Wu et al., 2022). The core module in Transformer is the self-attention module, which revolutionises NLP by efficiently handling sequential data and capturing long-range dependencies (Vaswani et al., 2017). LLMs feature in-context learning, generating coherent, contextually relevant responses suitable for interactive applications, and reinforcement learning from human feedback for continuous improvement (Brown et al., 2020; Christiano et al., 2017; Ziegler et al., 2019).

Robot: A robot is defined as having a control system, a programmed actuation mechanism, and some autonomy for positioning, manipulation, or movement by the International Standards Organisation (ISO) 8373:2021 (Web 5, 2021).

According to ISO 8373:2021, robots are divided into industrial, service, and medical categories based on their intended applications. Their definitions are;

- Industrial robots are machines that are employed for manufacturing functions in manufacturing environments.
- Service robots must execute beneficial tasks for humans or equipment. The two main categories of robots relate to personal and professional tasks.
- Medical robots are designed for use as medical electrical devices or systems.

The classification of tasks performed by service robots, as defined in ISO 8373:2021, is presented in Figure 1.2.

PERSONAL TASKS	PROFESSIONAL TASKS
☐ Handling or serving of items	☐ Handling of items
☐ Transportation	☐ Person transportation
☐ Physical support	☐ Surveillance
☐ Providing guidance or information	☐ Providing guidance or information
☐ Grooming	☐ Inspection
☐ Cooking and food handling	☐ Cooking and food handling
☐ Cleaning	☐ Cleaning

Figure 1.2: Service Robots Task Checklist Adopted from ISO 8373:2021

Although the Service Robot is defined by Wirtz et al. (2018) as communicating, interacting, and delivering a service to the customers of an organisation, the ISO 8373:2021 standard has no borders such as those between customers or workers. Service robots are expected to be used in various environments, particularly workplaces. As the Coronavirus Disease 2019 (COVID-19) pandemic spread, marketers urgently needed to know how to utilise robots to minimise direct contact with consumers (S. S. Park et al., 2021). Since the COVID-19 pandemic, service robots have become increasingly common in various workplaces, working more closely with humans (Saari et al., 2022). This has resulted in increased public awareness of robots.

Compared to other robot types, social robots are expected to interact with humans more naturally and are capable of analysing hearing, visual, and tactile inputs (Peter and Kühne, 2018). Research and development continue for social service robots that can perform personal or professional tasks in a variety of settings, such as healthcare (Alaiad et al., 2014; Alaiad and Zhou, 2014; N. Chen, 2018; Komariyah et al., 2024;

Vichitkraivin and Naenna, 2021; Yeoh and Chin, 2022; Zhang, 2024) education (Guggemos et al., 2020), customer service (Abdelhakim et al., 2023; Kaiser et al., 2024; Kraus et al., 2024; Pande and Gupta, 2023) and offices (Okafuji et al., 2020). Since these environments are often social, social robots are being explored as a potential means to enhance the services provided, including their social capabilities.

According to several Human Computer Interaction (HCI) and Human Robot Interaction (HRI) studies, the best way to communicate with humans is for a machine to express itself in a human-like expression (Breazeal, 2003; Hegel, Muhl, et al., 2009).

1.10. Outline of Dissertation

The content of this thesis is arranged as follows. The relevant academic literature on the acceptance of service robots in working environments is summarised in Chapter 2. The study's conceptual framework and hypotheses are presented in Chapter 3. The survey, data collection stages, sample selection procedure, and analysis methods in the study are discussed in Chapter 4. The results of the analysis are shown in Chapter 5. The results are discussed in Chapter 6. The study's conclusion is presented in Chapter 7. The survey questions for this research are shown in Appendix A.

2. LITERATURE REVIEW

2.1. Theoretical Foundation

Fong et al. (2003) emphasise two important points in social robot design: Firstly, as suggested by DiSalvo et al. (2002), a robot's morphology should be compatible with its intended functions. Secondly, the design of a robot should incorporate a certain degree of "robotness" to prevent the human user from developing harmful misconceptions of the robot's capabilities (Duffy, 2003). In addition, to achieve a positive human-robot interaction, a robot's social behaviours must be consistent with the humans (Walters et al., 2008).

Some studies suggest that humanoid robots are better suited as colleagues in organisations, and their appearance can be a predictor (Destephe et al., 2015; Hegel, Lohse, et al., 2009). Robot anthropomorphism is characterised by making robots human-like (S. Xu et al., 2024). When the degree of anthropomorphism increases, the robot's behaviour should match its appearance to avoid entering the uncanny valley (Mori et al., 2012). The Uncanny Valley curve is illustrated in Figure 2.1.

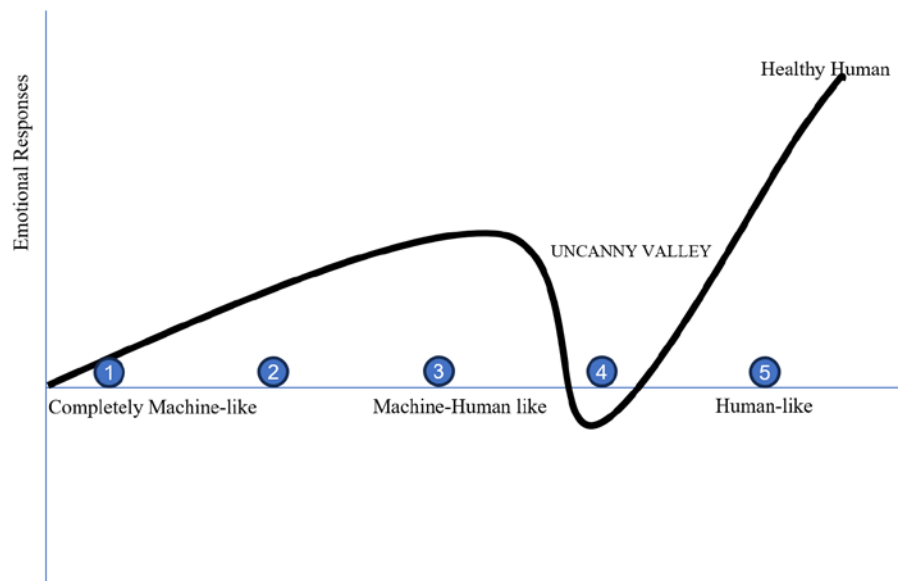


Figure 2.1: The Uncanny Valley (Mori et al., 2012)

Technology Acceptance Models (TAMs), or mixed models depending on the working environment, were the preferred method of many robot acceptance researchers (Cippelletti et al., 2024; Y. Kim, 2023; Saari et al., 2022). The robot acceptance model used in this study is a UTAUT for working professionals in the office. UTAUT can be applied to artificial intelligence tools and is frequently utilised in technology acceptance models for various technology tools (Venkatesh, 2022). Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which provides a comprehensive framework for understanding the variables influencing technology adoption and use. Social Cognitive Theory, Innovation Diffusion Theory, Technology Acceptance Model, Theory of Reasoned Action, Theory of Planned Behaviour, and Model of PC Utilization are just a few of the well-known models and theories that UTAUT incorporates to explain user intentions and behaviours (Venkatesh et al., 2003). Figure 2.2. shows how the UTAUT constructs relate to these theories.

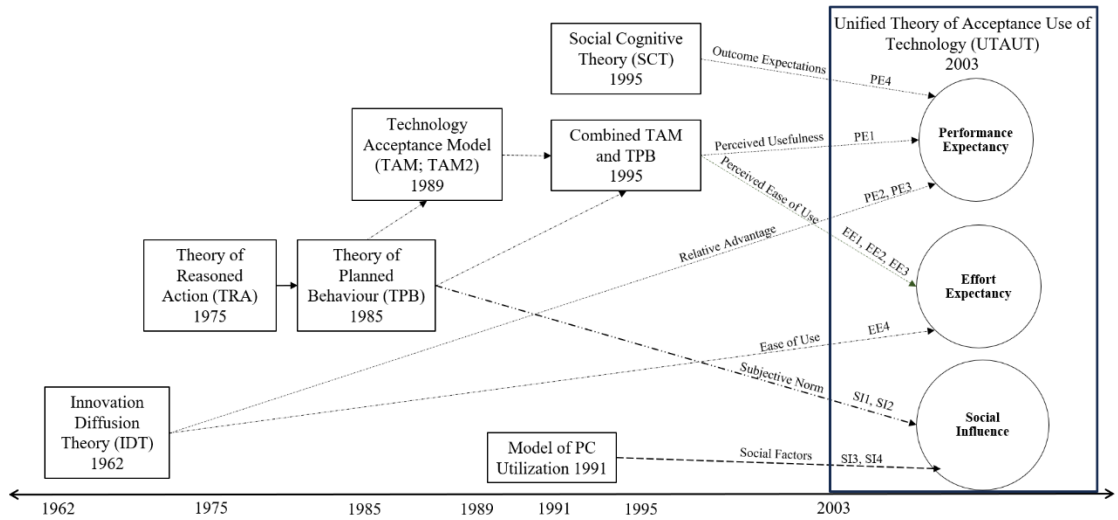


Figure 2.2: The UTAUT Constructs and Related Theories

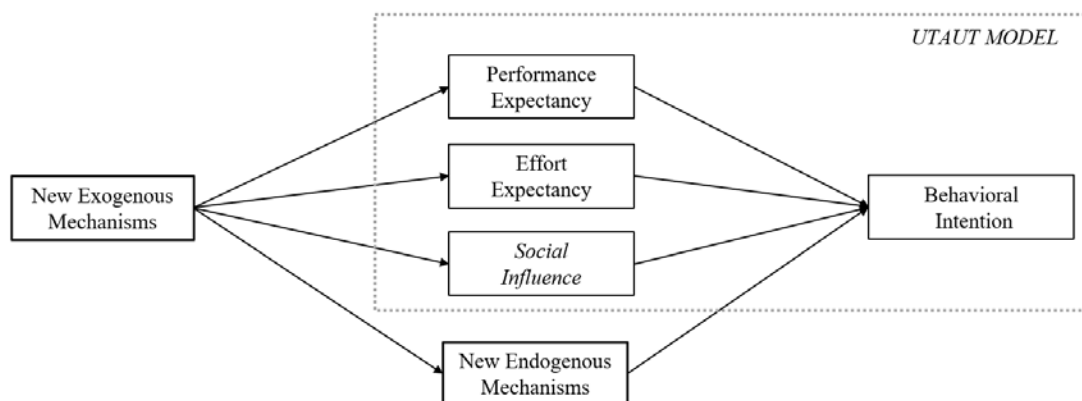
Performance Expectancy: Performance Expectancy is a construct of UTAUT (Venkatesh et al., 2003), where the item PE1 originated from the “Perceived usefulness” (Davis, 1989; Davis et al., 1989); the items, PE2 and PE3 originated from the “Relative Advantage” (Moore and Benbasat, 1991); the item, PE4 originated from the “Outcome Expectations-Performance and (D. Compeau et al., 1999; D. R. Compeau and Higgins, 1995).

Effort Expectancy: Effort Expectancy is a construct of UTAUT (Venkatesh et al., 2003), where the items EE1, EE2, and EE3 originated from the “Perceived ease of use” variable, which was originally (Davis, 1989; Davis et al., 1989), and has been used in Technology Acceptance Models (TAM). The item EE4 originated from the “Ease of use” variable, which was originally introduced by Moore and Benbasat (1991), and has been used in Innovation Diffusion Theory (IDT).

Social Influence: Social influence is a construct of UTAUT (Venkatesh et al., 2003). The first two items, SI1 and SI2 originated from the “Subjective Norm” variable from (Ajzen, 1991; Davis et al., 1989; Fishbein and Ajzen, 1975; Mathieson, 1991; Taylor and Todd, 1995a, 1995b), and these items have been used in the Theory of Reasoned Action (TRA). The items SI3 and SI4 originated from the “Social Factors” variable Thompson et al. (1991), and these items have been used in Innovation Diffusion Theory (IDT).

The theory is more compact and widely applicable because the UTAUT model has fewer constructs and relationships (Tamilmani et al., 2021).

The adoption and utilisation of new technology in the workplace are explained by the UTAUT (Oulmakki et al., 2024). The original TAM and UTAUT models are modified in all model proposals for social robot research (Ghazali et al., 2020; Heerink et al., 2010). This theory is also open to extensions for understanding the relationships between new constructs and UTAUT constructs, as shown in Figure 2.3.



Notes: (1) Boxes with darker lines present UTAUT extensions.
(2) Italic style for social influence presents a multidimensional construct.

Figure 2.3: UTAUT Extensions Adapted from (Venkatesh et al., 2016)

2.2. Review of Existing Studies

The first literature search on the Web of Science, using the keywords “robot acceptance (All Fields) AND structural equation model (All Fields),” revealed 141 articles (Access date: January 31, 2025). Although no time limit was set, the results spanned the period from 2013 to 2025. 8 of the records were proceedings, letters, or meeting abstracts, which were excluded from the review in the screening step.

Second literature search on the Web of Science using the keywords “robot acceptance (All Fields) AND Performance Expectancy (All Fields) AND Effort Expectancy (All Fields) AND Social Influence (All Fields)” revealed 33 articles (Access date: January 31, 2025). Although no time limit was set, the results spanned the period from 2013 to 2025. 4 of the records were proceedings, letters, or meeting abstracts. 12 of the records were duplicated from the first research. 16 records were excluded from the review in the screening step.

Third literature research on the Web of Science using the keywords “UTAUT (All Fields) AND robot (ALL FIELDS)” revealed 88 articles (Access date: January 31, 2025). 19 of the records were proceedings, letters, or meeting abstracts. 29 of the records were duplicated from the first and second research. Therefore, 48 records were excluded in the screening step.

Fourth literature search on the Web of Science using the keywords “Perceived Sociability (All Fields) INCLUDE robot” listed 29 documents (Access date: 31/1/2025). From this literature research, the proceedings (n=18) records were excluded from the screening step.

The research process is adapted from the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines (Page et al., 2021). The results are illustrated in Figure 2.4.

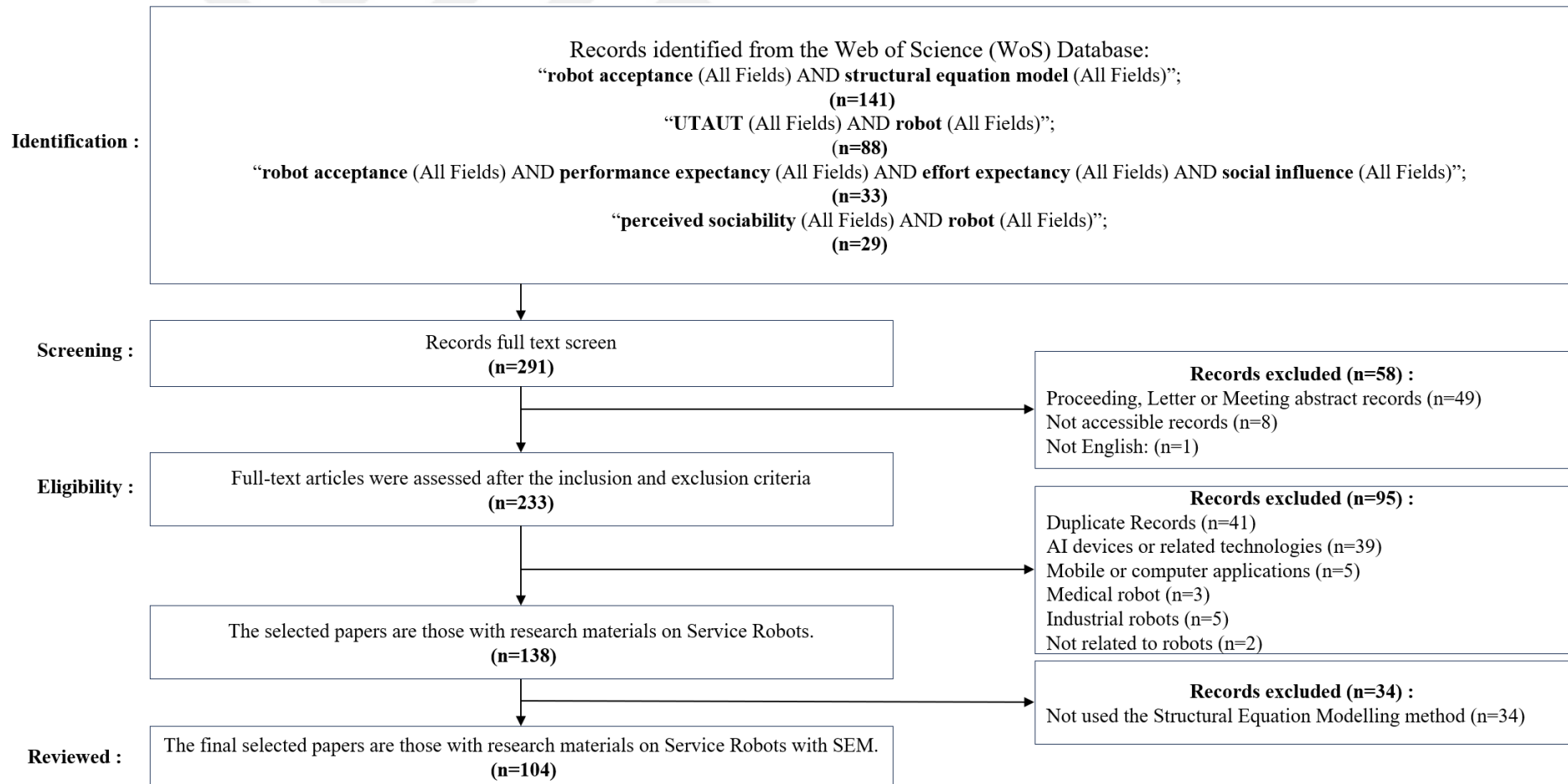


Figure 2.4: Flowchart Adapted from the PRISMA Guidelines

Records from the research related to service robots, as per ISO 8323:2021, and utilising structural equation modelling were selected.

The 22 results had the same relationships with the UTAUT model. From 22 results, five studies related to human-robot co-working in various environments were identified, including healthcare (Komariyah et al., 2024; Vichitkraivin and Naenna, 2021), education (Ates and Polat, 2025), hospitality (Abdelhakim et al., 2023), and agriculture (Rübcke Von Veltheim et al., 2022). The remaining results, related to customers, students, patients, or individuals in various environments, are shown in Table 2.1. Performance Expectancy, Effort Expectancy, Social Influence, and Behavioural Intention to use are key UTAUT constructs (Venkatesh et al., 2003). Based on the original UTAUT model, Facilitating Conditions and Use Behaviour should also be considered when using the technology (Venkatesh et al., 2003, 2016, p. 20). The dependent variable for predicting the acceptance of new technologies is behavioural intention to use (BI). According to the literature review results in Table 2.1, this dependent variable was used in several types of expressions and UTAUT relationships.

Table 2.1: Literature Review Results Related to UTAUT Relationships

Location (Country)	Sample Group	Environment and/or Application Area	PE->BI	EE->PE	EE->BI	SI->BI	Behavioural Intention (BI)- Related Expressions	Source
Germany	Professionals	Farm/ Agriculture	Yes	–	Yes	Yes	Behavioral intention	(Rübcke Von Veltheim et al., 2022)
Germany	General users	Domestic General	–	–	No	Yes	Intention to use	(Kraus et al., 2024)
The Netherlands	Elderly Adults	Domestic Healthcare	–	–	–	Yes	Intention to use	(Heerink et al., 2010)
USA	Patients	Domestic Healthcare	Yes	Yes	No	Yes	Usage intention	(Alaiad et al., 2014)
USA	Patients	Domestic Healthcare	Yes	Yes	No	Yes	Intention to use	(Alaiad and Zhou, 2014)
Malaysia	Patients	Domestic Healthcare	Yes	–	No	Yes	Intention to Adopt	(Yeoh and Chin, 2022)

Table 2.1: Literature Review Results Related to UTAUT Relationships (Continued)

Location (Country)	Sample Group	Environment and/or Application Area	PE->BI	EE->PE	EE->BI	SI->BI	Behavioural Intention (BI)-Related Expressions	Source
China	Elderly Adults	Domestic Healthcare	Yes	–	–	–	Behavioral Intention	(Sun et al., 2024)
China	Elderly Adults	Domestic Healthcare	Yes	–	No	No	Usage intention	(Zhang, 2024)
Thailand	Professionals	Hospital/ Healthcare	Yes	–	Yes	Yes	Behavioral Intention	(Vichitkraiv n and Naenna, 2021)
Indonesia	Professionals	Rehabilitatio n clinics/ Healthcare	Yes	–	No	Yes	Intention to Adopt	(Komariyah et al., 2024)
Switzerland	Student/ Learners	University/ Education	Yes	–	Yes	Yes	Behavioral Intention	(Guggemos et al., 2020)
United Arap Emirates	Student/ Learners	University/ Education	Yes	–	No	Yes	Behavioral Intention	(Suhail et al., 2024)

Table 2.1: Literature Review Results Related to UTAUT Relationships (Continued)

Location (Country)	Sample Group	Environment and/or Application Area	PE->BI	EE->PE	EE->BI	SI->BI	Behavioural Intention (BI)- Related Expressions	Source
Türkiye	Professionals	Schools/ Education	Yes	–	Yes	Yes	Behavioral Intention	(Ates and Polat, 2025)
India	Customer	Restaurant/ Hospitality	–	–	Yes	–	Willingness to accept to use	(Pande and Gupta, 2023)
Malasia and Egypt	Professionals	Restaurant/ Hospitality	Yes	–	Yes	Yes	Intention to Adopt	(Abdelhakim et al., 2023)
India	Customer	Restaurant/ Hospitality	Yes	–	Yes	No	Service Robot Acceptance	(Mandal et al., 2025)
Spain	Customer	Front Office/ Retail (Stores)	–	–	–	Yes	Intention to use	(Forgas-Coll et al., 2022)
Spain	Customer	Supermarket/ Retail (Stores)	Yes	–	No	Yes	Intention to use	(Subero-Navarro et al., 2022)

Table 2.1: Literature Review Results Related to UTAUT Relationships (Continued)

Location (Country)	Sample Group	Environment and/or Application Area	PE->BI	EE->PE	EE->BI	SI->BI	Behavioural Intention (BI)- Related Expressions	Source
Czech Republic	Customer	Supermarket/ Retail (Stores)	Yes	–	Yes	–	Willingness to use	(Osakwe et al., 2024)
France	Customer	Delivery/ Transportation	Yes	–	Yes	Yes	Behavioral Intention	(Oulmakk i et al., 2024)
Spain	Customer	University campus shuttle/ Transportation	Yes	–	No	Yes	Usage Intention	(Quinones et al., 2024)
Germany	Customer	Delivery/ Transportation	Yes	Yes	Yes	Yes	Behavioral Intention	(Kaiser et al., 2024)

The relationships measured statistically using structural equation modelling were found to be related to perceived sociability, which used the items from (Heerink et al., 2010), as shown in the literature review. Table 2.2 shows the relationship constructs with Perceived Sociability.

Table 2.2: The Result of the Literature Review on the Construct of Perceived Sociability

Source	Relationship	Related Model
(Forgas-Coll et al., 2022; Heerink et al., 2010; Shin and Choo, 2011)	Perceived Sociability → Perceived Enjoyment	ALMERE
(Shin and Choo, 2011)	Perceived Sociability → Attitude toward Robots	ALMERE
(Heerink et al., 2010)	Perceived Sociability → Social Presence	ALMERE
(Heerink et al., 2010)	Trust → Perceived Sociability	ALMERE

According to Shin and Choo (2011), the sociability of robots also affects their usefulness; however, they did not measure the relationship between them.

Service robots are expected to increase user satisfaction and operational efficiency (Wirtz et al., 2018). These early designs, experiments, and applications indicate a broadening vision for the use of robots in work environments, including social settings, rather than being limited to factories, which was their primary application in the past. With the advancement of generative AI based on large language models, the AI capabilities of robots are likely to be significantly enhanced.

The systematic literature review classified service robots co-working with professionals in working environments (n = 18). Figure 2.5 illustrates a detailed graphic.

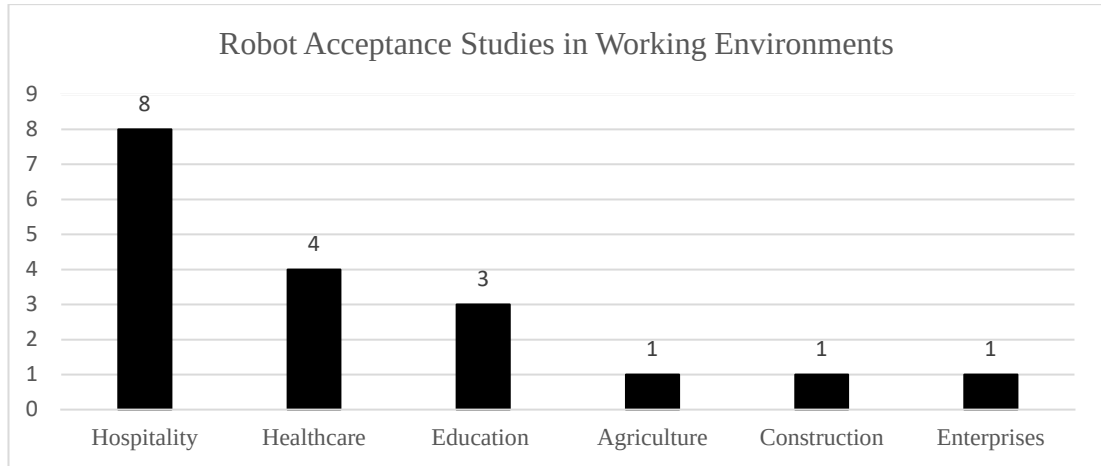


Figure 2.5: Human-Robot Co-working Acceptance Studies in the Working Environment: The Result of the Literature Review

In the hospitality sector, service robots are usually used as co-workers in the same environment. Robots in professional tasks such as cooking and food handling have replaced humans (Abdelhakim et al., 2023; Khan and Mehmood, 2024) as well as the handling of items (Song et al., 2022). The results of the literature review related to the hospitality working environment are listed in Table 2.3.

Table 2.3: Human-Robot Co-Working in Hospitality Environment from Robot Acceptance Literature

Location (Country)	Robot Type	Focus Group	Environment and or Application Area	Authors
Türkiye	Service robot	Gen Z Employees	Hotel	(Ali et al., 2023)
China	Service robot (Delivery robot)	Hotel Employees	Hotel	(Song et al., 2022)
		Hotel Managers		
11 Countries: Brazil, Canada, Greece, India, Israel, Japan, Romania, Spain, Türkiye, the United Kingdom, and the United States	Service robot		Hotel	(Pizam et al., 2022)

Table 2.3: Human-Robot Co-Working in Hospitality Environment from Robot Acceptance Literature (Continued)

Location (Country)	Robot Type	Focus Group	Environment and or Application Area	Authors
India	Service robot	Hotel Employees	Restaurant and Hotel	(Mukherjee et al., 2021)
USA	Service robot	Experienced Hospitality Employees	Restaurant and Hotel	(Horpynich et al., 2025)
Pakistan	Service robot	Fast-Food Workers	Restaurant	(Khan and Mehmood, 2024)
Malaysia and Egypt	Service robot	Fast-Food Employers	Restaurant	(Abdelhakim et al., 2023)
USA	Service robot	Hospitality Employees	Hotel, Restaurant, Tourism	(Parvez et al., 2022)

In healthcare, service robots are being utilised to support healthcare professionals in patient care. Healthcare service robots, also referred to as socially assistive robots, are expected to provide a certain level of emotional and cognitive support (Weerarathna et al., 2023). Service robots in healthcare typically perform professional tasks, including handling items (Vichitkraivin and Naenna, 2021) and providing information and guidance (Khaksar et al., 2021; Komariyah et al., 2024; Navarro et al., 2024). The results of the literature review related to the healthcare working environment are listed in Table 2.4.

Table 2.4: Human-Robot Co-Working in Healthcare Environment from Robot Acceptance Literature

Location (Country)	Robot Type	Focus Group	Environment and/or Application Area	Authors
France	Mobile telepresence robot	Teachers and students who are professionals in Physical Activity	Remote working	(Navarro et al., 2024)

Table 2.4: Human-Robot Co-Working in Healthcare Environment from Robot Acceptance Literature (Continued)

Location (Country)	Robot Type	Focus Group	Environment and/or Application Area	Authors
Australia	Socially assistive robots (SARs)	Elder people- aged care practitioners and therapists	Residential care place	(Khaksar et al., 2021)
Thailand	Service Healthcare Robot	Medical Staff	Hospital	(Vichitkraivin and Naenna, 2021)
Indonesia	Socially assistive robots (SARs)	Experienced occupational therapists in handling children with Autism	Rehabilitation clinics	(Komariyah et al., 2024)

Educational service robots may support teaching activities by providing personalised learning and creating engaging, interactive learning environments (OECD, 2021). Educational robots have been utilised in professional tasks to provide guidance and information for students (Ates and Polat, 2025; Kossewska and Kłosowska, 2020; E. Park and Kwon, 2016).

Table 2.5: Human-Robot Co-Working in Education Environment from Robot Acceptance Literature

Location (Country)	Robot Type	Focus Group	Environment and/or Application Area	Authors
Poland	Educational Robot	Teachers and therapeutic staff for children with disabilities	School/ Classroom	(Kossewska and Kłosowska, 2020)
Türkiye	Educational Robot	Science Teachers	School/ Classroom	(Ates and Polat, 2025)
Asia, Europe, North America, and others	Teaching Assistant Robot	Parent, Teacher, or researcher in kindergarten or elementary school	School/ Classroom	(E. Park and Kwon, 2016)

Research on robots and human-robot cooperation is gradually evolving, with new topics being explored in various work environments beyond hospitality (S. Choi et al., 2021), healthcare, and education. These include construction (S. Park et al., 2023), agriculture (Rübcke Von Veltheim et al., 2022), and enterprises (M. J. Choi et al., 2018), as shown in Table 2.6.

Table 2.6: Human-Robot Co-Working in Other Environments from Robot Acceptance Literature

Location (Country)	Robot Type	Focus Group	Environment and/or Application Area	Authors
USA	Co-robot	Construction personnel	Construction Site	(S. Park et al., 2023)
Germany	Autonomous Field Robot	Farmers	Farm / Agriculture	(Rübcke Von Veltheim et al., 2022)
Korea	Collaborative robot replacement instead of industrial robots	Managers	Small and Medium-sized Enterprises	(M. J. Choi et al., 2018)

There is no evidence to suggest that the research on the acceptance of service robots in office environments was statistically analysed using structural equation modelling, nor is there a relationship between Perceived Sociability and Behavioural Intention to use the robot as presented in the literature review.

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

3.1. Conceptual Framework

The first study examined anthropomorphism, specifically measuring which robot appearance participants preferred as a coworker in their office environment, in comparison with the Uncanny Valley Theory.

The second study tests the traditional acceptance model using the UTAUT and adding perceived sociability as an endogenous mechanism to the UTAUT model. The Unified Technology Acceptance and Use Theory (UTAUT) Model (Venkatesh et al., 2003), evaluates robot acceptance using traditional acceptance theory. This study examined the connections among Behavioural Intention to use robots, Performance Expectation, Effort Expectation, and Social Influence. These are the primary constructs for the original model, despite UTAUT extensions. This study also examined the relationship between Behavioural Intention to use robots and Perceived Sociability as a new endogenous mechanism. The conceptual framework of the research is illustrated in Figure 3.1.

As robots in office workplaces are likely to be social robots, the second study will evaluate whether perceived sociability plays a role in robot acceptance or not. Although previous studies on robot acceptance demonstrated a correlation between perceived sociability and UTAUT constructs (Conti et al., 2017; Han and Conti, 2020; Heerink et al., 2010), there is not enough evidence that this relationship holds for intention to use with the use of structural equation modelling.

The context of technology acceptance was identified with eight dimensions (Venkatesh et al., 2016). The seven context dimensions are organised into two levels: the discrete level, which encompasses the task, social, and physical dimensions, and the omnibus level, which comprises the who, where, when, and why dimensions (Johns, 2006). The eighth dimension is the technology class that is specially used in the technology acceptance context (Venkatesh et al., 2016). The context dimensions of the proposed research model are shown in Table 3.1.

Table 3.1: Context Dimensions of the Proposed Research Model

Context dimension	Johns' Conceptualisation	Proposed Research Model
User class	Who: the occupational and demographic context.	British and Turkish professionals who are experienced in offices
Technology class	No such dimension.	Social Service Robots with Gen AI
Task class	Task: autonomy, resources, etc.	Human-Robot Co-working
Time/event class	When: the time (absolute and relative) at which the research was conducted, or research events occur.	Following the COVID-19 pandemic, perceptions shifted towards robots. Following the adoption of Generative AI and Large Language Models, robots now require less code than before.
Organisation class	Social context: social density, social structure, social influence, etc.	Experienced office professionals
Location class	Where: the location of the research site (region, culture, industry).	The United Kingdom and Türkiye
Environment class	Physical context: built environment, decor, etc.	Office Environment
Rationale class	Why: the rationale for conducting the research or collecting research data.	There is limited research on the office environment in human-robot co-working, particularly in the analysis of structural equation modelling (SEM) data. That is why this rationale class was chosen in this research.

STUDY 1:
ROBOT APPEARANCE

Survey Question: “If you have a chance to work with a robot colleague, which appearance do you prefer? Please slide the number that best suits you on this scale from 1 (machine-like) to 5 (human-like).”



STUDY 2:
PROPOSED UTAUT MODEL with PERCEIVED SOCIABILITY

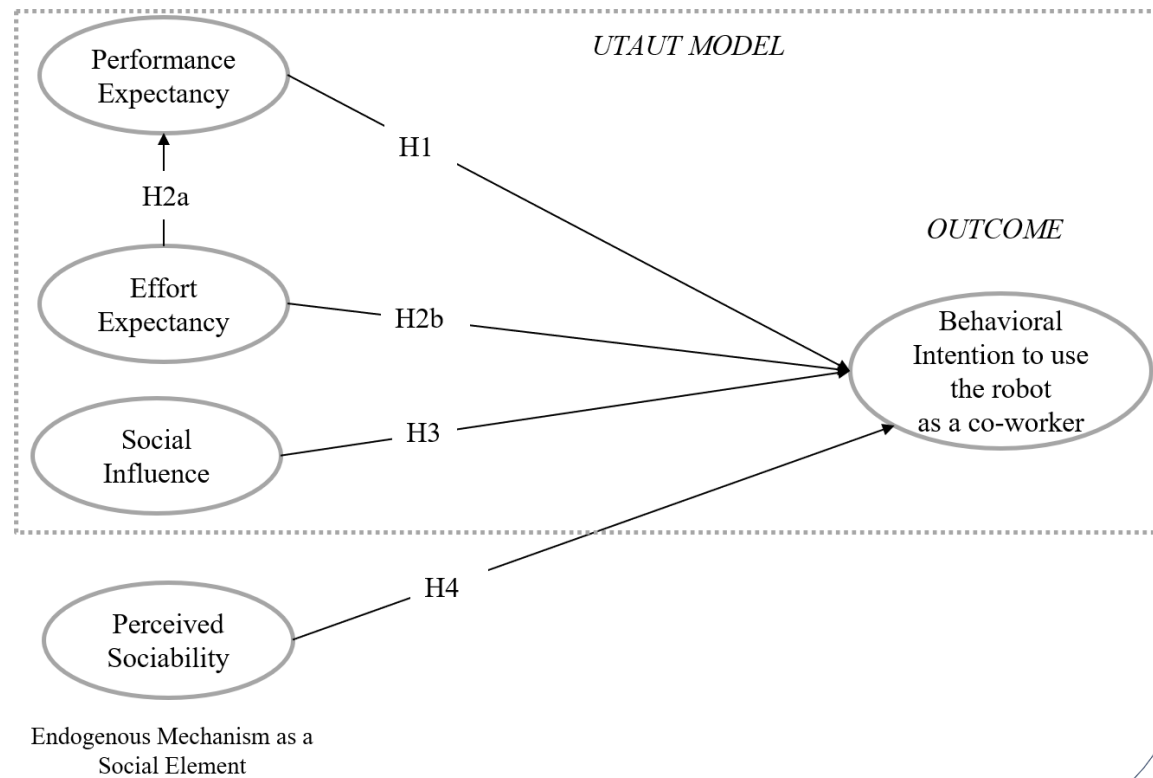


Figure 3.1: Conceptual Framework

3.2. Research Hypotheses

According to Venkatesh et al. (2003), Performance Expectancy refers to an individual's belief that utilising a system will enhance their work performance. Performance Expectancy and Behavioural Intention to use were found to be significantly correlated in related robot acceptance studies that used the UTAUT framework (Abdelhakim et al., 2023; Alaiad et al., 2014; Alaiad and Zhou, 2014; Ates and Polat, 2025; Guggemos et al., 2020; Kaiser et al., 2024; Komariyah et al., 2024, 2024; Mandal et al., 2025; Navarro et al., 2024; Osakwe et al., 2024; Oulmakki et al., 2024; Quinones et al., 2024; Rübcke Von Veltheim et al., 2022; Suhail et al., 2024; Sun et al., 2024; Vichitkraivin and Naenna, 2021; Yeoh and Chin, 2022; Zhang, 2024).

Thus, this hypothesis was proposed:

H1: Performance Expectancy (PE) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

Effort Expectancy assesses individuals' ease of use of new technologies. Effort Expectancy (EE) is an element of the UTAUT framework (Venkatesh et al., 2016). It is the degree of ease associated with using the system (Venkatesh et al., 2003). Effort Expectancy (EE) is both positively and negatively associated with innovation (H.-W. Kim et al., 2007).

The Technology Acceptance Model has demonstrated that perceived ease of use is related to perceived usefulness (Davis, 1989; Davis et al., 1989). In some studies on robot acceptance, perceived ease of use was found to have a relationship with perceived usefulness (Heerink et al., 2010; Wirtz et al., 2018), and effort expectancy was shown to have a significant relationship with performance expectancy (Alaiad et al., 2014; Alaiad and Zhou, 2014; Kaiser et al., 2024). According to Vroom (1964), there is a positive relationship between Effort and Performance, which is the belief in organisational behaviour that putting in extra effort results in increased performance expectancy (Davis, 1989). From a technological system usage perspective, when the system is easier to use, it should make the system more useful (Davis, 1993). Therefore, the Performance Expectancy would increase when the technological system is easy to use or requires minimal effort.

Thus, this hypothesis was proposed:

H2a: Effort Expectancy (EE) is significantly related to Performance Expectancy (PE) in an office environment.

Some research has demonstrated that using the UTAUT framework in a robot acceptance model mostly leads to finding a significant relationship between Effort Expectancy and Behavioural Intention to use (Abdelhakim et al., 2023; N. Chen, 2018; Guggemos et al., 2020; Kaiser et al., 2024; Pande and Gupta, 2023; Vichitkraivin and Naenna, 2021). On the other hand, some studies showed that Effort Expectancy has no significant relationship with Behavioural Intention to use, such as using autonomous public shuttles (Quinones et al., 2024), domestic healthcare robots for patients (Alaiad et al., 2014; Alaiad and Zhou, 2014; Yeoh and Chin, 2022; Zhang, 2024), healthcare robots (Komariyah et al., 2024) and education robots (Suhail et al., 2024), especially when the technological device does not require any human intervention.

Thus, this hypothesis was proposed:

H2b: Effort Expectancy (EE) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

Social Influence refers to the influence of other people's thoughts while using new technology (Venkatesh et al., 2003). Social Influence is a multi-dimensional construct that could be enriched (Isabelle and Sandrine, 2009; Venkatesh et al., 2016). Social Influence is correlated with Behavioural Intention in robot acceptance literature, as shown in Table 2.1. However, two studies found no significant relationship between Social Influence and behavioural intention. The first study focuses on the Eldercare robot in a domestic environment (Zhang, 2024), while the other examines the service robot in a restaurant setting (Mandal et al., 2025).

Thus, this hypothesis was proposed:

H3: Social Influence (SI) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

Perceived sociability refers to how able the robot is perceived to be in showing social behaviour (Heerink et al., 2010). The social skills of a robot are crucial for human adoption (Wirtz et al., 2018). Additionally, Coeckelbergh (2012) states that human-robot interactions have developed into social relationships. According to Kadylak et al. (2023), "friendliness" is equivalent to "perceptions of robot sociability."

Sociability should be considered in social robot acceptance models because it is one of the key hedonic factors, according to (De Graaf and Ben Allouch, 2013). Perceived Sociability is related to social presence, which was measured by (Heerink et al., 2008, 2010). (Wirtz et al., 2018) showed Perceived Sociability as a social-emotional factor in the Service Robot Acceptance Model (SRAM) framework, directly related to service robots' acceptance without any measurement.

Unfortunately, the literature contains limited data on robot acceptance, using structural equation modelling to examine the relationship between Perceived Sociability and Behavioural Intention to use. Table 2.2 illustrates the relationship constructs with Perceived Sociability, as identified in the literature review presented in Chapter 2.

Perceived Sociability items were adapted from the ALMERE robot acceptance model (Heerink et al., 2010). UTAUT constructs are found to be correlated with Perceived Sociability by (Heerink et al., 2010; Kyounga et al., 2024). Perceived Sociability is an extension of UTAUT's endogenous mechanism for a "social element" in the model.

Thus, this hypothesis was proposed:

H4: Perceived Sociability (PS) is significantly related to Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

4. MATERIALS AND RESEARCH METHODOLOGY

4.1. Materials

In this study, office-experienced participants watched a video of ADA7 in an office environment to assess their reactions to the robot. ADA7 was developed by AKIN Robotics (Akinrobotics, 2024). ADA7 is a humanoid robot, shown in Figure 4.1.

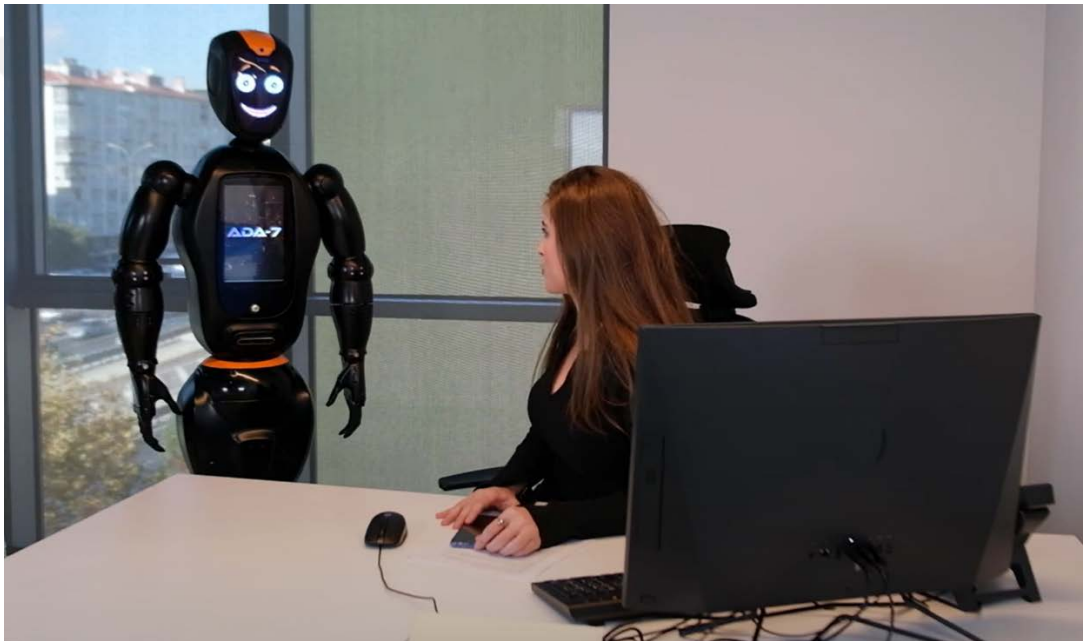


Figure 4.1: Working with Robot ADA7 in the Office Environment

ADA7 can speak Turkish, English, Russian, German, Spanish, Polish, French, Dutch, and Arabic. She processes instructions, questions, and responds using generative AI. ADA7 can see, hear, and walk. She possesses social skills that enable her to communicate and interact with humans using ChatGPT, respond with tactile reactions, and access Enterprise Resource Planning (ERP) software systems. This research video was designed and developed with AKINROBOTICS. It aimed to demonstrate human-robot co-working in an office environment. While watching the video, the participants imagined themselves working alongside the robot in their office environment. In the video's scenario, ADA7 (she) can communicate socially, access information about the

organization, and respond to the worker. The summary of the video's manuscript is below.

- The robot said greetings and compliments to her colleague.
- She checked the information from the system about the worker's absence that the colleague requested.
- She addressed where the worker's room was in the company.
- She enquired about invoice details.
- She checked the documents made by her human colleague.
- The robot ordered a hot drink for her colleague.

The video links are available in the Turkish language version at <https://youtu.be/teTwvgjMwOs> and the English language version at <https://youtu.be/kWlbssN0P2A>.

4.2. Research Methodology

4.2.1. Design of the Questionnaire

The purpose of this study is to explore how office professionals react to robots.

Given the continuing evolution of robot technology, a survey approach was selected to collect data in two locations. The research questionnaire was designed to ensure validity and reliability, utilising widely used theoretical frameworks in Chapters Two and Three. There were 19 items in all, with five variables. A Five-point Likert scale, with one (1) meaning "strongly disagree" to five (5) meaning "strongly agree," was used for scoring each item. Each page of the questionnaire's variable items included a notice that read, "Please select your opinions as if you are co-working with this robot in your office environment".

Demographic data, including gender, age, education, employment status, robot experience, and perceptions of the robot's appearance as a coworker, were also collected. Both Turkish and English versions were adopted for the survey. Table 4.1 displays both language versions, constructs originating from theories, and original questions. All the survey questions are shown in Appendix A.

Table 4.1: Measurement Variables Adapted and Implemented from (Venkatesh et al., 2003)

Theory Based	Theory-based Constructs	Item Code	UTAUT Construct	UTAUT Original Questions	ALMERE Original Questions	Construct Name	Item Code	Survey Questions (English)	Survey Questions (Turkish)
Technology Acceptance Model (TAM, TAM2, Combined TAM-TPB)	Perceived Usefulness (Davis, 1989; Davis et al., 1989)	U6	Performance Expectancy (Venkatesh et al., 2003)	I would find the system useful in my job.		Performance Expectancy	PE1	I would find this robot useful in my job.	Bence bu robot benim işime yarar.
Innovation Diffusion Theory (IDT)	Relative Advantage (Moore and Benbasat, 1991)	RA1	Performance Expectancy (Venkatesh et al., 2003)	Using the system enables me to accomplish tasks more quickly.		Performance Expectancy	PE2	Using this robot enables me to accomplish tasks more quickly.	Bence bu robot bana birçok konuda yardımcı olabilir.
Innovation Diffusion Theory (IDT)	Relative Advantage (Moore and Benbasat, 1991)	RA5	Performance Expectancy (Venkatesh et al., 2003)	Using the system increases my productivity.		Performance Expectancy	PE3	Using this robot increases my productivity.	Robot ile çalışmak benim için kullanışlı olacaktır.
Social Cognitive Theory (SCT)	Outcome Expectations (D. Compeau et al., 1999; D. R. Compeau and Higgins, 1995)	OE7	Performance Expectancy (Venkatesh et al., 2003)	If I use the system, I will increase my chances of getting a raise.		Performance Expectancy	PE4	If I use this robot, I will increase my chances of getting a raise.	Eğer bu robotu kullanırsam, zam alma şansы yakalayabilirim.
Technology Acceptance Model (TAM, TAM2, Combined TAM-TPB)	Perceived Ease of Use (Davis, 1989; Davis et al., 1989)	EOU3	Effort Expectancy (Venkatesh et al., 2003)	My interaction with the system would be clear and understandable.		Effort Expectancy	EE1	My interaction with this robot would be clear and understandable.	Robotla etkileşimim açık ve anlaşılır olur.
Technology Acceptance Model (TAM, TAM2, Combined TAM-TPB)	Perceived Ease of Use (Davis, 1989; Davis et al., 1989)	EOU5	Effort Expectancy (Venkatesh et al., 2003)	It would be easy for me to become skillful at using the system.		Effort Expectancy	EE2	It would be easy for me to become skillful at using this robot.	Robot kullanmakta ustalaşmak benim için kolay olacaktır.

Table 4.1: Measurement Variables Adapted and Implemented from (Venkatesh et al., 2003) (Continued)

Theory Based	Theory-based Constructs	Item Code	UTAUT Construct	UTAUT Original Questions	ALMERE Original Questions	Construct Name	Item Code	Survey Questions (English)	Survey Questions (Turkish)
Technology Acceptance Model (TAM, TAM2, Combined TAM-TPB)	Perceived Ease of Use (Davis, 1989; Davis et al., 1989)	EOU6	Effort Expectancy (Venkatesh et al., 2003)	I would find the system easy to use.		Effort Expectancy			
							EE3	I would find this robot easy to use.	Robotun kullanımını kolay buldum.
	Ease of Use (Moore and Benbasat, 1991)	EU4	Effort Expectancy (Venkatesh et al., 2003)	Learning to operate the system is easy for me.		Effort Expectancy		Learning to operate this robot is easy for me.	Robotu kullanmayı öğrenmek benim için çok kolay.
							EE4		
	Subjective Norm (Ajzen, 1991; Davis et al., 1989; Fishbein and Ajzen, 1975; Mathieson, 1991; Taylor and Todd, 1995a, 1995b)	SN1	Social Influence (Venkatesh et al., 2003)	People who influence my behaviour think that I should use the system.	I think the staff would like me using the robot.	Social Influence		I think the staff would like me using the robot.	Bence, robot kullanıyor olmam iş arkadaşlarımın hoşuna gider.
							SI1		
Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB)	Subjective Norm (Ajzen, 1991; Davis et al., 1989; Fishbein and Ajzen, 1975; Mathieson, 1991; Taylor and Todd, 1995a, 1995b)	SN2	Social Influence (Venkatesh et al., 2003)	People who are important to me think that I should use the system.	I think it would give a good impression if I should use the robot.	Social Influence		I think it would give a good impression if I should use the robot.	Robot kullanırsam, çevremde iyi bir izlenim bırakacağımı düşünüyorum.
							SI2		

Table 4.1: Measurement Variables Adapted and Implemented from (Venkatesh et al., 2003) (Continued)

Theory Based	Theory-based Constructs	Item Code	UTAUT Construct	UTAUT Original Questions	ALMERE Original Questions	Construct Name	Item Code	Survey Questions (English)	Survey Questions (Turkish)
35	Model of PC Utilization	SF2	Social Influence (Venkatesh et al., 2003)	The senior management of this business has been helpful in the use of the system.	I think the senior management would be helpful in the use of the robot.	Social Influence	SI3	I think the senior management would be helpful in the use of the robot.	İşim ile ilgili olarak yöneticilerim robot kullanımına yardım edeceğini düşünüyorum.
	Model of PC Utilization				In general, the organisation would support the use of the robot.	Social Influence		In general, the organisation would support the use of the robot.	Genel olarak şirket organizasyonu, robot kullanımını destekleyecektir.
		PS1	Perceived Sociability (Heerink et al., 2010)		I consider the robot a pleasant conversational partner.	Perceived Sociability	PS1	I consider the robot a pleasant conversational partner.	Bu robotun keyifli bir sohbet arkadaşı olduğunu düşünüyorum.
					I find the robot pleasant to interact with.	Perceived Sociability		I find the robot pleasant to interact with.	Bu robotla etkileşim kurmayı keyifli bulurum.
		PS3	Perceived Sociability (Heerink et al., 2010)		I feel the robot understands me.	Perceived Sociability	PS3	I feel the robot understands me.	Bu robotun beni anladığını hissederim.
					I think the robot is nice.	Perceived Sociability		I think the robot is nice.	Bence bu robot güzel.
		PS2	Perceived Sociability (Heerink et al., 2010)				PS2		

Table 4.1: Measurement Variables Adapted and Implemented from (Venkatesh et al., 2003) (Continued)

Theory Based	Theory-based Constructs	Item Code	UTAUT Construct	UTAUT Original Questions	ALMERE Original Questions	Construct Name	Item Code	Survey Questions (English)	Survey Questions (Turkish)
Extensively used in previous theories.	Behavioural intention to use the system (Davis et al., 1989)	BI1	Behavioural Intention (Venkatesh et al., 2003)	I intend to use the system in the next (n) months.		Behavioural Intention	BI1	I intend to use this robot in the near future.	Yakın gelecekte robot kullanmaya niyetim var.
Extensively used in previous theories.	Behavioural intention to use the system (Davis et al., 1989)	BI2	Behavioural Intention (Venkatesh et al., 2003)	I predict I would use the system in the next (n) months.		Behavioural Intention	BI2	I predict I would use this robot in the near future.	Yakın gelecekte robot kullanacağımı ön görüyorum.
Extensively used in previous theories.	Behavioural intention to use the system (Davis et al., 1989)	BI3	Behavioural Intention (Venkatesh et al., 2003)	I plan to use the system in the (n) months.		Behavioural Intention	BI3	I plan to use this robot in the near future.	Yakın gelecekte robot kullanmayı planlıyorum.

4.2.2. Data Collection

The study focused on office-experienced workers or potential workers. The survey included a video showing human-robot collaboration in the office environment, which lasted two minutes and twenty-four seconds. The survey was created using SurveyMonkey.com and distributed to participants via online platforms, including LinkedIn, WhatsApp, and email. Data was collected from the UK and Türkiye between October 2023 and January 2024. From the United Kingdom, 50 participants volunteered, and an additional 252 participants were recruited through the Prolific platform. From Türkiye, 405 participants volunteered for the survey. The survey was approximately completed in six minutes.

Data from participants who were not from the United Kingdom or Türkiye and did not have office experience were removed. Participants who completed the survey in under 4 minutes were also excluded. In conflict and missing-value data were also eliminated. After data reduction, there were 273 data from Türkiye and 273 data from the United Kingdom. Figure 4.2 illustrates the data reduction procedure.

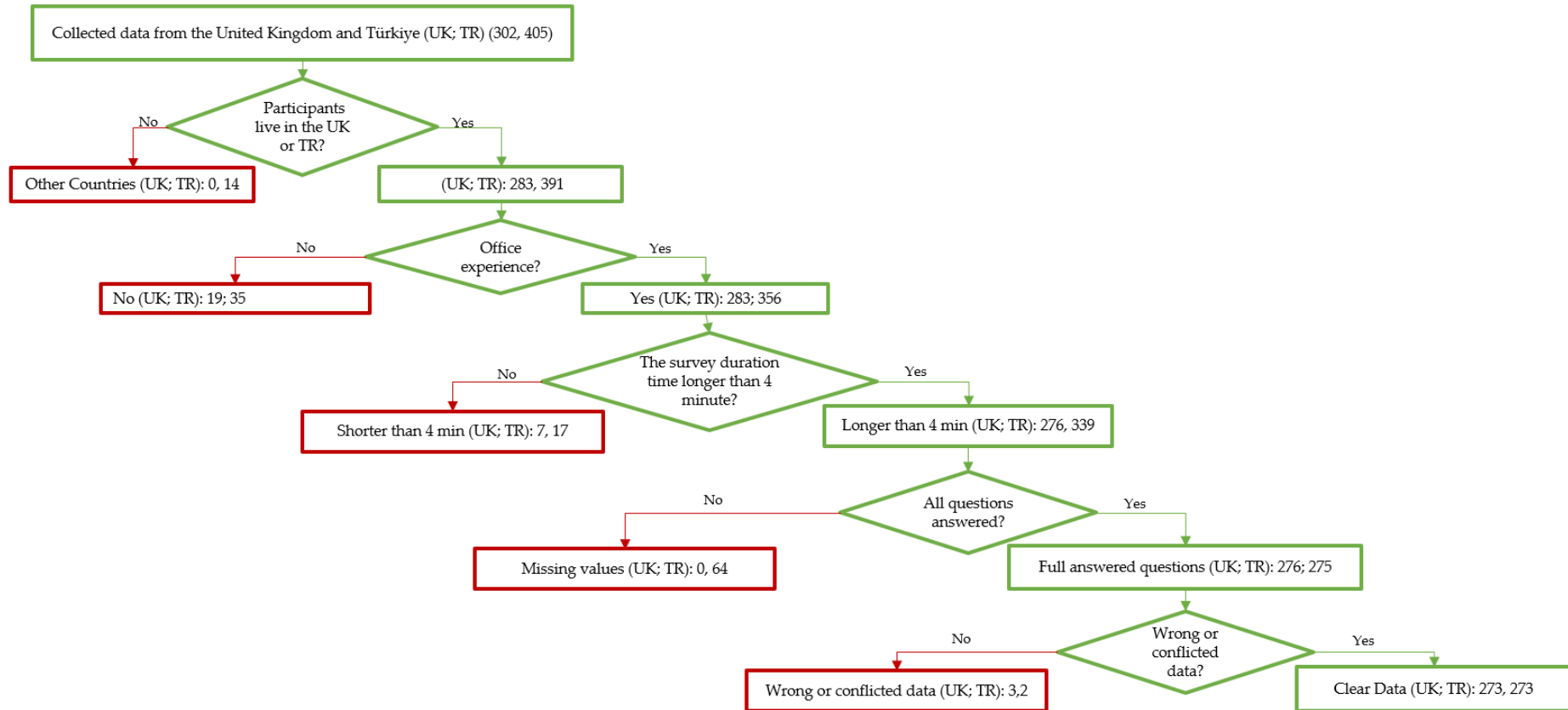


Figure 4.2: The Data Reduction Procedure

5. DATA ANALYSIS AND RESULTS

5.1. Overview

This chapter presents the empirical findings of this research. The methods and analyses are conducted using the statistical technique discussed in Chapter 4. First, the preliminary results are shown in this Chapter. The conceptual framework was then analysed. The research's conceptual framework comprises two studies. Study 1 investigated the robot's appearance, which will be co-worker with the participants. Study 2 measured and tested the hypotheses.

5.2. Preliminary Results

The 546 office-experienced respondents had different demographic characteristics. This research examined the survey results of 546 office-experienced adults. The generation classification is widely used in workplaces and was adopted from Dimock 2019. Generation Y (ages 27-42) had the highest proportion of participants in each dataset. As shown in Table 5.1, %74,5 of participants had a diploma in higher education or above.

Table 5.1: General Demographic Characteristics, Robot Experience, Intention to Purchase a Robot, and Robot Appearance Preferences as a Co-worker

Description		Complete Data (n= 546)	UK Data (n=273)	TR Data (n=273)
		Frequency Percentage (%)	Frequency Percentage (%)	Frequency Percentage (%)
Gender	Female	298 (54.6 %)	163 (59.7%)	135 (49.5%)
	Male	246 (45.1%)	109 (39.9%)	137 (50.2%)
	Prefer not to answer	2 (0.4%)	1 (0.4%)	1 (0.4%)
	Total	546 (100%)	273 (100%)	273 (100%)

Table 5.1: General Demographic Characteristics, Robot Experience, Intention to Purchase a Robot, and Robot Appearance Preferences as a Co-worker (Continued)

Description		Complete Data (n= 546)	UK Data (n=273)	TR Data (n=273)
		Frequency Percentage (%)	Frequency Percentage (%)	Frequency Percentage (%)
Age Groups and Generations	78-95 (Silent) 1928-1945	4 (0.7%)	1 (0.4%)	3 (1.1%)
	59-77 (Baby Boomer) 1946-1964	62 (11.4%)	25 (9.2%)	37 (13.6%)
	43-58 (Gen X) 1965-1980	161 (29.5%)	66 (24.2%)	95 (34.8%)
	27-42 (Gen Y) 1981-1996	276 (50.5%)	152 (55.7%)	124 (45.4%)
	18-26 (Gen Z) 1997-2012	43 (7.9%)	29 (10.6%)	14 (5.1%)
Total		546 (100%)	273 (100%)	273 (100%)
Education	IB/WB/ A Level School Graduate	63 (11.5%)	52 (19.0%)	11 (4.0%)
	First-degree level qualification	76 (13.9%)	65 (23.8%)	11 (4.0%)
	Diploma in higher education	200 (36.6%)	46 (16.8%)	154 (56.4%)
	University in higher degrees (e.g. MSc., PhD.)	207 (37.9%)	110 (40.3%)	97 (35.5%)
	Total	546 (100%)	273 (100%)	273 (100%)
Employment	Employed, working full-time	412 (75.5%)	206 (75.5%)	11 (4.0%)
	Employed, working part-time	68 (12.5%)	55 (20.1%)	11 (4.0%)
	Not employed and/or looking for work	19 (3.5%)	7 (2.6%)	154 (56.4%)
	Retired	47 (8.6%)	5 (1.8%)	97 (35.5%)
	Total	546 (100%)	273 (100%)	273 (100%)
Robot Experience	Yes, at home	298 (54.6%)	162 (59.3%)	136 (49.8%)
	Yes, at work	53 (9.7%)	25 (9.2%)	28 (10.3%)
	Yes, elsewhere	13 (2.4%)	7 (2.6%)	6 (2.2%)
	No	182 (33.3%)	79 (28.9%)	103 (37.7%)
	Total	546 (100%)	273 (100%)	273 (100%)
Intention to Purchase a Robot	Yes, within the next year	85 (15.6%)	48 (17.6%)	37 (13.6%)
	Yes, in 1 to 5 years	161 (29.5%)	96 (35.2%)	65 (23.8%)
	Yes, in more than 5 years	45 (8.2%)	26 (9.5%)	19 (7.0%)
	No	102 (18.7%)	44 (16.1%)	58 (21.2%)
	I already have one	153 (28.0%)	59 (21.6%)	94 (34.4%)
Total		546 (100%)	273 (100%)	273 (100%)

Table 5.1: General Demographic Characteristics, Robot Experience, Intention to Purchase a Robot, and Robot Appearance Preferences as a Co-worker (Continued)

Description		Complete Data (n= 546)	UK Data (n=273)	TR Data (n=273)
		Frequency Percentage (%)	Frequency Percentage (%)	Frequency Percentage (%)
Office Experience	Yes	546 (100%)	273 (100%)	273 (100%)
	1 “Machine-like” robot	130 (23.8%)	52 (19.0%)	78 (28.6%)
Robot Appearance Preferences	2 “More machine- less human-like” robot	153 (20.0%)	102 (37.4%)	51 (18.7%)
	3 “Machine-human-like” robot	142 (26.0%)	66 (24.2%)	76 (27.8%)
	4 “Less machine-more human-like” robot	48 (8.8%)	35 (12.8%)	13 (4.8%)
	5 “Human-like” robot	73 (13.4%)	18 (6.6%)	55 (20.1%)
Total		546 (100%)	273 (100%)	273 (100%)

According to Special Eurobarometer 460, “Attitudes towards the impact of digitisation and automation on daily life report” in 2017, the United Kingdom (10 %) used or currently uses a robot at home, work, or elsewhere (Web 2, 2017). Our study results show that the usage of robots at home, work, or elsewhere in the United Kingdom has risen to 71.1% in 2024. Türkiye had no data in 2017 from Eurobarometer; however, our survey results show that Türkiye (62.3%) has used or currently uses a robot at home, work, or elsewhere. This research showed that the highest robot usage environment is at home in the UK and Türkiye. The intention to purchase and use a robot in the UK (83.9%) is slightly higher than in Türkiye (78.8%).

5.3. Study 1- The Results of Robot Appearance

Question of the Survey: “If you have a chance to work with a robot colleague, which appearance do you prefer? Please slide the number that best suits you on this scale from 1 (machine-like) to 5 (human-like).”

The complete data (Türkiye and the UK) were collected from 546 office-experienced professionals. According to Murphy et al. (2017), people in the uncanny valley area may never completely accept robots.

The participant responses are graphically displayed in Figure 5.1.

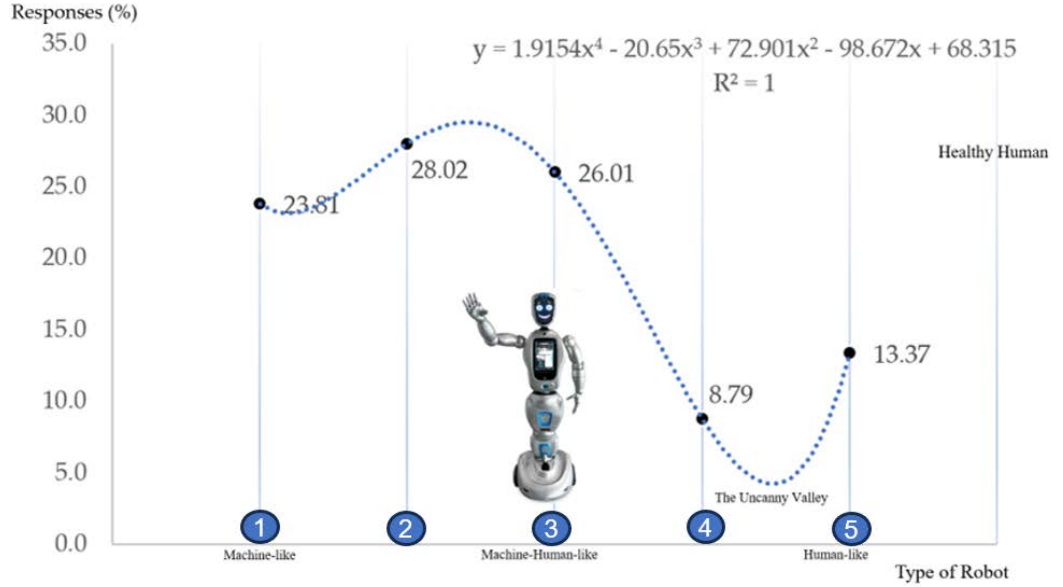


Figure 5.1: The Uncanny Valley from Participant Responses

The polynomial curve in the graph resembles the uncanny valley curve. The polynomial curve's mathematical equation is:

$$y = 1.915x^4 - 20.65x^3 + 72.901x^2 - 98.672x + 68.315 \quad (4.1)$$

The findings on preferences for robot appearance varied, as can be seen below:

23.8% of respondents chose "machine-like" robots, as measured in Category 1, 28.0% selected "more machine-less human-like" robots in Category 2, 26.0% selected "machine-human-like" robots, 8.8% selected "less machine-more human-like" robots, and 13.4% selected "human-like" robots in Category 3.

According to the survey's findings, 77.84% of respondents stated that they would prefer to work in an office setting with "machine-like robots," "less machine-like robots," or "machine-human-like robots." The "less machine-more human-like" robots in a situation have the lowest preference rate and fall into the valley. The research robot, ADA7, looks machine-human-like and does not fall within the Uncanny Valley.

These results align with the Uncanny Valley Theory, which suggests that participants may feel uncomfortable when robots resemble humans too closely but not exactly like a real human (Saneyoshi et al., 2022).

5.4. Study 2- Research Model

Smart PLS v.4.1.0.9 used the partial least squares structural equation modelling (PLS-SEM) approach to evaluate the suggested hypotheses (Sarstedt et al., 2016). Unlike covariance-based approaches, PLS-SEM is a variance-based technique that does not require a large sample size with a normal distribution (Reinartz et al., 2009).

This method was chosen for the following reasons:

- a) All the model's constructs are reflective (Dijkstra and Henseler, 2015).
- b) The analysis focuses on testing a theoretical framework from a predictive perspective.

The significance of the path coefficients was determined using 5000 bootstrap samples to ensure the stability of the estimation coefficient values. This method provides a more accurate and reliable estimate, making it suitable for the objectives of this investigation.

Study 2 followed the reporting style of PLS-SEM analysis, a two-stage approach suggested by previous studies (Henseler and Chin, 2010). The evaluation of the measurement model's steps is below.

- Indicator reliability
- Internal consistency, which includes Cronbach's alpha, composite reliability (ρ_C), and reliability coefficient (ρ_a)
- Convergent validity (AVE)
- Discriminant validity

The evaluation of the structural model's steps is below.

- Collinearity (VIF)
- Significance and relevance of the structural model relationships (path coefficients)
- Explanatory power (R^2) and Predictive power (Q^2)

- Model comparisons

5.5. Measurement Model

The assessment of the measurement model provides the basis for assessing the quality of the study's constructs. Different criteria apply to reflective and formative constructs in SmartPLS4. This study has a reflective measurement model. The measurement model is illustrated in Figure 5.2. Assessing the factor loadings is the first step in evaluating the quality criteria. Next, the construct validity and reliability are established.

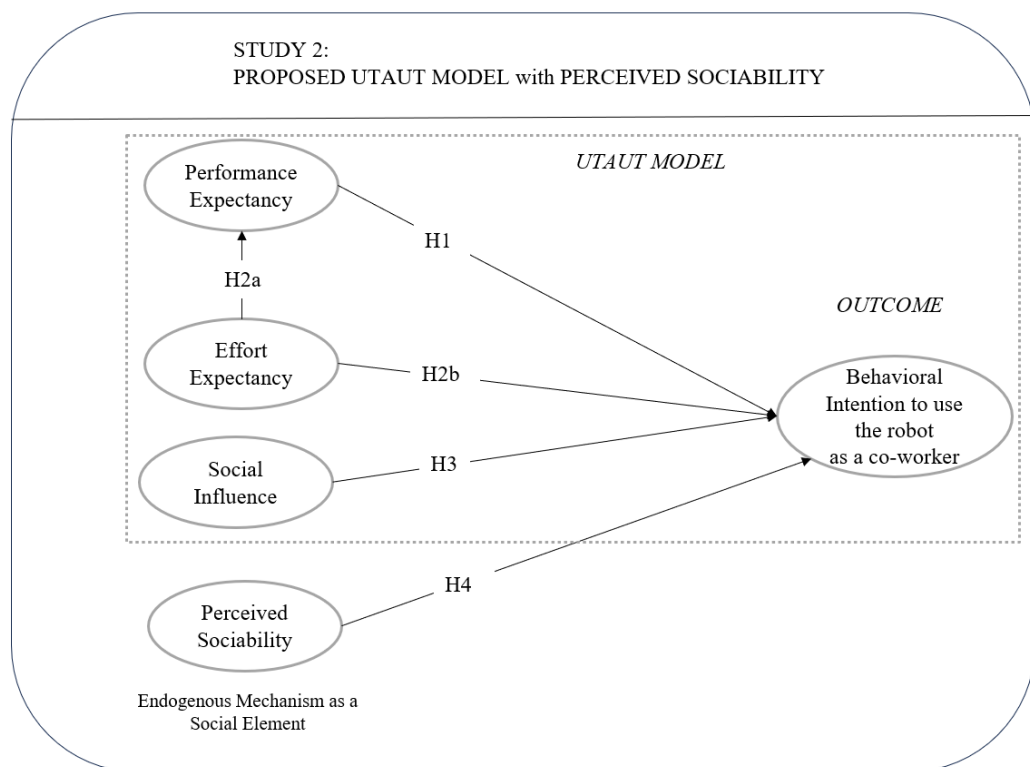


Figure 5.2: The Measurement Model

5.5.1. Indicator Reliability

All indicator outer loadings of the reflectively measured should be higher than a threshold of 0.708 (Hair et al., 2019). If the outer loadings are smaller than 0.4, the item should be deleted from the construct (Bagozzi et al., 1991; Hair et al., 2011). Table 5.2 shows the outer loadings.

Table 5.2: Outer Loadings of the Proposed Measurement Model

Construct	Item	Loadings		
		Complete Data	UK Data	TR Data
Performance Expectancy (PE)	PE1	0.931	0.932	0.933
	PE2	0.935	0.927	0.946
	PE3	0.931	0.930	0.931
	PE4	0.711	0.791	0.620
Effort Expectancy (EE)	EE1	0.827	0.840	0.826
	EE2	0.868	0.851	0.883
	EE3	0.897	0.879	0.912
	EE4	0.878	0.876	0.876
Social Influence (SI)	SI1	0.845	0.890	0.781
	SI2	0.866	0.904	0.813
	SI3	0.847	0.850	0.843
	SI4	0.849	0.881	0.806
Perceived Sociability (PS)	PS1	0.876	0.904	0.841
	PS2	0.922	0.925	0.913
	PS3	0.810	0.774	0.852
	PS4	0.846	0.858	0.835
Behavioral Intention (BI)	BI1	0.962	0.966	0.951
	BI2	0.957	0.958	0.948
	BI3	0.964	0.970	0.953

Note(s): TR = Dataset of Türkiye; UK = Dataset of the United Kingdom; Complete = Türkiye and the United Kingdom Dataset

Without the item of PE4 in the TR dataset, all the items exceeded the value of 0.708. PE4 outer loading value is between 0.60 and 0.70. Therefore, the item was not deleted. Indicator reliability, which is the bivariate correlation between the indicator and the construct, is defined as the square of the indicator loading (Hulland, 1999). For the item's reliability to be accepted, the indicator should explain more than 50% of its variance (Hair et al., 2020). The indicator reliability values are reported in Table 5.3.

Table 5.3: Indicator Reliability of the Proposed Measurement Model

Construct	Item	Indicator Reliability (Loading ²)		
		Complete Data	UK Data	TR Data
Performance Expectancy (PE)	PE1	0.9	0.9	0.9
	PE2	0.9	0.9	0.9
	PE3	0.9	0.9	0.9
	PE4	0.5	0.6	0.4
Effort Expectancy (EE)	EE1	0.7	0.7	0.7
	EE2	0.8	0.7	0.8
	EE3	0.8	0.8	0.8
	EE4	0.8	0.8	0.8

Table 5.3: Indicator Reliability of the Proposed Measurement Model (Continued)

Construct	Item	Indicator reliability (Loading ²)		
		Complete Data	Construct	Item
Social Influence (SI)	SI1	0.7	0.8	0.6
	SI2	0.7	0.8	0.7
	SI3	0.7	0.7	0.7
	SI4	0.7	0.8	0.6
Perceived Sociability (PS)	PS1	0.8	0.8	0.7
	PS2	0.9	0.9	0.8
	PS3	0.7	0.6	0.7
	PS4	0.7	0.7	0.7
Behavioral Intention (BI)	BI1	0.9	0.9	0.9
	BI2	0.9	0.9	0.9
	BI3	0.9	0.9	0.9

Note(s): PE =Performance Expectancy; EE =Effort Expectancy; SI =Social Influence; PS =Perceived Sociability; BI =Behavioral Intention; TR =Dataset of Türkiye; UK =Dataset of the United Kingdom; Complete =Türkiye and the United Kingdom Dataset

For the item PE4 in the TR dataset, the outer loading was 0.635 (Table 5.2), and the indicator reliability remained lower than 50% (Table 5.3). According to Hair et al. (2020), when the outer loading is bigger than 0.40 but smaller than 0.70, the construct's internal consistency reliability and convergent validity should be analysed. The indicator will be deleted if the construct, Performance Expectancy, does not meet the recommended thresholds.

5.5.2. Internal Consistency, Reliability and Convergent Validity

Cronbach's alpha is the traditional criterion for assessing the reliability of internal consistency. The reliability is calculated using the alpha criterion based on the intercorrelations of the observed indicator variables. Cronbach's alpha value is expected to be higher than 0.80 for the reliability (Nunnally, 1967).

Composite reliability (ρ_c) is another measure of internal consistency reliability. This reliability measure is calculated, considering the different outer loadings of the indicator variables. Composite reliability (ρ_c) should exceed the recommended value of 0.80 (Bagozzi and Yi, 1988). When the Cronbach's alpha and composite reliability have extreme values, Dijkstra (2009) proposed that the consistent reliability coefficient (ρ_a) should be higher than 0.70 (Henseler et al., 2016). According to (Hair et al., 2019), the ρ_a reliability metric is typically positioned between the

Cronbach's alpha and composite reliability values, making it a good compromise between the two metrics.

The degree to which a measure positively correlates with other measures of the same construct is known as convergent validity. The average variance extracted (AVE) is a frequently used metric to demonstrate convergent validity at the construct level. AVE is computed by dividing the number of indicators by the sum of the squared loadings. For convergent validity, AVE should exceed 0.50 (Hair et al., 2010).

Table 5.4 displays the findings of Cronbach's alpha, Composite reliability (CR) for internal consistency, and Convergent Validity (AVE). According to the data analysis results, all components and datasets had Cronbach's alpha values higher than 0.8, which suggests a respectable degree of reliability. The composite reliability (rho_c) exceeded the recommended threshold of 0.80, and composite reliability (rho_a) values were higher than 0.70. All datasets had AVE values between 0.66 and 0.93, higher than the suggested cutoff value.

Table 5.4: Assessment of Internal Consistency, Reliability and Convergent Validity of the Datasets

Dataset	Construct	Cronbach's Alpha	Reliability Coefficient (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Complete	PE	0.901	0.923	0.933	0.778
	EE	0.891	0.899	0.924	0.753
	SI	0.874	0.875	0.913	0.725
	PS	0.887	0.897	0.922	0.747
	BI	0.959	0.960	0.973	0.924
UK	PE	0.918	0.927	0.943	0.805
	EE	0.885	0.896	0.920	0.743
	SI	0.904	0.906	0.933	0.777
	PS	0.888	0.898	0.924	0.752
	BI	0.963	0.964	0.976	0.930
TR	PE	0.884	0.925	0.923	0.755
	EE	0.899	0.913	0.929	0.766
	SI	0.827	0.829	0.885	0.658
	PS	0.884	0.896	0.920	0.741
	BI	0.947	0.947	0.966	0.904

Note(s): PE =Performance Expectancy; EE =Effort Expectancy; SI =Social Influence; PS =Perceived Sociability; BI =Behavioral Intention; TR =Dataset of Türkiye; UK =Dataset of the United Kingdom; Complete =Türkiye and the United Kingdom Dataset

The TR dataset's Performance Expectancy (PE) construct met the recommended reliability (CR), internal consistency (Cronbach's alpha), and convergent validity (AVE) threshold. Therefore, the PE4 item was not erased from the analyses.

5.5.3. Discriminant Validity

The heterotrait-monotrait (HTMT) ratios, Fornell-Larcker criteria, and cross-loadings are examined to establish discriminant validity. As a more accurate means of assessing discriminant validity, (Henseler et al., 2015) introduced the heterotrait-monotrait ratio of correlations (HTMT). HTMT is calculated as the ratio of the average correlations between indicators across different constructs (i.e., heterotrait-heteromethod correlations) to the geometric mean of the average correlations among indicators within the same construct (i.e., monotrait-heteromethod correlations). Conceptually, HTMT estimates what the true correlation between two constructs would be if they were measured without error, that is, assuming perfect reliability. To verify discriminant validity, the HTMT values should be less than 0.90, and a conservative threshold of 0.85 is recommended for conceptually different constructs (Henseler et al., 2015). The results of the HTMT ratios for each dataset are detailed in Table 5.5.

Table 5.5: Assessment of Discriminant Validity of the Datasets (HTMT)

Dataset	Construct	BI	EE	PE	PS	SI
Complete	BI					
	EE	0.468				
	PE	0.702	0.653			
	PS	0.568	0.534	0.664		
	SI	0.689	0.546	0.706	0.545	
UK	BI					
	EE	0.531				
	PE	0.753	0.678			
	PS	0.641	0.627	0.677		
	SI	0.782	0.610	0.778	0.653	
TR	BI					
	EE	0.458				
	PE	0.664	0.637			
	PS	0.620	0.442	0.674		
	SI	0.552	0.495	0.600	0.466	

Note(s): PE =Performance Expectancy; EE =Effort Expectancy; SI =Social Influence; PS =Perceived Sociability; BI =Behavioral Intention; TR =Dataset of Türkiye; UK =Dataset of the United Kingdom; Complete =Türkiye and the United Kingdom Dataset

The Fornell-Larcker criterion confirms discriminant validity. The Fornell-Larcker criterion is a decision rule based on a comparison between the squared construct correlations and the average variance extracted (AVE) (Fornell and Larcker, 1981). According to the Fornell-Larcker criterion, a construct should share more variance with its indicators than with indicators of any other construct (Fornell and Larcker, 1981). This criterion suggests that the correlation coefficient between all dimensions should be less than the square root of AVE (Hair et al., 2010). The extracted AVE's square root is represented by the diagonal numbers in Table 5.6, while the non-diagonal numbers represent the correlations between constructs. The values meet discriminant validity requirements.

Table 5.6: Assessment of Discriminant Validity of the Datasets (Fornell-Lacker Criterion)

Dataset	Construct	BI	EE	PE	PS	SI
Complete	BI	0.961				
	EE	0.439	0.868			
	PE	0.652	0.603	0.882		
	PS	0.528	0.485	0.595	0.864	
	SI	0.631	0.490	0.624	0.484	0.852
UK	BI	0.965				
	EE	0.500	0.862			
	PE	0.708	0.625	0.897		
	PS	0.596	0.560	0.614	0.867	
	SI	0.731	0.555	0.708	0.590	0.881
TR	BI	0.951				
	EE	0.433	0.875			
	PE	0.610	0.596	0.869		
	PS	0.578	0.417	0.599	0.861	
	SI	0.489	0.438	0.504	0.407	0.811

Note(s): Square roots of AVE shown on diagonal with bold; PE =Performance Expectancy; EE =Effort Expectancy; SI =Social Influence; PS =Perceived Sociability; BI =Behavioral Intention; TR =Dataset of Türkiye; UK =Dataset of the United Kingdom; Complete =Türkiye and the United Kingdom Dataset

The cross-loading tables, Tables 5.7, 5.8, and 5.9, show that each indicator presents the highest correlations in the factor with its corresponding variable in each dataset, which are highlighted in bold. Each dataset meets this requirement of discriminant validity.

Table 5.7: Assessment of Discriminant Validity of the Complete Dataset (Cross Loadings)

Item	BI	EE	PE	PS	SI
BI1	0.962	0.421	0.638	0.518	0.623
BI2	0.957	0.419	0.610	0.475	0.598
BI3	0.964	0.425	0.634	0.527	0.599
EE1	0.434	0.827	0.621	0.507	0.486
EE2	0.339	0.868	0.457	0.370	0.392
EE3	0.374	0.897	0.505	0.387	0.419
EE4	0.354	0.878	0.473	0.391	0.379
PE1	0.611	0.594	0.931	0.558	0.575
PE2	0.581	0.582	0.935	0.522	0.559
PE3	0.622	0.556	0.931	0.564	0.573
PE4	0.478	0.363	0.711	0.451	0.497
PS1	0.415	0.352	0.458	0.876	0.381
PS2	0.517	0.439	0.564	0.922	0.471
PS3	0.406	0.407	0.472	0.810	0.356
PS4	0.474	0.471	0.551	0.846	0.451
SI1	0.525	0.398	0.520	0.431	0.845
SI2	0.564	0.451	0.568	0.454	0.866
SI3	0.529	0.414	0.521	0.411	0.847
SI4	0.531	0.403	0.516	0.351	0.849

Note(s): BI= Behavioral Intention; EE= Effort Expectancy; PE= Performance Expectancy; PS= Perceived Sociability; SI= Social Influence.

Table 5.8: Assessment of Discriminant Validity of the UK Dataset (Cross Loadings)

Item	BI	EE	PE	PS	SI
BI1	0.966	0.498	0.696	0.576	0.732
BI2	0.958	0.467	0.665	0.548	0.684
BI3	0.970	0.481	0.686	0.600	0.697
EE1	0.518	0.840	0.636	0.526	0.569
EE2	0.396	0.851	0.478	0.430	0.462
EE3	0.389	0.879	0.486	0.465	0.437
EE4	0.391	0.876	0.520	0.490	0.416
PE1	0.678	0.629	0.932	0.600	0.683
PE2	0.624	0.578	0.927	0.541	0.645
PE3	0.654	0.573	0.930	0.582	0.630
PE4	0.578	0.445	0.791	0.471	0.578
PS1	0.525	0.439	0.528	0.904	0.524
PS2	0.582	0.514	0.596	0.925	0.615
PS3	0.491	0.483	0.479	0.774	0.388
PS4	0.456	0.507	0.520	0.858	0.502
SI1	0.656	0.511	0.600	0.537	0.890
SI2	0.676	0.493	0.628	0.553	0.904
SI3	0.610	0.478	0.638	0.505	0.850
SI4	0.631	0.475	0.633	0.482	0.881

Note(s): BI= Behavioral Intention; EE= Effort Expectancy; PE= Performance Expectancy; PS= Perceived Sociability; SI= Social Influence

Table 5.9: Assessment of Discriminant Validity of the TR Dataset (Cross Loadings)

Item	BI	EE	PE	PS	SI
BI1	0.951	0.392	0.586	0.574	0.466
BI2	0.948	0.424	0.563	0.511	0.465
BI3	0.953	0.420	0.591	0.563	0.464
EE1	0.447	0.826	0.628	0.480	0.433
EE2	0.320	0.883	0.448	0.317	0.330
EE3	0.383	0.912	0.530	0.318	0.402
EE4	0.332	0.876	0.424	0.299	0.338
PE1	0.548	0.568	0.933	0.537	0.427
PE2	0.559	0.597	0.946	0.523	0.442
PE3	0.604	0.550	0.931	0.572	0.489
PE4	0.383	0.300	0.620	0.457	0.411
PS1	0.404	0.264	0.397	0.841	0.249
PS2	0.529	0.366	0.541	0.913	0.332
PS3	0.452	0.332	0.493	0.852	0.375
PS4	0.572	0.440	0.595	0.835	0.421
SI1	0.369	0.287	0.419	0.340	0.781
SI2	0.416	0.425	0.491	0.390	0.813
SI3	0.412	0.361	0.366	0.345	0.843
SI4	0.389	0.341	0.359	0.243	0.806

Note(s): BI= Behavioral Intention; EE= Effort Expectancy; PE= Performance Expectancy; PS= Perceived Sociability; SI= Social Influence.

The summary of the measurement model for complete data is shown in Tables 5.10, 5.11, and 5.12.

Table 5.10: Results Summary for Measurement Model with Complete Data

Latent Variable	Indicators	Convergent Validity			Internal Consistency Reliability			Discriminant Validity HTMT Significantly lower than 0.85?
		Loadings > 0.70	Indicator Reliability > 0.50	AVE > 0.50	Cronbach's Alpha >0.80	Reliability (rho_a) >0.70	Reliability (rho_c) >0.70	
Performance Expectancy (PE)	PE1	0.93	0.87	0.778	0.901	0.923	0.933	Yes
	PE2	0.94	0.87					
	PE3	0.93	0.87					
	PE4	0.71	0.51					
Effort Expectancy (EE)	EE1	0.83	0.68	0.753	0.891	0.899	0.924	Yes
	EE2	0.87	0.75					
	EE3	0.90	0.80					
	EE4	0.88	0.77					
Social Influence (SI)	SI1	0.85	0.71	0.725	0.874	0.875	0.913	Yes
	SI2	0.87	0.75					
	SI3	0.85	0.72					
	SI4	0.85	0.72					
Perceived Sociability (PS)	PS1	0.88	0.77	0.747	0.887	0.897	0.922	Yes
	PS2	0.92	0.85					
	PS3	0.81	0.66					
	PS4	0.85	0.72					
Behavioural Intention (BI)	BI1	0.96	0.93	0.924	0.959	0.96	0.973	Yes
	BI2	0.96	0.92					
	BI3	0.96	0.93					

Table 5.11: Results Summary for Measurement Model with UK Data

		Convergent Validity			Internal Consistency Reliability			Discriminant Validity
		Loadings	Indicator Reliability	AVE	Cronbach's Alpha	Reliability (rho_a)	Reliability (rho_c)	HTMT
Latent Variable	Indicators	> 0.70	> 0.50	> 0.50	>0.80	>0.70	>0.70	Significantly lower than 0.85?
Performance Expectancy (PE)	PE1	0.93	0.87	0.805	0.918	0.927	0.943	Yes
	PE2	0.93	0.86					
	PE3	0.93	0.86					
	PE4	0.79	0.63					
Effort Expectancy (EE)	EE1	0.84	0.71	0.743	0.885	0.896	0.92	Yes
	EE2	0.85	0.72					
	EE3	0.88	0.77					
	EE4	0.88	0.77					
Social Influence (SI)	SI1	0.89	0.79	0.777	0.904	0.906	0.933	Yes
	SI2	0.90	0.82					
	SI3	0.85	0.72					
	SI4	0.88	0.78					
Perceived Sociability (PS)	PS1	0.90	0.82	0.752	0.888	0.898	0.924	Yes
	PS2	0.93	0.86					
	PS3	0.77	0.60					
	PS4	0.86	0.74					
Behavioural Intention (BI)	BI1	0.97	0.93	0.93	0.963	0.964	0.976	Yes
	BI2	0.96	0.92					
	BI3	0.97	0.94					

Table 5.12: Results Summary for Measurement Model with TR Data

Latent Variable	Indicators	Convergent Validity			Internal Consistency Reliability			Discriminant Validity
		Loadings	Indicator Reliability	AVE	Cronbach's Alpha	Reliability (rho_a)	Reliability (rho_c)	HTMT Significantly lower than 0.85?
Performance Expectancy (PE)	PE1	0.93	0.87	0.755	0.884	0.925	0.923	Yes
	PE2	0.95	0.89					
	PE3	0.93	0.87					
	PE4	0.62	0.38					
Effort Expectancy (EE)	EE1	0.83	0.68	0.766	0.899	0.913	0.929	Yes
	EE2	0.88	0.78					
	EE3	0.91	0.83					
	EE4	0.88	0.77					
Social Influence (SI)	SI1	0.78	0.61	0.658	0.827	0.829	0.885	Yes
	SI2	0.81	0.66					
	SI3	0.84	0.71					
	SI4	0.81	0.65					
Perceived Sociability (PS)	PS1	0.84	0.71	0.741	0.884	0.896	0.920	Yes
	PS2	0.91	0.83					
	PS3	0.85	0.73					
	PS4	0.84	0.70					
Behavioural Intention (BI)	BI1	0.95	0.90	0.904	0.947	0.947	0.966	Yes
	BI2	0.95	0.90					
	BI3	0.95	0.91					

5.6. Structural Model

The model presented in this study has two dependent (endogenous) variables: Performance Expectation and Behavioural Intention, while Effort Expectation, Social Influence, and Perceived Sociability are the independent (exogenous) variables.

5.6.1. Collinearity Statistics (VIF)

The Variance Inflation Factor (VIF) in a reflective measurement model measures the degree of collinearity between constructs. The VIF values should be smaller than 3 (Becker et al., 2015). The VIF values for each endogenous construct combination are displayed in Table 5.13. All the VIF values are smaller than 3. Therefore, there are no collinearity problems in any of the datasets.

Table 5.13: Assessment of Collinearity Statistics (VIF) of the Datasets

	Complete Dataset	UK Dataset	TR Dataset
PE -> BI	2.282	2.523	2.141
EE -> PE	1.000	1.000	1.000
EE -> BI	1.672	1.819	1.620
SI -> BI	1.733	2.215	1.423
PS -> BI	1.648	1.851	1.603

Note(s): BI= Behavioral Intention; EE= Effort Expectancy; PE= Performance Expectancy; PS= Perceived Sociability; SI= Social Influence; TR = Dataset of Türkiye; UK = Dataset of the United Kingdom; Complete = Türkiye and the United Kingdom Dataset

5.6.2. Hypothesis Testing

The structural model was examined after the measurement model was analysed. The significance of the path coefficients was determined using 5000 bootstrap subsamples. The results, shown in Table 5.14, highlight the significance and path coefficients of the hypothesised relationships.

Table 5.14: Assessment of Direct Relationships of the Datasets

Dataset	Hypothesis	Path Coefficients	T Values	P Values	95% Percentile Confidence Intervals	Results
Complete	H1: PE -> BI	0.357	7.665	0.000***	0.434	Supported
	H2a: EE ->PE	0.603	18.045	0.000***	0.656	Supported
	H2b:EE -> BI	-0.022	0.552	0.290ns	0.041	Not Supported
	H3:SI -> BI	0.341	8.046	0.000***	0.412	Supported
	H4: PS -> BI	0.161	3.585	0.000***	0.236	Supported
UK	H1: PE -> BI	0.331	5.533	0.000***	0.429	Supported
	H2a:EE ->PE	0.625	16.166	0.000***	0.686	Supported
	H2b:EE -> BI	-0.030	0.595	0.276 ns	0.050	Not Supported
	H3: SI -> BI	0.416	6.491	0.000***	0.525	Supported
	H4: PS -> BI	0.163	2.866	0.002**	0.256	Supported
TR	H1: PE -> BI	0.311	4.373	0.000***	0.426	Supported
	H2a: EE ->PE	0.596	10.489	0.000***	0.687	Supported
	H2b:EE -> BI	0.039	0.655	0.256 ns	0.138	Not Supported
	H3: SI -> BI	0.194	3.792	0.000***	0.279	Supported
	H4: PS -> BI	0.297	4.336	0.000***	0.409	Supported

Note(s): * $p < 0.05$, ** $p < 0.01$, *** p , ns: not significant; BI= Behavioral Intention; EE= Effort Expectancy; PE= Performance Expectancy; PS= Perceived Sociability; SI= Social Influence; TR = Dataset of Türkiye; UK = Dataset of the United Kingdom; Complete = Türkiye and the United Kingdom Dataset

H1: Performance Expectancy is significantly related to Behavioural Intention to use the robot as a co-worker in an office environment.

For each dataset, Performance Expectancy is significantly related to Behavioural Intention to use the robot as a co-worker. Thus, H1 was supported; Complete Dataset ($\beta=0.357$, $t=7.665$, $p=0.000$), the UK Dataset ($\beta=0.357$, $t=5.533$, $p=0.000$), the TR Dataset ($\beta=0.311$, $t=4.373$, $p=0.000$).

H2a: The Effort Expectancy is significantly related to Performance Expectancy.

For each dataset, Effort Expectancy is significantly related to Performance Expectancy. Thus, H2a was supported; Complete Dataset ($\beta=0.603$, $t=18.045$, $p=0.000$), the UK Dataset ($\beta=0.625$, $t=16.166$, $p=0.000$), the TR Dataset ($\beta=0.596$, $t=10.489$, $p=0.000$).

H2b: Effort Expectancy is significantly related to Behavioural Intention to use the robot as a co-worker in an office environment.

For each dataset, Effort Expectancy is not significantly related to Behavioural Intention to use the robot as a co-worker in an office environment. Thus, H2b was not supported; Complete Dataset ($\beta=-0.022$, $t=0.552$, $p=0.290$), the UK Dataset ($\beta=-0.030$, $t=0.595$, $p=0.276$), the TR Dataset ($\beta=0.039$, $t=0.655$, $p=0.256$).

H3: Social Influence is significantly related to Behavioural Intention to use the robot as a co-worker in an office environment.

For each dataset, Social Influence is significantly related to Behavioural Intention to use the robot as a co-worker in an office environment. Thus, H3 was supported; Complete Dataset ($\beta=0.341$, $t=8.046$, $p=0.000$), the UK Dataset ($\beta=0.416$, $t=6.491$, $p=0.000$), the TR Dataset ($\beta=0.194$, $t=3.792$, $p=0.000$).

H4: Perceived Sociability is significantly related to Behavioural Intention to use the robot as a co-worker in an office environment.

For each dataset, Perceived Sociability is significantly related to Behavioural Intention to use the robot as a co-worker in an office environment. Thus, H4 was supported; Complete Dataset ($\beta=0.161$, $t=3.585$, $p=0.000$), the UK Dataset ($\beta=0.163$, $t=2.866$, $p=0.000$), the TR Dataset ($\beta=0.297$, $t=4.336$, $p=0.000$).

The statistical model of the complete dataset is shown in Figure 5.3. The statistical models for the UK and TR datasets are illustrated in Figure 5.4.

The Results of the Complete Dataset

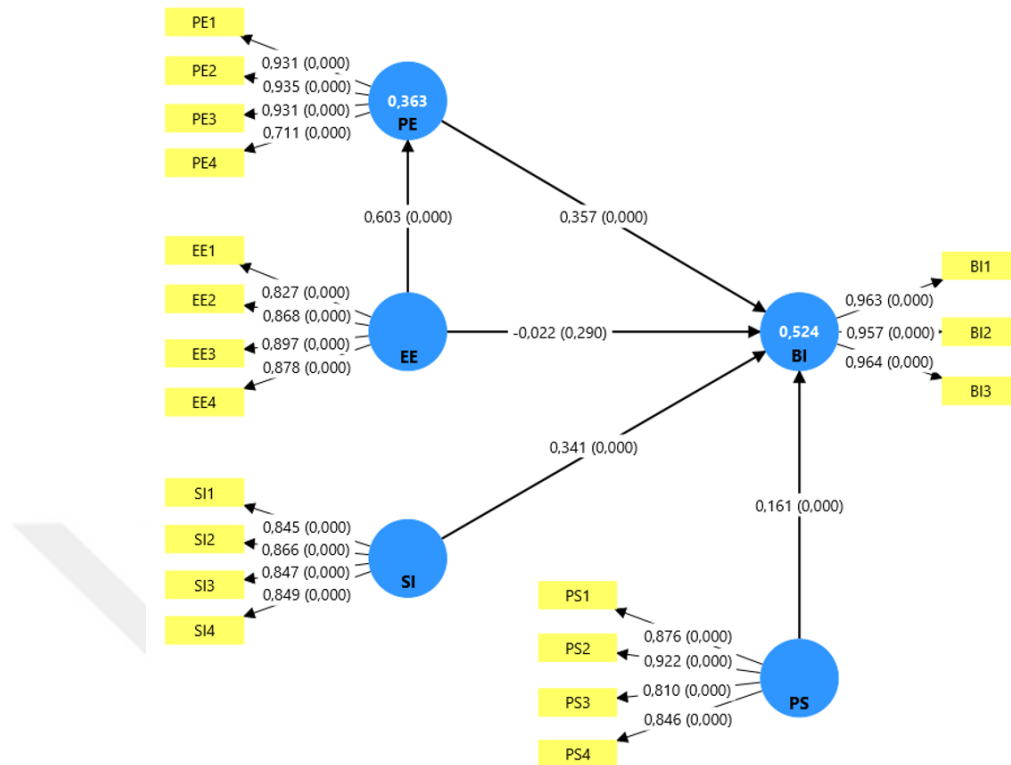
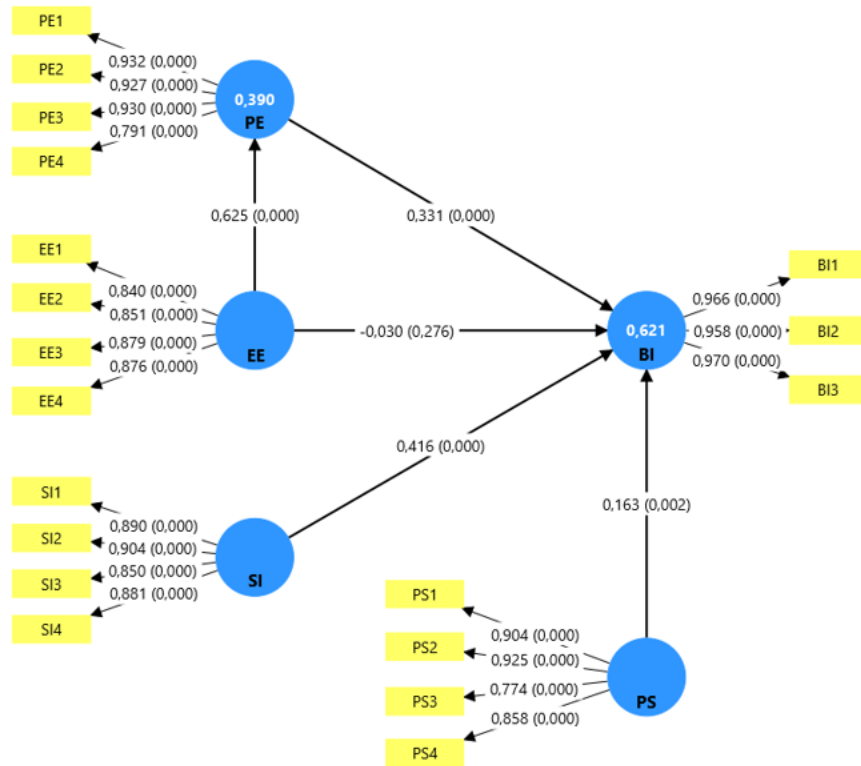


Figure 5.3: The Model of Complete Dataset

Note(s): Circle values = R square

The Results of the UK Dataset



The Results of the TR Dataset

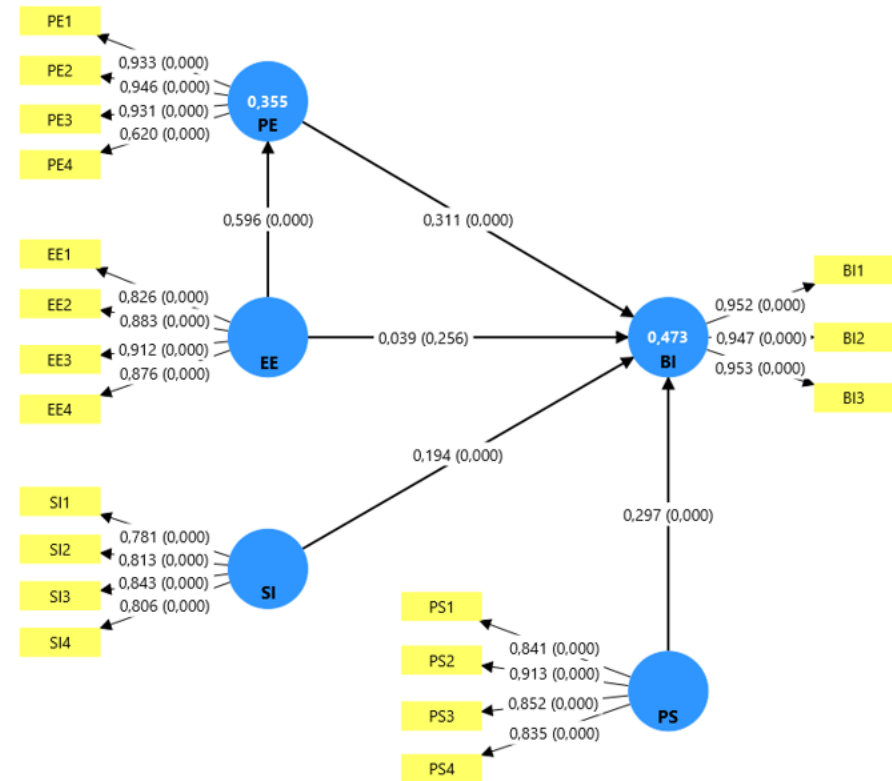


Figure 5.4: Comparison Results of the Models Between the UK and TR Datasets

Note(s): Circle values = R square

Additionally, the study evaluated a model's predictive power in Q^2 and explanatory power (simple predictive power) in R^2 . Explanatory power (R^2) is a coefficient of determination that is the value that shows what percentage of the endogenous variable is explained by the exogenous variables. The values are classified as three levels: weak ($R^2 \geq 0.25$), moderate ($R^2 \geq 0.50$), and strong ($R^2 \geq 0.75$) (Hair et al., 2020). The relationships help explain Behavioural Intention to use the robot in co-working office environments, with complete dataset R^2 values of 0.436, 0.546 for the UK dataset, and 0.466 for the TR dataset. Additionally, the blindfolding technique was employed to determine the values of Q in SmartPLS4. The model's relevance and sufficiency are indicated when Q^2 values are higher than zero (0) (Hair et al., 2020). All of the model's datasets have predictive relevance, as demonstrated by Table 5.15, where the Q^2 values are greater than 0.

Table 5.15: Adequacy and Relevance of the Model for all Datasets

Dataset	Performance	Expectancy	Behavioral Intention	
	R^2	Predictive Q^2	R^2	Predictive Q^2
Complete	0.363	0.360	0.524	0.436
UK	0.390	0.385	0.621	0.546
TR	0.355	0.346	0.473	0.396

Note(s) : TR = Dataset of Türkiye; UK = Dataset of the United Kingdom; Complete = Türkiye and the United Kingdom Dataset

5.6.3. Comparison of the Concept Model

The study's model was compared with the original UTAUT model in the SmartPLS4 data analysis tool to determine the best-fitting model. Not only are parsimonious models that are good at explaining the data, that is, those with high R^2 values, but also simple models are usually preferred by researchers, as such models are more likely to generalise to other research settings (Sharma et al., 2021). The research model and the original UTAUT model have the same R^2 values.

Particularly suitable for PLS-SEM-based model selection tasks, Sharma et al. (2019) identified the Bayesian information criterion (BIC) (Schwarz, 1978), and the Geweke and Meese (GM) criterion (Geweke and Meese, 1981).

In the estimation of PLS path models, Sharma et al. (2021) similarly find that the BIC and GM also achieve a good trade-off between model fit and out-of-sample predictive power. The two models were compared in Figure 5.5, using the BIC criterion with SmartPLS4.

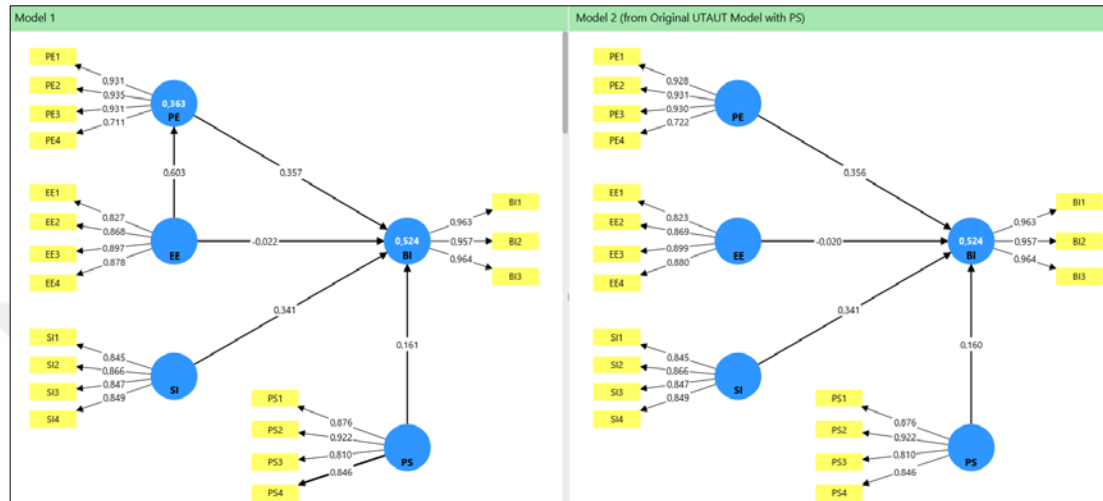


Figure 5.5: The Study Model Comparison with the UTAUT Original Model

Note(s): Circle values = R square

According to Sharma et al. (2021), the model with the lowest BIC value is regarded as the best model in the collection. Table 5.16 displays the BIC comparison results.

Table 5.16: The Model's BIC Criteria for all Datasets

	BIC Model 1	BIC Model 2
BI (Complete)	-374.424	-374.374
BI (UK Dataset)	-237.783	-374.370
BI (Türkiye Dataset)	-148.020	-374.370

According to Table 5.16, the model used in this study, which is part of the complete dataset, is the best. For the UK and TR's dataset models, the original UTAUT model, Model 2, is the best.

6. DISCUSSION

Industry 5.0 is envisioned as being about human-robot co-working (Web 3, 2024; Sharma et al., 2024; Tuffaha, 2024). Therefore, in the working environment, the issue of robot acceptance is crucial (Saari et al., 2022; Van Looy, 2022). The findings underscore the critical importance of human-robot collaboration in achieving the objectives of Industry 5.0, particularly in promoting work environments that prioritise human well-being and creativity. Robots intended for office settings should not only fulfil functional tasks but also demonstrate cultural adaptability to enhance acceptance across varied workplace contexts. To facilitate effective integration, organisations are encouraged to implement structured training initiatives and foster environments that support meaningful interaction between human employees and robotic systems (Nahavandi, 2019). Furthermore, the development of ethical and sustainable policy frameworks is crucial for guiding the responsible deployment of robotic technologies. Such measures not only align with the human-centric vision of Industry 5.0 but also help ensure that technological innovation contributes positively to both organisational productivity and employee well-being.

This research had two studies.

The first study examines the robot appearance preferences of professionals in office environments as potential colleagues. The participants with preferences as a co-worker for less machine-more human-like robots (Category 4) and human-like robots (Category 5) prioritise sociability, likely due to expectations of meaningful and human-like interactions in office environments. However, according to Study 1, Category 4 included the unwanted physical appearance of robots, which led participants to fall into the curve, as mentioned in the literature, known as the uncanny valley theory (Destephe et al., 2015; Mori, 1970; Saneyoshi et al., 2022; Walters et al., 2008). Conversely, it was observed that participants with a preference for machine-like robots (Category 1) and those who prefer more machine-less human-like robots (Category 2) shared some concerns about interacting and co-working with robots. Machine-human-like robots (category 3) appeal broadly (26%) due to their perceived utility and sociability, and this category was not located in the uncanny valley.

According to study 1, the ADA7 robot is a safe place for participants' perceptions. By considering these appearance preferences and their psychological implications, the study provides actionable insights for developing robots that are both visually appealing and functionally effective in workplace settings.

The second study examines whether professionals in office environments are willing to accept robots in the workplace. The Unified Theory of Acceptance and Use of Technology (UTAUT) is a research model widely adopted in numerous technology acceptance studies (Tamilmani et al., 2021; Venkatesh et al., 2016). The UTAUT model has also been applied in researching robot acceptance in healthcare (Alaiad and Zhou, 2014; N. Chen, 2018; Vichitkraivin and Naenna, 2021; Yeoh and Chin, 2022), hospitality (Abdelhakim et al., 2023; Chi et al., 2023; Pande and Gupta, 2023), and education (Guggemos et al., 2020; Suhail et al., 2024). To investigate robot acceptance in office workplaces (Venkatesh et al., 2012), we utilised the UTAUT model. This study includes UTAUT constructs such as performance expectancy, effort expectancy, and social influence (Venkatesh, 2022). The Perceived Sociability from the ALMERE Robot Acceptance Model was also designed to explore the elderly acceptance of assistive social agents (Heerink et al., 2010). Given that office environments also function as social workplaces for employees (Voordt and Jensen, 2023), this study hypothesised that Perceived Sociability may play a role in the acceptance of robots in workplaces. As a result, to research robot acceptance in office work environments, our research model examines the relationships among Performance Expectancy, Effort Expectancy, Social Influence, Perceived Sociability, and the Behavioural Intention to use robots. We conducted empirical studies in two different locations, namely the United Kingdom and Türkiye. The survey was developed to include established measures of UTAUT constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Behavioural Intention to use. Perceived Sociability was used as an endogenous mechanism as a construct. Since the use of robots is not yet widespread, before the survey, participants viewed a video showcasing potential interactions between employees and a social robot in an office environment. The ADA7 social robot, developed by AKINROBOTICS, was featured in this video. The ADA7 is designed as a social robot and possesses the necessary technologies to function effectively as a coworker in an office setting. The ADA7 can engage in conversations with employees, perform common office tasks such as error checking in documents,

and assist with administrative duties. Participants were asked to respond to the survey questions as if they were co-working with this robot.

The data was analysed separately for each country and combined for an overall analysis in the second study. Analysis of the three datasets results in statistically significant relationships between Performance Expectancy, Social Influence, and Perceived Sociability and Behavioural Intention to use robots. Moreover, Effort Expectancy is significantly related to Performance Expectancy, consistent with findings from previous related studies (Alaiad et al., 2014; Alaiad and Zhou, 2014; Kaiser et al., 2024). However, their research settings are not working environments.

The analysis showed that Effort Expectancy does not have a significant relationship with the Behavioural Intention to use robots as a co-worker in an office environment. According to Venkatesh, (2025), the importance of Effort Expectancy in relation to Behavioural Intention may be questioned as technology evolves. Within the UTAUT model, this finding about the non-significance of Effort Expectancy on the Intention to use robots provides an empirical answer to such questions. This finding is also in line with findings from Vichitkraivin and Naenna, (2021), indicating that the impact of Effort Expectancy diminishes as robots become more autonomous. The results are the same across the three datasets for the UK, Türkiye and Complete. According to the Special Eurobarometer 554 study on Artificial Intelligence and the Future of Work, each of the 27 EU member countries has a positive perception of the use of robots and Artificial Intelligence in the workplace (Web 1, 2025). Consequently, workplaces in many different cultures and countries will probably accept robots. However, evidence from a much larger dataset spanning several nations may be needed to confirm universal robot acceptance. Furthermore, national cultures are impacted by modernisation and globalisation, which results in standardisation in educational, cultural, and industrial systems that promote a uniform transnational culture (Koshy et al., 2023). As we approach Industry 5.0, with societies increasingly adopting artificial intelligence independently, the importance of cultural dimensions may lead to a decline in the acceptance of robots in the near future.

These results directly affect the design and deployment of robots in office settings. According to the relationship between the intention to use robots in the workplace and perceived sociability, perceived sociability will play a significant role in robot acceptance. This research recommends that robot designers focus on developing social

capabilities, including effective communication, enjoyable interactions, and other related skills to enhance acceptance. Practically, the findings are helpful for robot companies and business decision-makers in designing and implementing AI-based robots in office environments. Organisations can further promote acceptance by fostering a climate that supports robot adoption, resulting in increased productivity through effective integration.

6.1. Theoretical Implications

Study 1 demonstrated that Mori's Uncanny Valley Theory remains relevant (Mori, 1970). Study 2 enhances our understanding of how the Unified Theory of Acceptance and Use of Technology (UTAUT) model can be adopted to investigate the acceptance of robots, particularly in office environments, which was identified as a literature gap. By analysing the relationship between Perceived Sociability and Behavioural Intention to use the robot as a co-worker, Study 2 enhanced our understanding of how Perceived Sociability influences robot acceptance within the UTAUT framework. Study 2 also investigated the relationship between Performance Expectancy and Effort Expectancy (Davis, 1989; Vroom, 1964). Furthermore, our study is among the pioneering empirical studies demonstrating that Effort Expectancy, a key construct in the UTAUT model, may not be a significant predictor in the domain of robot acceptance (Venkatesh, 2025). In addition, Thormundsson (2024) as mentioned, the AI Revolution started in 2022. After the AI Revolution, some studies showed that Effort Expectancy has no significant relationship with Behavioural Intention to use, such as using autonomous public shuttles (Quinones et al., 2024), domestic healthcare robots for patients (Yeoh and Chin, 2022; Zhang, 2024), healthcare robots (Komariyah et al., 2024) and education robots (Suhail et al., 2024). Robots have been using generative AI; therefore, they do not require any human intervention.

6.2. Practical Implications

The implications of integrating robotic systems and Artificial Intelligence into organisational environments are multifaceted. This section outlines the practical consequences of such integration for human resources professionals, robot designers and engineers, as well as top-level management.

6.2.1. Implications for Human Resources (HR)

Training Programs: Training programs can be designed to familiarise employees with robot functionalities and reduce apprehension. Furthermore, aligning robot capabilities with employees' performance expectations can enhance perceived usefulness, thereby increasing acceptance.

The deployment of robots in organisational contexts requires a systematic revision of onboarding and annual training processes. Periodic "Artificial Intelligence Awareness" programs should be designed and implemented to raise awareness among employees regarding the use of AI technologies. These programs should be updated regularly to reflect ongoing technological advancements. Additionally, the potential opportunities and risks related to the use of robots should be embedded within the training curriculum to enhance organisational readiness.

Job Descriptions and Workflows: Tasks that do not generate significant added value, such as routine administrative operations, can be transferred to robots. As a result, job roles may be redesigned through simplification, enrichment, or reallocation of responsibilities. This may necessitate an update in job descriptions and workflow systems. Moreover, focus group studies could be conducted to assess how robots can be used more effectively in office environments and to capture employee perspectives on their integration.

6.2.2. Implications for Robot Designers and Engineers

Additionally, paying attention to the aesthetic design of robots can help avoid Mori's "Uncanny Valley" effect, further improving user acceptance. For example, designs should focus on incorporating human-like traits that enhance usability and approachability while maintaining distinct non-human features to set clear expectations of the robot's capabilities. Achieving this balance can improve user comfort and acceptance, particularly in office environments where frequent human-robot interactions are expected.

Algorithmic Design and Data Security: To protect organisations from digital threats, robot designers should develop AI systems with enhanced cybersecurity frameworks. These systems must ensure data privacy and protection against cyberattacks.

Additionally, robots operating in office settings should be equipped with privacy-sensitive features to safeguard employee data and ensure compliance with personal privacy rights.

Physical Appearance and Functional Consistency: The physical appearance of robots should be designed with careful consideration of Mori's Uncanny Valley theory, which emphasises the importance of aligning a robot's appearance with human expectations. Robots should exhibit external characteristics that correspond with their functional abilities in order to avoid perceptual discomfort and to increase acceptance.

Social Interaction Capabilities: Study 2 results show a significant relationship between perceived sociability (PS) and behavioural intention (BI), emphasising the importance of designing robots with advanced social capabilities. Robot developers should prioritise features that enable effective communication, emotional responsiveness, and user-friendly interactions. For example, incorporating natural language processing and adaptive learning algorithms can enhance robots' ability to engage with users in a meaningful way.

Robots are often perceived as social entities within organisational contexts. Enhancing robots' social capabilities, such as recognising employee voices and addressing them by their name, may foster a more human-like interaction and strengthen their perceived sociability, ultimately contributing to a more cohesive workplace environment.

6.2.3. Implications for Top Management

Before making procurement decisions regarding robotic technologies, management should conduct a comprehensive analysis of employee preferences regarding the physical and behavioural characteristics of robotic co-workers. Procurement decisions should not be based solely on technical specifications, but also consider human factors such as comfort, acceptance, and alignment with organisational culture. Top management aiming to integrate robots into office environments should create a supportive climate for adoption. This includes fostering positive social influence through management endorsement and peer support for the use of robots.

6.3. Limitations and Future Research Directions

This study primarily relied on quantitative data collected through a 5-point Likert scale questionnaire. While this approach provided generalisable findings, it may not capture the full spectrum of participants' attitudes and behaviours. Future research could explore the use of alternative scales, such as 7-point or 10-point Likert scales, to capture more nuanced opinions and enhance the depth of responses. Additionally, the exclusive reliance on quantitative methods is a limitation, as it may overlook the subtleties of human experiences. Incorporating qualitative methods, such as interviews or focus groups, in future studies could provide richer insights and validate the constructs examined in this research. Another limitation lies in the potential biases associated with using video scenarios to simulate human–robot interactions. While video scenarios add an experiential dimension, participant perceptions based on these scenarios may not fully translate into real-world behaviours. Future research could address this limitation by complementing video scenarios with live demonstrations or hands-on interactions with robots, thereby providing a more accurate assessment of human–robot interaction dynamics.

This study also acknowledges the challenges related to ethical concerns. Issues such as data privacy, algorithmic bias, and the potential misuse of robots for surveillance purposes warrant careful consideration. Future research could explore the development of ethical frameworks and transparent policies to guide the responsible integration of robots in office environments.

Lastly, socioeconomic inequality is a significant problem. Richer companies might be the only ones with access to cutting-edge robotic technologies, which may increase inequality. In order to prevent job displacement and guarantee that everyone benefits equally from the use of robots, workforce reskilling and the development of inclusive policies will be essential. A more thorough understanding of these issues and the development of strategies for the fair integration of technology could result from broadening the research's focus to include organisations in various socioeconomic contexts. Future research might, for instance, look into how public-private partnerships or subsidised robotics programs can help close the accessibility gap.

The rapid advancement of robotic technologies is another limitation, as the findings from this study may become less applicable as new generations of robots with

enhanced capabilities emerge. Future research could adopt longitudinal study designs to track changes in acceptance patterns over time, particularly as robots become more autonomous, interactive, and socially adept. Additionally, investigating the scalability of robot integration across different organisational sizes and sectors would further enrich the understanding of their potential impact. While this study focused on participants from two culturally distinct regions, the findings may not fully capture the broader global diversity in robot acceptance. Expanding future research to include participants from a wider range of cultural backgrounds, as well as varying age groups, industries, and educational levels, could provide more representative insights. This would be particularly useful for identifying universal versus culture-specific factors influencing robot acceptance. Ultimately, future studies could explore the practical challenges that organisations encounter when implementing robots in office environments. Topics such as the cost-effectiveness of robot adoption, the integration of robots with existing workflows, and employee training programs deserve further exploration to provide actionable recommendations for organisations considering robotic technologies.

7. CONCLUSION

In the era of Industry 5.0, robots and machines will focus on tasks that Non Value-Added tasks for humans, while humans will focus on creative tasks. Collaboration between humans and robots will be the clearest example of Industry 5.0. It is crucial to think of robots as coworkers to achieve this vision. The question of whether robots can be regarded as co-workers in an office setting was investigated in this study. Two independent studies have formed our research. We asked office workers in the first study which robot appearance they liked best in a coworker. Examining all the data from both countries generated an interesting result. The uncanny valley theory and the result of the general curve of office workers' preferences for robot coworkers overlapped. The Unified Theory of Acceptance and Use of Technology (UTAUT) served as the foundation for the second study. The three separate datasets were determined: the complete dataset, the United Kingdom, and Türkiye. To investigate the relationship of using the robot as a co-worker, the UTAUT model's Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) were modified for the second research model. We employed a social service robot in our study. The Perceived Sociability (PS) variable was added to the model because social robots may soon be used in office settings. The relationship between perceived sociability and the intention to use robots was also investigated. Three distinct datasets were analysed, and the findings were equivalent. The findings indicate that Social Influence (SI), Perceived Sociability (PS), and Performance Expectancy (PE) are positively and significantly correlated with the Behavioural Intention (BI) to use the robot as a co-worker in an office environment.

The findings offer recommendations for robotic technology suppliers and organisations looking to implement human-robot collaboration environments. Social impact encourages co-operation between humans and robots. Manufacturers of robotic technology ought to concentrate on creating more sociable and productive robots. The results of this study can be expanded upon in future investigations. Data from different countries may be collected and analysed to determine whether the factors influencing robot acceptance are universal. Various factors could be examined to improve our understanding of factors influencing robot acceptance. To enhance our understanding

of sociability and provide guidance to robot developers, the concept of Perceived Sociability can be explained in detail. This study could be expanded to include workplaces other than offices. The results derived from theoretical frameworks of UTAUT will assist in developing robot technology acceptance models that are better suited for investigating the acceptance of robots for human-robot co-working in Industry 5.0.

The limitation of this research is that most survey participants had no experience working with robots, as current office environments lack widespread robot use. Their responses are based on their intentions to use robots, as visualised through the video demonstrating potential robot interactions in the workplace. As with many similar studies, the sample size could be increased. Furthermore, the study could be replicated in other countries.

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BIOGRAPHY

Gözde Döven started her bachelor's degree in Mining and Mineral Engineering from Dokuz Eylül University in Türkiye in 2003. She received an associate's degree in International Business from Anadolu University in Türkiye in 2007. Then, she received a bachelor's degree in Mining and Mineral Engineering from Dokuz Eylül University in Türkiye in 2008, followed by another bachelor's degree in Business Administration and Management from Anadolu University in 2011. In 2013, she completed a Master of Business Administration degree at Gebze Institute of Technology in Türkiye. In 2017, she began her Ph.D. in the Business Administration Department at Gebze Technical University and participated in an Erasmus exchange program at Mendel University in Brno, Czech Republic, in 2018. She has over eight years of experience in the cement industry, working in the Integrated Management Systems Department and the Human Resources Department. Her research interests include Industry 5.0, process management, human-robot collaboration, and human resources.

PUBLICATIONS AND PRESENTATIONS FROM THE THESIS

Döven G., Sezen B., Demir K. A., Balcioğlu Y. S, (2025), “Industry 5.0: Are we going to accept robots as co-workers in office environments? An empirical analysis”, Applied Sciences, 15(3), 1591. <https://doi.org/10.3390/app15031591>

Demir K. A., Döven G., Sezen B., (2019), “Industry 5.0 and human-robot co-working”, Procedia Computer Science, 158, 688–695. <https://doi.org/10.1016/j.procs.2019.09.104>



APPENDICES

APPENDIX-A: The Survey of this Research

Robot Acceptance in an Office Environment

This survey is conducted to collect data for the PhD thesis of Gözde DÖVEN, a PhD student at Gebze Technical University Graduate Institute, Department of Business Administration in Türkiye.

The data will only be used for scientific purposes and will never be shared with third parties and organisations.

The estimated completion time of our survey is 6 minutes. Our survey consists of a 3 minute 30 seconds long audio video and 18 multiple-choice questions that take about 3 minutes to answer.

This study has received approval from the Gebze Technical University Human Research Ethics Committee (E-43633178-199-163055).

If you have any discomfort or disadvantage during the research, please feel free to quit the survey.

Thank you very much for your participation.

Q1. What is your gender?

Answer Choices

- ☐ Female
- ☐ Male
- ☐ Prefer not to answer.

Q2. What is your year of birth? (Please write below)

Answer:

Q3. Where do you live?

Answer Choices

- ☐ United Kingdom
- ☐ Türkiye
- ☐ Other (please specify)

Q4. Your level of education

Answer Choices

- ☐ IB/WB/A Level/School Graduate
- ☐ First-degree level qualification, including foundation degrees, graduate membership of a professional institute, etc.
- ☐ Diploma in higher education
- ☐ University higher degree (e.g. MSc, PhD)
- ☐ Other (please specify)

Q5. Which of the following categories best describes your employment status?

Answer Choices

- ☐ Employed, working full-time
- ☐ Employed, working part-time
- ☐ Not employed and/or looking for work
- ☐ Retired
- ☐ Other (please specify)

Q6. Have you ever worked in an office environment?

Answer Choices

- ☐ Yes
- ☐ No
- ☐ Other (please specify)

A robot is defined here as an autonomous, mobile machine which can assist humans in everyday tasks e.g. as a kind of co-worker helping on the factory floor or as a robot cleaner, or in activities which may be dangerous for humans, like search and rescue in disasters. Robots can come in many shapes or sizes, including human-like. Traditional kitchen appliances, such as a blender or a coffee maker, are not robots.

Q7. Have you ever used, or are you currently using such robots at home or at work (e.g. Alexa or a robotic vacuum cleaner at home or an industrial robot at work)?

Answer Choices

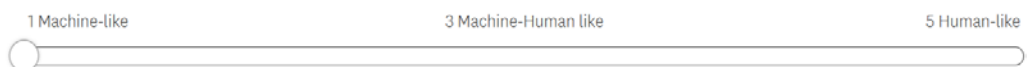
- ☐ Yes, at home
- ☐ Yes, at work
- ☐ Yes, elsewhere
- ☐ No

Q8. Would you consider purchasing a robot for your home?

Answer Choices

- ☐ Yes, within the next year.
- ☐ Yes, in 1 to 5 years.
- ☐ Yes, in more than 5 years.
- ☐ No
- ☐ I already have one.

Q9. If you have a chance to work with a robot colleague, which appearance do you prefer? Please slide the number that best suits you on this scale from 1 (machine-like) to 5 (human-like).



Q10. Please imagine your office environment while you are watching this video. Please click the video to watch. <https://youtu.be/kWlbssNOP2A>

Answer Choices

☐ Please click the box after watching the video.

Please respond to Questions 11 to 15 using the following 5-point Likert Scale:

1= Strongly disagree

2= Disagree

3= Neither agree nor disagree

4= Agree

5= Strongly agree

Q11. Performance (Please select your opinions as if you are co-working with this robot in your office environment.)

1	2	3	4	5
---	---	---	---	---

I would find this robot useful in my job.

1	2	3	4	5
---	---	---	---	---

Using this robot enables me to accomplish tasks more quickly.

1	2	3	4	5
---	---	---	---	---

Using this robot increases my productivity.

1	2	3	4	5
---	---	---	---	---

If I use this robot, I will increase my chances of getting a raise.

Q12. Effort Expectancy (Please select your opinions as if you are co-working with this robot in your office environment.)

1	2	3	4	5
---	---	---	---	---

My interaction with this robot would be clear and understandable.

1	2	3	4	5
---	---	---	---	---

It would be easy for me to become skilful at using this robot.

1	2	3	4	5
---	---	---	---	---

I would find this robot easy to use.

1	2	3	4	5
---	---	---	---	---

Learning to operate this robot is easy for me.

Q13. Social Influence (Please select your opinions as if you are co-working with this robot in your office environment.)

1	2	3	4	5
---	---	---	---	---

I think the staff would like me using the robot.

1	2	3	4	5
---	---	---	---	---

I think it would give a good impression if I should use the robot.

1	2	3	4	5
---	---	---	---	---

I think the senior management would be helpful in the use of the robot.

1	2	3	4	5
---	---	---	---	---

In general, the organisation would support the use of the robot.

Q14. Perceived Sociability (Please select your opinions as if you are co-working with this robot in your office environment.)

1	2	3	4	5
---	---	---	---	---

I consider the robot a pleasant conversational partner.

1	2	3	4	5
---	---	---	---	---

I find the robot pleasant to interact with.

1	2	3	4	5
---	---	---	---	---

I feel the robot understands me.

1	2	3	4	5
---	---	---	---	---

I think the robot is nice.

Q15. Behavioural Intention to use Robots as a co-worker (Please select your opinions as if you are co-working with this robot in your office environment.)

1	2	3	4	5
---	---	---	---	---

I intend to use this robot in the near future.

1	2	3	4	5
---	---	---	---	---

I predict I would use this robot in the near future.

1	2	3	4	5
---	---	---	---	---

I plan to use this robot in the near future.