MBA Thesis

Applying the Technology Acceptance Model to AI decisions in the Swedish Telecom Industry

Authors
Kashan Ali & Kim Freimann

Supervisor
Jonas Månsson

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DEPARTMENT OF INDUSTRIAL ECONOMICS

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The author(s) declare(s) that they have completed the thesis work independently. All external sources are cited and listed under the References section. The thesis work has not been submitted in the same or similar form to any other institution(s) as part of another examination or degree.

Author information:

Kashan Ali
syedkashanali@gmail.com

Kim Freimann
kim.freimann@gmail.com

Department of Industrial Economics
Blekinge Institute of Technology
SE-371 79 Karlskrona, Sweden

Website: www.bth.se
Telephone: +46 455 38 50 00
Fax: +46 455 38 50 57

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List of Abbreviations

AI	Artificial intelligence
ATU	Attitude towards AI use
BI	Behavioural intention
CSP	Communication service providers
CFA	Confirmatory Factor Analysis
CFI	Comparative fit index
PEU	Perceived ease of use
PU	Perceived usefulness
RMSEA	Root mean square error of approximation
RPA	Robotic process automation
SEM	structural equation modelling
SN	Subjective norms
SRMR	Standardized root mean square residual
TAM	Technology Acceptance Model
TLI	Tucker-Lewis index
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behaviour
UTAUT	Unified Theory of Acceptance and Use of Technology

Abstract

- **Purpose**
  Artificial Intelligence is one of the trend areas in research. It is applied in many different contexts successfully including Telecom sector. The purpose of this study is to replicate the study done in application of AI in medical sector to understand the similar challenges of using AI in the Telecom sector.
- **Design/Methodology/approach**
  Online questionnaire-based empirical study is used, and 190 responses were collected. First authors compare the general Technology acceptance model framework used in the medical sector and compare it with the non-AI users. Afterwards, this study proposes the improved TAM model that best fit into the Telecom sector. Later, this study uses the proposed improved model to compare the AI and non-AI users to understand acceptance of AI-technology tools application in the Telecom sector.
- **Findings**
  Confirmatory Factor analysis revealed that the general TAM model fit is adequate and applicable in Medical sector as well as in the Telecom sector. Also, hypothesis testing using SEM concluded that the general supported paths between the constructs and variables related to PU, PEU, SN, ATU, and BI in the medical sector is not same as in the Telecom sector.
- **Research limitations**
  Results are based on the limited datasets from one of the larger companies in Telecom sector which could leads to inherent biases. Authors not sure if "AI-technology tools" in the questions have common understanding across all the respondents or not.
- **Results**
  TAM model cannot be generalized across the sectors. Improved model has been developed used in Telecom sector to analyze the user's behavior and acceptance of AI-technology. Extended model has been proposed which can be used as a continuation of this study.

Keywords: Medical, Telecom, Artificial Intelligence, Network Intelligence, Technology acceptance model (TAM), Confirmatory Factor analysis (CFA), Structural equation modelling (SEM), Perceived usefulness (PU), Perceived Ease of Use (PEU), Subjective Norms (SN), Attitude Towards AI Use (ATU), Behavioural Intention (BI).

1. Introduction

Artificial intelligence (AI) has been around for more than six decades. Early publications have identified six roles for knowledge-based systems (later replaced by AI): Assistant, critic, second opinion, expert consultant, tutor, and automaton (Bader, Edwards, Harris-Jones, & Hannaford, 1988). Later findings have suggested that AI (e.g. expert systems) can be used to replace human decision makers for structured or semi-structured decisions, but it would be better to use them as a decision support tool for dealing with unstructured decisions at the strategic level in organizations (Edwards, Duan, & Robins, 2000). In recent research Davenport & Ronanki (2018) examined 152 AI deployment projects that are making use of AI-based systems across a wide range of business functions and processes. 250 Executive were interviewed where 35% of them stated that their goals for AI initiatives was to make better decisions. Obstacles include managers who do not understand the technology and difficulties finding enough expertise. Some AI practitioners and researchers have argued that AI should be used to augment human judgement rather than automation (Wilson & Daugherty, 2018).

For the last ten years, the number of AI applications have grown rapidly, due to more sophisticated algorithms, increased processing power and the availability of large databases (Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug, & Tchatchouang Wanko, 2020). AI may contribute as much as $16 trillion (or 14%) to the world economy of 2030 in increased productivity and consumption side-effects (PwC, 2019). AI contributions could be as diverse as autonomous fleets for ride sharing (automotive industry), fraud detection and anti-money laundering (financial services), personalized design and production (retail) or early identification of potential pandemics and tracking incidence of the disease to help prevent and contain its spread (healthcare) (PwC, 2019).

Lin et al. (2021), Esteva et al. (2019) and Geras et al. (2019) have listed many potential benefits of AI in healthcare, such as providing second opinions or support during the medical diagnosis process and applying computerized technologies to radiology, pathology, and dermatology for image analysis to improve the accuracy and reliability of the diagnosis. Wearable devices can be used to assist and record the measurement of body health and machine learning can assist doctors in improving the accuracy of cancer diagnosis and detection (Yetisen, Martinez-Hurtado, Ünal, Khademhosseini, & Butt, 2018) (Cruz & Wishart, 2006). Because of the potential importance of AI in healthcare, Lin et al. (2021) have emphasized the importance of understanding what relevant factors that influence medical staff's learning of AI applications. These factors could be medical staff's understanding, attitudes, and behavioural intentions regarding AI applications, as well as personal beliefs and the expectations of peers, supervisors, and organizations.

Similar to healthcare, AI applications in telecom have drastically increased. They provide end users with faster data services and better network services using auto network optimization and complex network monitoring. This helps telecom vendors to customize consumers service, reduce operational cost with network automation and find new revenue streams. AI also helps monitoring connected IoT devices. AI and automation are needed to detect system failures while monitoring a large number of devices. AI also helps problem discovery and anomaly network detection leading to efficiency gains and reduction in manual operations. (Ekudden, 2021) (Laurin, u.d.)

Artificial intelligence is also used to analyse human sentiments, e. g. customers calling a helpline or monitoring student learning. AI will provide feedback to the service providers in different sectors through Social media monitoring, Brand monitoring, Market research and Voice of employee to improve service quality (Mesevage, 2020).

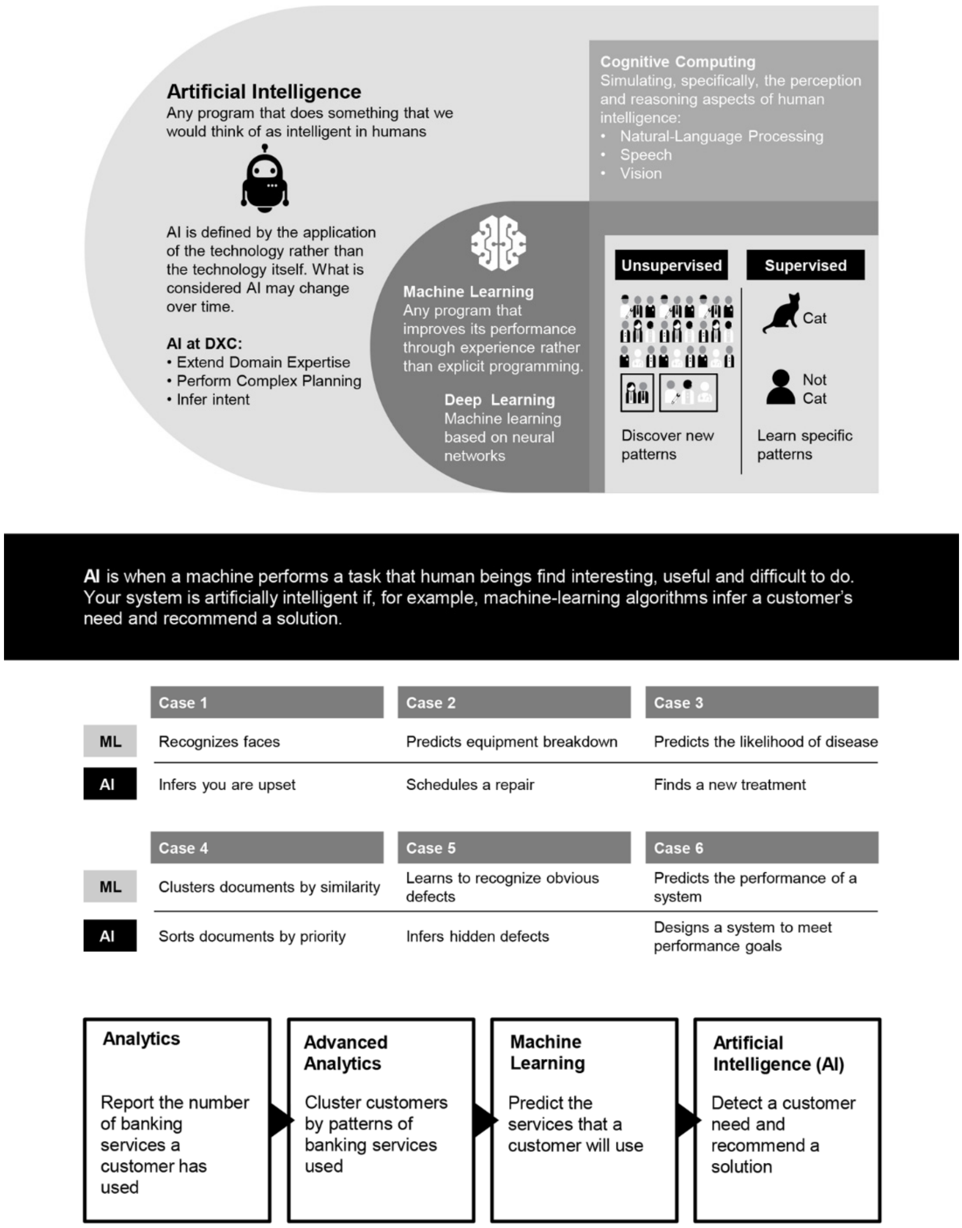
This study aims at exploring how relevant factors influence telecom staff's intention of learning AI applications by replicating the results in Lin et al. (2021) on how relevant factors influence medical staff's intention of learning AI applications, using data on the telecom sector. Since the technology innovation is the same in both healthcare and telecom, i.e. AI applications, this study investigates whether factors affecting the intention to learn AI applications are the same for medical staff and telecom staff.

2. Theoretical framework

2.1. Introduction to AI

There is no universal definition of AI, but it is best described in a non-technical manner: “AI is any program that does something that we would think of as intelligent in humans.” (Overton, 2018). The main reason to use intelligent technology is to improve the business. Companies in many different industries have concluded that their business would improve using intelligent technology, e. g. industries as medical, telecom and construction. Both flexibility and automation would increase when applying AI solutions.

Figure 1 The role of AI and the relationships between terms like AI, machine learning, and analytic *(Overton, 2018)*



2.2. Decision making using AI in the Telecom industry

Communication service providers (CSPs) have already focused their investments in the AI areas:

1) Network optimization
2) Predictive and Preventive maintenance
    a. Intelligent fraud management
3) Virtual Assistants especially during the pandemic
4) Robotic process automation (RPA) with less human interaction
5) Enhanced, streamlined customer experience
6) Organize and structure application/device data.

(Churchill, 2021) (Rzymska, 2020)

Another study reflects some of the main challenges to implement Artificial Intelligence for operators in the telecom sector. (Rzymska, 2020)

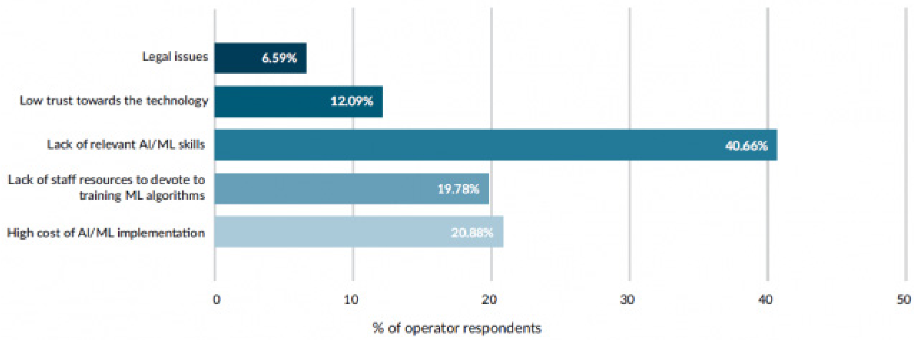


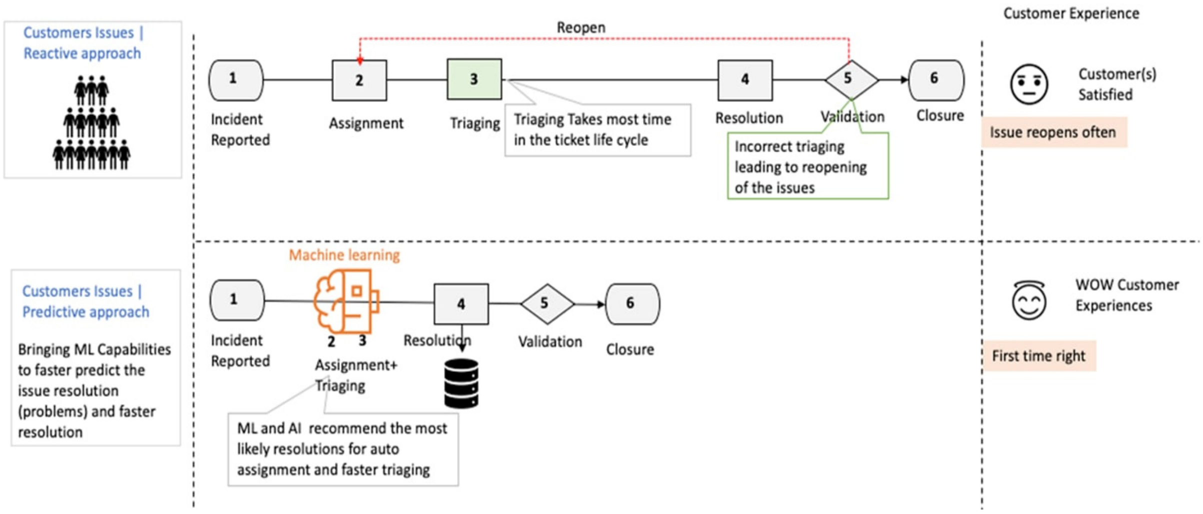
Figure 2 Main challenges to implement AI/ML in Telecom operators (Rzymska, 2020)

The telecom industry has in recent years started to use Artificial Intelligence (**AI**) to improve network and customer experience. AI is used to prevent problems before they occur in the network. Pre-emptive support, empowered by close collaboration and always-on delivery, addresses critical performance. AI in the form of chatbots can reduce mundane, manual tasks to a minimum. AI can make it easier for customers to complain, and proactively engage to prevent complaints. (Pozuelo, 2021)

Communication Service Providers (CSP) working together with other telecom partners in Sweden use AI to help planning and prediction of healthcare demands and resources. For example, to improve COVID-19 treatment planning and predict supply demand needs. (Ericsson, 2021)

AI and ML algorithm has been used to help application service providers manage and automatically resolve trouble tickets, while improving user experience and operational efficiency. (Wenting Sun, 2020)

Figure 3 Trouble ticket processing process (manual vs. machine learning) (Wenting Sun, 2020)



Telecom vendor offers Software as a service application which is distributed in nature and requires improved performance. They use AI to monitor solution that can learn to identify and categorize anomalous system behavior, and thereby improve incident resolution times. *(Butakov, 2020)*

"Telecom AI is still very much a work in progress, our research indicates that it is already possible to reach a high degree of practical autonomous operation in networks by combining existing AI techniques within a flexible architecture to form what we at Ericsson call the cognitive layer." Ericsson CTO Erik Ekudden's view on the key role of connectivity (Henrik Basilier, 2021)

2.3. The Technology Acceptance Model

The Technology Acceptance Model (TAM) has been used in a variety of studies and many different industries. It consists of a conceptual framework that beliefs about ease of use and usefulness of a technology predict attitudes towards the technology and subsequent acceptance and use. Accordingly, Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude Towards technology Use (ATU) and Behavioural Intention (BI) are central factors in the Technology Acceptance Model. In addition to the general model, some studies have modified the general TAM framework and developed a model specific to their study. The following studies have used the TAM framework:

1) *The integration of video games in family-life dynamic using TAM framework*:

"Empirical studies using the technology acceptance model (TAM) have mainly focused on utilitarian technologies. The purpose of this paper is to extend the TAM in order to develop a more nuanced understanding of the family dynamic around video game acceptance within households." (Bassiouni, 2019)

2) *Consumer e-shopping acceptance using TAM framework with extended model*:

"Consumer perceptions of usefulness and attitude toward e-shopping influence intention to shop online, while perceived ease of use does not influence attitude toward e-shopping. Shopping enjoyment and trust play significant roles in consumers' adoption of e-shopping." (Ha, 2009)

3) *Explaining Internet Banking behaviour using popular models of user's behaviour:*

   "This paper uses structural equation modelling to ascertain the extent to which 3 popular models of users' behaviour—theory of reasoned action (TRA), theory of planned behaviour (TPB), and technology acceptance model (TAM)—are predictive of consumers' behaviour in the context of Internet banking. Unlike other tests of these models, this paper employs independent measures of actual behaviour, as well as behavioural intention. The results indicate that TAM is superior to the other models and highlights the importance of trust in understanding Internet banking behaviour." (Yousafzai, 2010)

4) *The Application of the Technology Acceptance Model Under Different Cultural Contexts: The Case of Online Shopping Adoption:*

   "Study develop an extended technology acceptance model that incorporates trust and perceived behavioural control and examine it in settings outside the United States to better understand the adoption of e-commerce across cultures." (Ashraf, 2014)

5) *Age and gender differences in online travel reviews and user-generated-content (UGC) adoption: extending the technology acceptance model (TAM) with credibility theory*

   "This study examines the effects of trustworthiness, expertise, perceived usefulness (PU), and perceived ease of use (PEOU) on usage intention toward user-generated content (UGC) and online reviews among female and male younger and older travellers using SEM." (Assaker, 2020)

To explore medical staff's intentions regarding AI applications, Lin et al. (2021) include Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude Towards technology Use (ATU) and Behavioural Intention (BI) in their Technology Acceptance Model. The model is extended with Subjective Norms (SN), to help understanding individual's acceptance and usage of new technology (Yu & Gagnon, 2009). Subjective Norms include pressure by organizations or other people's expectations, putting pressure an individual to take certain actions (Fishbein, 1975). This could directly influence the Behavioural Intention of the individual to use new technology (Venkatesh, 2000). Subjective Norms have also been shown to have influences on individual's intention to use such technology through affecting perceived usefulness (PU) and perceived ease of use (PEU) (Alhashmi, 2019), but not always (Azizi, 2019).

2.4. Research Questions:

RQ1. Is it possible to replicate the results in Lin et al. (2021) using data on the telecom sector?

RQ 1.1. That is, is the general technology acceptance model (TAM) with the constructs used (PU, PEU, ATU, BI and SN) for non-AI users in the medical sector in Lin et al (2021) applicable to non-AI-users in the telecom sector?

RQ 1.2. Is the final technology acceptance model with paths supported by hypothesis testing for non-AI users in the medical sector in Lin et al (2021) applicable to non-AI users in the telecom sector?

RQ2. Is there a difference in the final technology acceptance model with paths supported by hypothesis testing for non-AI users in the telecom sector and the final model with paths supported by hypothesis testing for AI users in the telecom sector?

2.5. Research model and hypotheses

This research model is based on the Technology Acceptance Model (TAM) and the four factors

1) Perceived usefulness (PU)
2) Perceived ease of use (PEU)
3) Attitude towards AI use (ATU)
4) Behavioural intention (BI)

Extended with

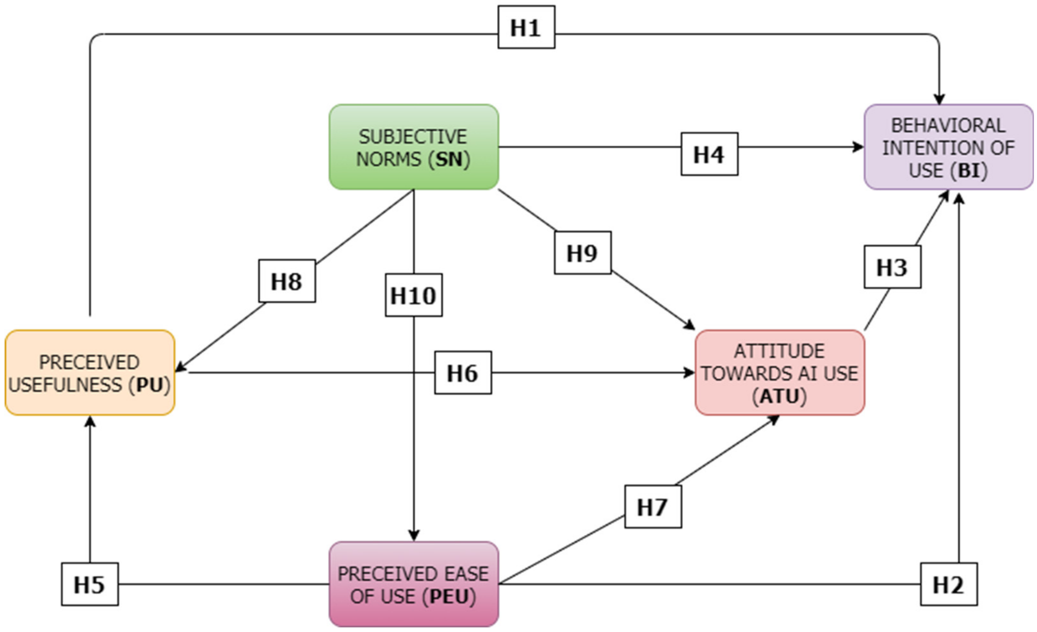
5) Subjective norms (SN)

To explore how telecom staff's perceived ease of use, usefulness, subjective norms, and attitudes towards AI applications could effect their behavioural intentions, the following research hypotheses are proposed in our study:

H1 Perceived usefulness (PU) has a significant positive effect on behavioural intention (BI).
H2 Perceived ease of use (PEU) has a significant positive effect on behavioural intention (BI).
H3 Attitude towards AI use (ATU) has a significant positive effect on behavioural intention (BI).
H4 Subjective norms (SN) has a significant positive effect on behavioural intention (BI).
H5 Perceived ease of use (PEU) has a significant positive effect on perceived usefulness (PU).
H6 Perceived usefulness (PU) has a significant positive effect on attitude towards AI use (ATU).
H7 Perceived ease of use (PEU) has a significant positive effect on attitude towards AI use (ATU).
H8 Subjective norms (SN) has a significant positive effect on Perceived usefulness (PU).
H9 Subjective norms (SN) has a significant positive effect on Attitude towards AI use (ATU).
H10 Subjective norms (SN) has a significant positive effect on Perceived ease of use (PEU).

Figure 4 summarizes the general technology acceptance model with possible relationships between any of the five constructs used (PU, PEU, ATU, BI and SN) and its corresponding hypothesis number.

Figure 4 Proposed research model used in this study with possible paths between constructs



3. Methodology

3.1. Participants

The participants of this study were staff at one of the Sweden's major telecom company as well as end users of their telecom products, determined by convenience sampling. There are also few participants (less than 5%) who work in the telecom industry, but at a different company. This survey is sent to staff developing AI and non-AI applications, users of AI and non-AI application and staff outside of technology like marketing, HR etc. However, the data we collected cannot reveal if the staff is actually developing the AI or non-AI application or the user of it.

190 questionnaires were collected. The demography of the sample is found in Table 1. The gender distribution of the participants was 86.4% male and 10.0% female, geographically based mainly in Sweden (53.8%) and Pakistan (10.6%). The sample consisted of 14.6% at an age of 21-30 years, 52.8% at an age of 31-40 years and 30.6% above 40 years of age at qualification levels of college degree (3.0%), bachelor's degree (24.6%), master's degree (63.3%) and doctoral degree (7.0%) respectively. The working experience of the telecom staff was 0-1 years (2.5%), 2-5 years (11.6%), 6-10 years (18.6%), 11-15 years (31.7%) and above 15 years (35.6%) including 52.3% telecom staff with experience of using AI-technology tools in their professional work. The experience with AI tools was 0-1 years (29.8%), 2-5 years (56.7%) and above 5 years (13.5%) respectively.

Table 1 Demography of sample, N = 190

Variable	Group	N	Percent
Sex	Male	165	86.84%
	Prefer not to say	6	3.16%
	Female	19	10.00%
Age	21-30	27	14.21%
	31-40	103	54.21%
	41-50	24	12.63%
	51-61	34	17.90%
Education	College Degree	5	2.63%
	Bachelor's Degree	48	25.26%
	Master's Degree	120	63.16%
	Doctoral Degree	14	7.37%
	Prefer not to say	3	1.58%
Work Experience	0-5 years	25	13.16%
	6-10 years	36	18.95%
	11-15 years	62	32.63%
	16-20 years	19	10.00%
	21-25 years	18	9.47%
	26 years and above	30	15.79%
AI Experience	0-1 years	29	15.26%
	2-5 years	57	30.00%
	6-10 years	7	3.68%
	11 years and above	5	2.64%
No AI Experience	-	92	48.42%
Location	Pakistan	21	11.05%
	Sweden	102	53.68%
	Other	65	34.21%

3.2. Instruments

This study is based on a study by Lin et al (2021) and applied their scale items, which were adapted from published sources that reported a high degree of reliability (Chiu, 2014); (Teo T. &., 2014); (Ursavaş, 2019); (Wu, 2011). A pilot study was conducted with four members of the development team for AI-technology tools to test question formulation.

The instrument consists of participants' demographic information, the 16 items analysed in the study by Lin et al (2021) out of 21 items found in appendix 9.1. Items that are marked as '*' are not used the analysis of this study. The original 16 items aim at investigating the participants' beliefs in five constructs. In terms of Perceived Usefulness (PU), participants will say "I believe that using AI-technology tools can assist my professional work"; in terms of Perceived Ease of Use (PEU), they will say "Learning to use AI-technology tools for professional work is easy for me"; referring to Subjective Norms (SN), they will mention "My supervisor or organization believes that I should employ the AI-technology tools to assist my professional work in the future"; referring to Attitude Towards AI Use (ATU), they will say "I have a generally favourable attitude toward learning to use AI-technology tools"; referring to Behavioural Intention (BI), they will mention "I intend to learn to use AI-technology tools for my professional work in the future".

The questionnaire used in this study applied a 5-point Likert scale, where 5 refers to *strongly agree* and 1 refers to *strongly disagree*. The final structure showed a satisfactory internal consistency and reliability, with most values of Cronbach's alpha ranging from 0.70 to 0.80 and only a few alpha values below 0.70.

3.3. Data analysis

This study uses STATA for analysis. The structure of the questionnaire was checked by "**C**onfirmatory **F**actor **A**nalysis (CFA) and the proposed hypotheses were verified using "***S****tructural* ***E****quation* ***M****odelling* (SEM). More details about CFA and SEM are found in appendix 9.7.

4. Results for Non-AI users

Research question 1.1: Is the general technology acceptance model with the constructs used (Perceived Usefulness, Perceived Ease of Use, Attitudes Towards AI Use, Behavioural Intention and Subjective Norms) for non-AI users at the medical sector in Lin et al. (2021) applicable to non-AI-users in the telecom sector? This research question will give an indication of the external validity of the Technology Acceptance Model (TAM). Since the Technology Acceptance Model has been successfully used in many different industries as mentioned in 2.2, we expect the model to apply to non-AI users in the telecom sector as well as in the medical sector.

To test if the constructs in the Technology Acceptance Model (Perceived Usefulness, Perceived Ease of Use, Attitudes Towards AI Use, Behavioural Intention and Subjective Norms) are applicable to data on non-AI users in the telecom sector, a confirmatory factor analysis (CFA) is carried out. The CFA tests if the questions in this study survey are adequate measures of the constructs (factors) PU, PEU, ATU, BI and SN indicated by sufficiently high standardized estimates (factor loadings). The CFA also tests if the measurement model provided by the constructs are applicable to the data collected by our survey, indicated by a set of fit indexes: χ2, the Tucker-Lewis index (TLI), the comparative fit index (CFI) and the root mean square error of approximation (RMSEA). Finally, the CFA measures the reliability and validity of the survey, indicated by Cronbach's alpha values, composite reliability (CR) and average variance extracted (AVE). To confirm that the general technology acceptance model with the constructs PU, PEU, ATU, BI and SN is applicable to non-AI-users in the telecom sector, reliability and validity need to be acceptable and the model fit not unacceptable.

4.1. The general TAM model – non-AI users

Confirmatory Factor Analysis (CFA) was used as measuring model. Full results are available in Appendix 9.2. The estimation of overall model fit was made by χ^2, the Tucker-Lewis index (TLI), the comparative fit index (CFI) and the root mean square error of approximation (RMSEA). (Hu & Bentler, 1999) indicate that the TLI and CFI show a good model fit if their statistics are greater than 0.95. They also report that RMSEA values less than 0.06 are acceptable.
The measurement model displayed a less than satisfactory fit to the sample data compared to the indications by (Hu & Bentler, 1999): (χ^2 = 218.249; χ^2/df = 2.322; TLI = 0.775; CFI = 0.823; RMSEA = 0.121). Although the results of the fit indexes are not very good, they still indicate that it is possible to fit a general model using the five constructs of the technology acceptance model to our data on non-AI users in the telecom sector.

Table 2 Results of the Confirmatory Factor Analysis for non-AI users

Items	Unstandardized Estimates	t-value (Coefficient /standard error)	Standardized Estimates (factor loadings)	Composite Reliability	Average Variance Extracted	Cronbach's Alpha	Mean	Standard deviation
PU				0.7905	0.5598	0.767	4.036	0.701
PU01#	1		0.704					
PU02	1.294	6.88	0.853					
PU03	1.103	5.64	0.674					
PEU				0.6254	0.3097	0.718	3.563	0.722
PEU01#	1		0.398					

PEU02	1.222	3.25	0.514					
PEU03	1.171	3.11	0.455					
PEU04	1.590	3.69	0.781					
SN				0.8049	0.5082	0.762	3.290	0.889
SN01#	1		0.717					
SN02	.926	5.53	0.702					
SN03	.956	5.65	0.779					
SN04	.640	3.98	0.486					
ATU				0.6480	0.4794	0.6433	4.196	0.756
ATU01 #	1		0.686					
ATU02	1.048	5.94	0.699					
BI				0.8473	0.6494	0.853	3.882	0.823
BI01#	1		0.845					
BI02	.955	7.50	0.766					
BI03	1.134	8.03	0.805					

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.* # value fixed at 1.000 for model identification purposes.

Table 2 describes the CFA results. The values of Cronbach's alpha of PU, PEU, SN, ATU, and BI were .767, .718, .762, .643 and .853, respectively, with values above 0.70 indicating a good internal consistency (reliability) of the constructs. The ranges of composite reliability (CR) were between 0.625 and 0.847, with values above 0.70 indicating a good CR. The average variance extracted (AVE) was mostly above an acceptable value of 0.5, ranging from 0.310 to 0.649, indicating that our survey had an acceptable convergence validity of the adopted constructs (Ab Hamid, Sami, & Mohmad Sidek, 2017). This means that the survey questions are appropriate to measure the constructs PU, PEU, SN, ATU, and BI.

Finally, to check if the constructs PU, PEU, SN, ATU, and BI differ from each other, discriminant validity is measured. The square roots of the average variance extracted (AVE) of the constructs (shown in parenthesis in the Table 3) should be greater than the correlation coefficients between constructs, shown without parenthesis in Table 3. This indicates that the constructs explain the variance of their own items better than the variance of other constructs. Since all square roots of AVE are greater than almost all correlation coefficients, we can conclude that the constructs PU, PEU, SN, ATU, and BI differ from each other (Ab Hamid, Sami, & Mohmad Sidek, 2017). E. g. the square root of AVE for PU (0.748) is greater than all correlation coefficients in the same column, showing correlation with PEU, SN, ATU and BI. This means that the general technology acceptance model is applicable to our data on the telecom sector.

Table 3 Correlation coefficients and square root of AVE shown in parenthesis for non-AI users

	PU	PEU	SN	ATU	BI
PU	(0.748)				
PEU	0.573	(0.556)			
SN	0.413	0.337	(0.713)		
ATU	0.681	0.641	0.468	(0.692)	
BI	0.674	0.615	0.414	0.651	(0.806)

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** =* behavioural *intention.*

Conclusions (RQ1.1): The results of the Confirmatory Factor Analysis show that model fit was not very good while reliability and validity of the constructs was found to be acceptable. This means that Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitudes Towards AI Use (ATU), Behavioural Intention (BI) and Subjective Norms (SN) are able to adequately measure the intention of both medical staff and telecom staff to use AI tools. We can therefore conclude that the general technology acceptance model is applicable to the telecom sector as well as in the medical sector, indicating good external validity of the technology acceptance model.

4.2. Telecom specific model – non-AI users

Research Question 1.2: Is the final technology acceptance model with paths supported by hypothesis testing for non-AI users in the medical sector in Lin et al (2021) applicable to non-AI users in the telecom sector? This research question will give an indication of the external validity of the best model developed in Lin et al. (2021) for non-AI users in the medical sector. If we manage to replicate the results using data on the telecom sector (i.e. similar factor loadings and model fit), this indicates that the model presented in Lin et al. (2021) also transfers to the telecom sector and will therefore expand the external validity in Lin et al. (2021) beyond the medical sector. If this is the case, we will carry on the rest of the research using the Lin et al. (2021) model, if not, we will develop a telecom specific model.

To test if the best model developed in Lin et al. (2021) is applicable to non-AI users in the telecom sector, we need to improve our own model and use a new CFA to compare factor loadings and model fit of our improved model to the model in Lin et al. (2021). Further, hypothesis testing using structural equation modelling is carried out to find which paths between constructs are supported by our survey data from the telecom sector and compare supported paths with the model in Lin et al. (2021).

The results of the CFA in chapter 4.1 shows several low factor loadings in Perceived Ease of Use (items PEU01 and PEU03) and Subjective norms (item SN04) together with a model fit which is not very good, as shown by the fit indexes. This indicates that a telecom specific model may be needed. We will now try to improve our model to test if our best model is similar to the best model in Lin et al. (2021). Full results are available in Appendix 9.3.

Structured equation modelling (SEM) is used to estimate the relationships between multiple dependent variables. In our study, SEM is used to estimate the regression coefficients for each pair of constructs (variables) among PU, PEU, SN, ATU, and BI and test if the relationship between the constructs is significant at 95% confidence level. Since we have hypothesized that all constructs are related to each other (hypotheses H1 through H10), this test will show which relationships between constructs are supported at 95% confidence level and contribute to a technology acceptance model specific to our data. This model is then compared to the model in Lin et al. (2021) to answer research question 1.2. on model transfer from medical sector to telecom sector. The bootstrap method is a non-parametric way of estimating the standard errors by creating sub samples of the original data, in our case 1000 subsamples. Bootstrapping does not require that all constructs are normally distributed.

The result of the using SEM (including the bootstrap method, 1000 iterations) on the relationships between the constructs (the structural model) displayed a satisfactory fit to the sample data.

Figure 5 Structural model (general model) with the supported and unsupported paths for non-AI users

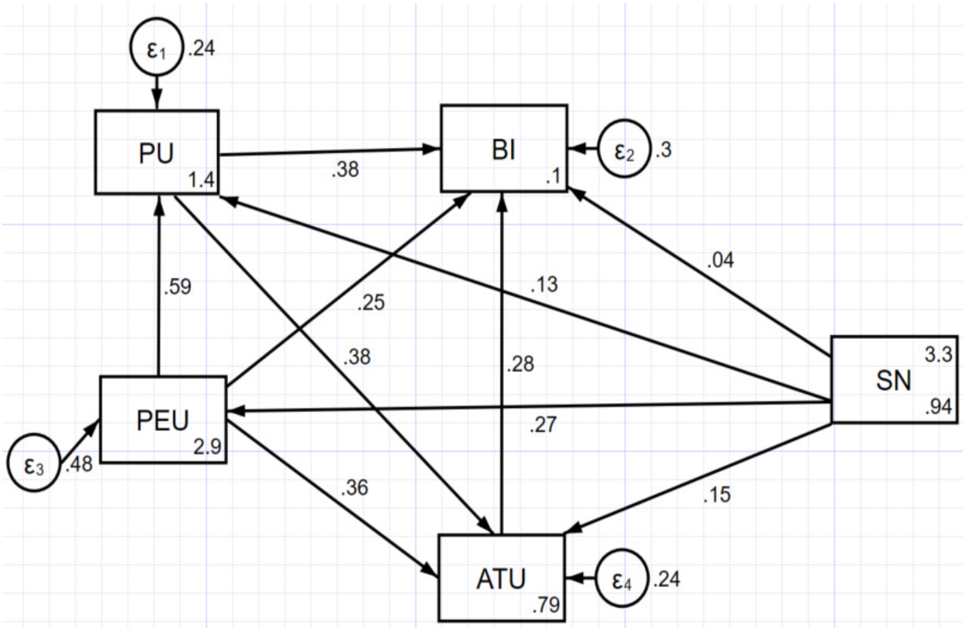


Table 4 shows the results of the hypotheses testing and which hypotheses that are supported by our data on non-AI users in the telecom sector.

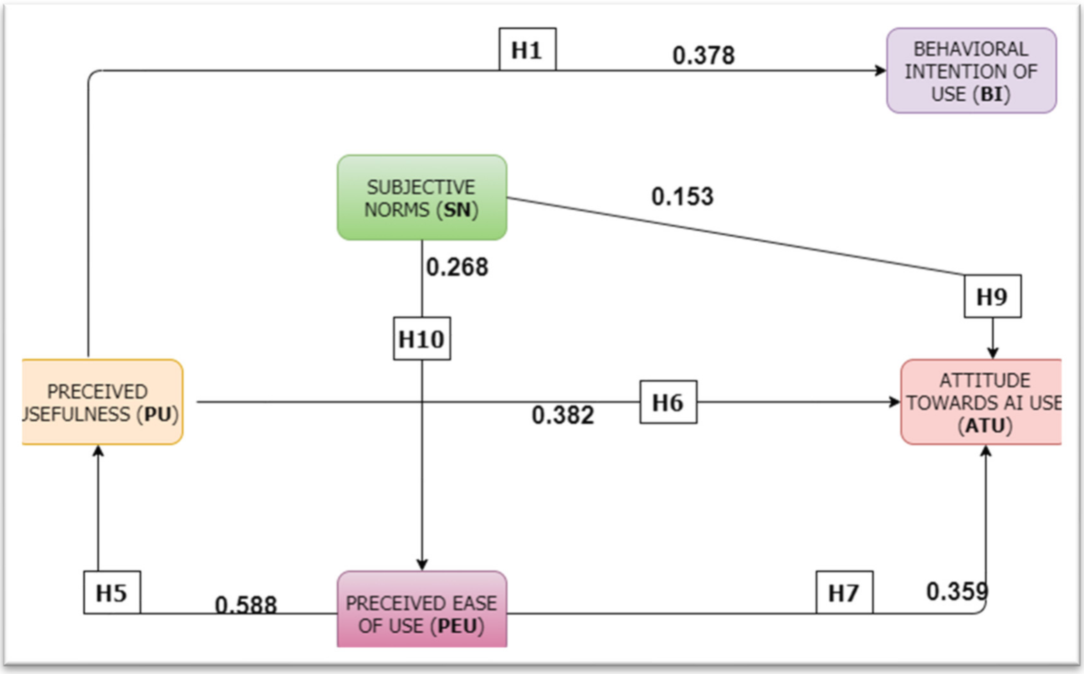
Table 4 Hypotheses testing results for non-AI users

Hypotheses	Path	Estimate	t-value	Bias-corrected		Significant p level	Result (95% CL)
				Lower	Upper		
H1	PU --> BI	0.378	2.06	0.019	0.737	0.045	Supported
H2	PEU --> BI	0.253	1.98	0.004	0.503	0.052	Not Supported
H3	ATU --> BI	0.278	1.63	0.063	0.620	0.117	Not Supported
H4	SN --> BI	0.039	0.59	0.000	0.170	0.558	Not Supported
H5	PEU -->PU	0.588	6.60	0.416	0.759	0.000	Supported
H6	PU --> ATU	0.382	3.41	0.158	0.606	0.001	Supported
H7	PEU --> ATU	0.359	3.67	0.159	0.606	0.000	Supported
H8	SN --> PU	0.134	1.84	0.000	0.276	0.065	Not Supported
H9	SN --> ATU	0.153	2.46	0.0288	0.277	0.014	Supported

H10	SN --> PEU	0.268	2.72	0.071	0.466	0.006	Supported

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

Figure 6 Supported model paths for non-AI users in the telecom sector



Conclusions (RQ1.2):

Figure 6 shows our best model for non-AI users in the telecom sector with all model paths that are supported. As shown in Table 4, all hypotheses were supported by our data except H2, H3, H4 and H8. Our best model is specific to the telecom sector. The best model in Lin et al. (2021) supports different paths between the constructs PU, PEU, SN, ATU, and BI than our model. We can therefore conclude that the model developed in Lin et al. (2021) does not transfer to the telecom sector, which limits the external validity of the model. The model in Lin et al. (2021) is shown below for comparison.

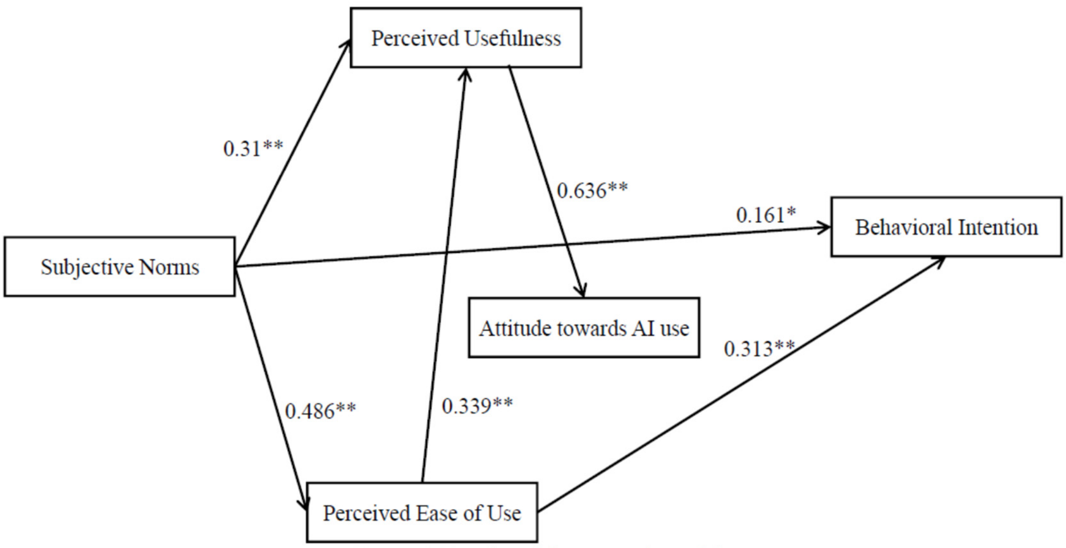


Figure 3. Results of the research model

4.3. Comparing the TAM model for non-AI users in the telecom sector and in the medical sector

Based on Lin et al (2021), four endogenous constructs were tested: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Subjective Norms (SN) and Attitudes Towards AI Use (ATU) to investigate their relation to the Behavioural Intention (BI) to use AI tools at a major telecom firm in Sweden. For non-AI users, the coefficient of variation of BI was determined by PU, PEU, SN and ATU with an explanatory power, R^2, of 0.548. This means that 54.8% of the changes in the Behavioural Intention to use AI tools at the telecom company were explained by Perceived Usefulness, Perceived Ease of Use, Subjective Norms and Attitudes Towards AI Use. Lin et al (2021) found that only 37.4% of the changes in Behavioural Intention to use AI tools at a medical centre in Taiwan could be explained by the same constructs (PU, PEU, SN and ATU).

Figure 7 Direct effects of constructs for non-AI users

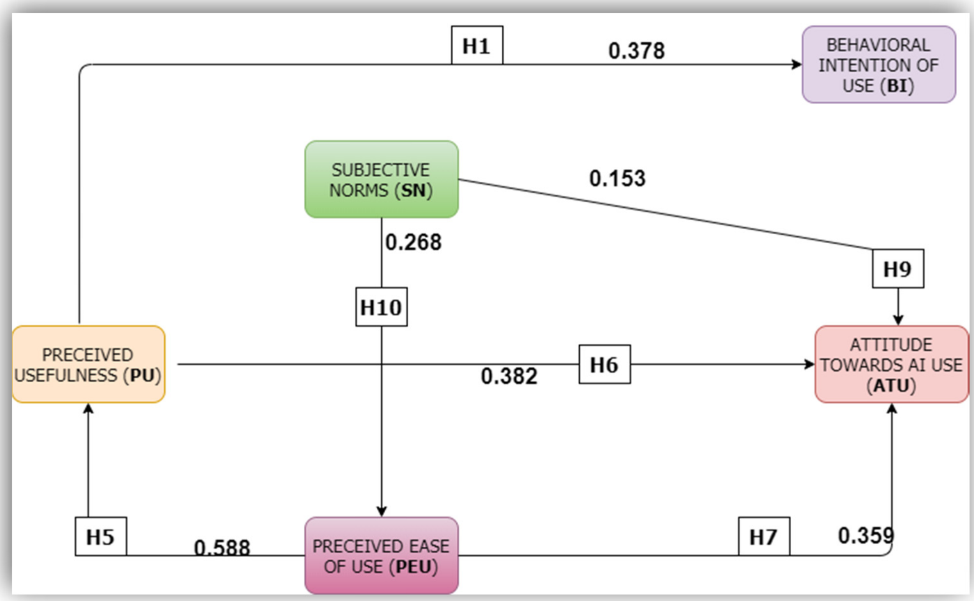


Table 5 Direct, Indirect, and Total effects of the research model for non-AI users

Endogenous Variable	Determinant	Standardized estimates		
		Direct	Indirect	Total
PU (R^2 = 0,509)	PEU	0.588	-	0.588
	SN	0.134	0.158	0.292
PEU (R^2 = 0,123)	SN	0.269	-	0.269
ATU (R^2 = 0,571)	PU	0.382	-	0.382
	PEU	0.359	0.225	0.584
	SN	0.153	0.208	0.362
BI (R^2 = 0,548)	PU	0.378	0.107	0.485
	PEU	0.279	-	0.279
	SN	0.254	0.385	0.639
	ATU	0.040	0.279	0.319

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

Similar to the findings by Lin et al (2021), the highest amount of variance was explained by the determinants of Attitudes Towards AI Use (ATU), 57.1% (Lin et al: 60%). The dominant determinant for ATU in our study is Perceived Ease of Use with an effect of 0.577 followed by Subjective Norms 0.467 and Perceived Usefulness 0.355, while Lin et al (2021) reported the dominant determinant of ATU to be Perceived Usefulness with total effect 0.636 followed by Subjective Norms 0.489 and Perceived Ease of Use 0.331. Attitudes Towards AI Use by telecom staff as well as medical staff are determined by PU, PEU and SN, but to telecom staff Perceived Ease of Use is the most important determinant while for medical staff Perceived Usefulness is the most important determinant. AI applications in the telecom sector have simplified many work tasks. In case of network failure, user notification is automated and network recovery much easier to achieve using AI applications, reducing lead times for network recovery. This affects the attitude of telecom staff towards AI applications.

Almost as high an amount of variance, 54.8%, was explained by the determinants of Behavioural Intention (BI). In contrast, Lin et al only reported 37.4% of the variance in BI explained by determinants. In our study, the dominant determinant of BI is Perceived Usefulness with total effect 0.413, followed by indirect effects of Subjective Norms 0.349 and Attitudes Towards AI Use 0.331. The total effect of Perceived Ease of Use on BI was 0.256. Direct effects of Subjective Norms and Attitudes Towards AI Use were not supported by hypothesis testing. Lin et al (2021) reported the dominant determinants of BI to be Subjective Norms with total effect 0.448 and Perceived Ease of Use 0.408, while direct effects of Perceived Usefulness and Attitudes Towards AI Use were not supported by hypothesis testing. Telecom staff's intention to use AI tools is mainly determined by the Perceived Usefulness while medical staff's intention to use AI tools is mainly determined by Subjective Norms and Perceived Ease of Use. Lin et al (2021) explain the importance of subjective norms for medical staff with "… medical staff generally need to work in teams. In such a team-working culture, they tend to accept the instructions or requests from the person at the management level in order to achieve the goal of the team." Some AI solutions in the telecom sector are very useful in terms of requiring less effort of telecom staff. E. g. if the AI solution manages network recovery rather than sending telecom staff to inspect the base station to fix the issue. This affects the intention of telecom staff to use AI solutions.

The explained variance in Perceived Usefulness was 50.9%, mainly determined by Perceived Ease of Use (PEU) with a total effect of 0.626 and indirect effects of Subjective Norms (SN) 0.219 while direct effects of Subjective Norms were not supported by hypothesis testing. Lin et al also report PEU (total effect 0.339) and SN (0.474) explaining the variation in Perceived Usefulness, but only 31,3%. In this case, Perceived Ease of Use is more important to telecom staff's perceived usefulness of AI tools while subjective norms are more important to medical staff's perceived usefulness of AI tools. Finally, 12.3% of the variance of Perceived Ease of Use (PEU) was determined by Subjective Norms (SN) with total effect 0.351. Lin et al report the same findings with 23.6% of the variance of PEU determined by SN with total effect 0.486. Again, subjective norms are more important to medical staff's perceived usefullness of AI tools than to telecom staff. Telecom staff without AI experience may focus more on the perceived ease of use of AI applications than subjective norms since the use of AI applications do not risk lives in the telecom sector.

5. Results: AI users

5.1. The general TAM model – AI users

Research Question 2: Is there a difference in the final technology acceptance model with paths supported by hypothesis testing for non-AI users in the telecom sector and the final model with paths supported by hypothesis testing for AI users in the telecom sector?

The procedure to test if our best model for non-AI users in the telecom sector is the best model for AI users as well, is similar to the procedure followed when testing if the best model in Lin et al. (2021) is the best model for non-AI users in the telecom sector as well: Confirmatory Factor Analysis is used on the data on AI users to find the best model for AI users and compare factor loadings and model fit with the best model for non-AI users. Then hypothesis testing using structural equation modelling is carried out to find which paths between constructs are supported by our survey data on AI users and compare supported paths with the best model on non-AI users. If we manage to replicate our best model for non-AI users with our data on AI users, this indicates that our best model for non-AI users transfers to AI users in the telecom sector and will therefore expand the external validity of our model.

Performing a CFA using only AI user data, the measurement model displayed a satisfactory fit to the sample data, better than the best model fit for non-AI users. Full results are available in Appendix 9.4. Trying to improve model fit by checking the covariances of the construct items, no correlations were found. Items SN02 and SN04 were excluded from further analysis since their factor loadings are low. A new CFA was performed without items SN02 and SN04. This model for AI users excludes different items than the best model for non-AI users (which excludes items PEU01, PEU03 and SN04). This means that our best model for AI users will be different from our best model for non-AI users. The results of the new CFA show that model fit, factor loadings and average variance extracted (AVE) have improved. Reliability and validity have remained unchanged.

Comparing our best model for AI users to our best model for non-AI users, our model for AI users has removed different items, has higher factor loadings and better model fit. This indicates that the best model for AI users may be different to the best model for non-AI users, limiting the model's external validity. To investigate which paths between constructs are supported by the data on AI users in the telecom sector, hypothesis testing using structured equation modelling (SEM) is carried out.

The result of the using structured equation modelling (including the bootstrap method, 1000 iterations) on the relationships between the constructs (the structural model) displayed a satisfactory fit to the sample data.

Figure 8 Structural model (general model) with the supported and unsupported paths for AI users

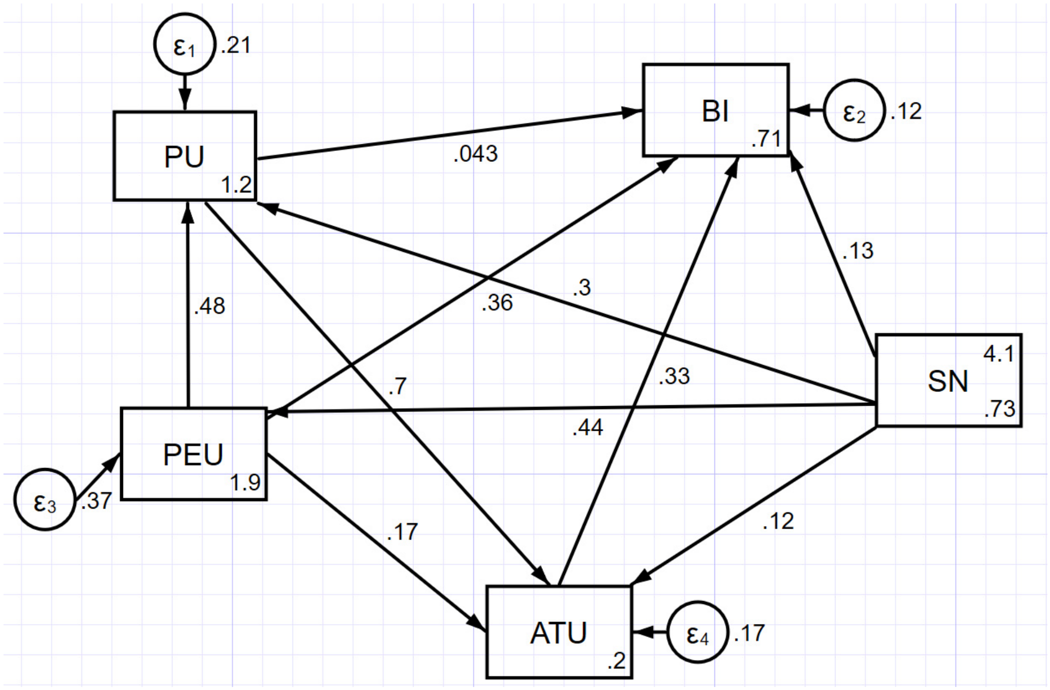


Table 6 Hypotheses testing results for AI users

Hypotheses	**Path**	**Estimate**	**t-value**	**Bias-corrected**		**Significant p level**	**Result (95% CL)**
				Lower	**Upper**		
H1	PU --> BI	0.043	0.357	0.000	0.280	0.722	Not Supported
H2	PEU --> BI	0.363	5.04	0.222	0.504	0.000	Supported
H3	ATU --> BI	0.325	3.36	0.136	0.516	0.000	Supported
H4	SN --> BI	0.132	2.22	0.016	0.249	0.026	Supported
H5	PEU -->PU	0.478	5.63	0.312	0.644	0.000	Supported
H6	PU --> ATU	0.696	6.58	0.489	0.903	0.000	Supported
H7	PEU --> ATU	0.170	2.28	0.024	0.315	0.024	Supported
H8	SN --> PU	0.301	4.19	0.160	0.441	0.000	Supported
H9	SN --> ATU	0.118	1. 81	0.000	0.246	0.080	Not Supported
H10	SN --> PEU	0.442	5.58	0.287	0.598	0.000	Supported

Note*.** ***PU *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.*

Figure 9 Fitted model for AI users

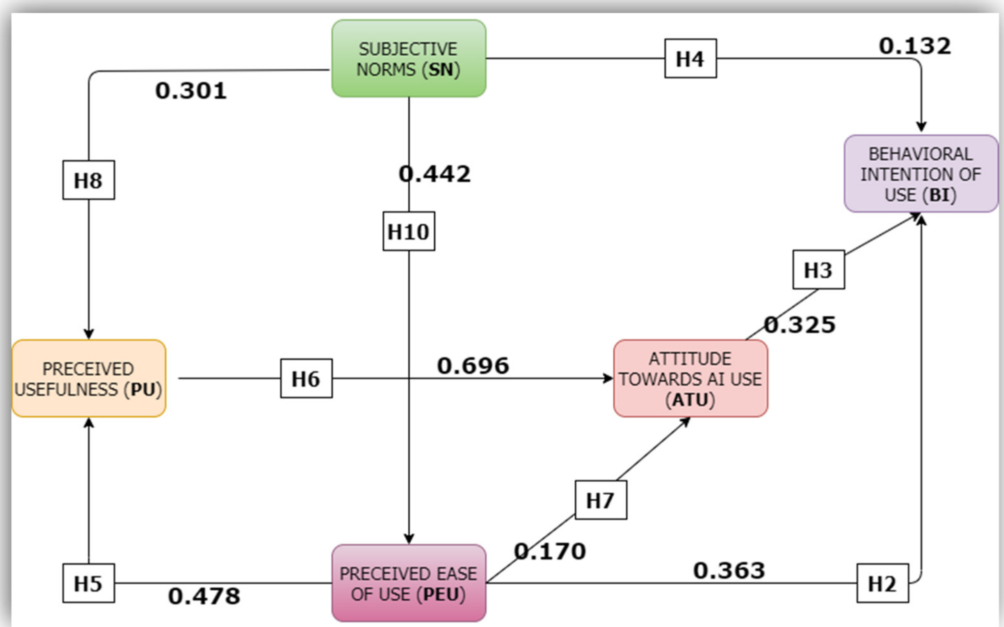


Figure 8 shows our best model with all model paths that are supported at 95% confidence level. Direct effects of the constructs are shown along the paths.

Conclusion (RQ2): As shown in Table 11, all hypotheses were supported by our data except H1 and H9. Our best model for non-AI users supports different paths between the constructs PU, PEU, SN, ATU, and BI than our best model for AI-users. We can therefore conclude that our model for non-AI users does not transfer to AI users, which limits the external validity of the model.

Table 10 Shows direct, indirect and total effects for the different constructs and their determinants.

Table 7 Direct, Indirect, and Total effects of the research model for AI users

Endogenous Variable	Determinant	Standardized estimates		
		Direct	Indirect	Total
PU (R2 = 0,563)	PEU	0.478	-	0.478
	SN	0.301	0.212	0.513
PEU (R2 = 0,282)	SN	0.442	-	0.443
ATU (R2 = 0,713)	PU	0.696	-	0.696
	PEU	0.170	0.333	0.503
	SN	0.118	0.432	0.551
BI (R2 = 0,731)	PU	0.043	0.227	0.270
	PEU	0.326	-	0.326
	SN	0.363	0.185	0.548
	ATU	0.133	0.362	0.495

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

5.2. Differences between AI users and non-AI users in the telecom sector

The same four endogenous constructs that were tested on non-AI users in Lin et al. (2021) were also tested on telecom staff with experience of AI tools to investigate their relation to the Behavioural Intention (BI) to use AI tools: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Subjective Norms (SN) and Attitudes Towards AI Use (ATU). For AI users, the coefficient of variation of BI was determined by the same constructs as for non-AI users: PU, PEU, SN and ATU but with a greater explanatory power, R^2, of 0.731. For AI users 73.1% of the changes in the Behavioural Intention to use AI tools at the telecom company were explained by Perceived Usefulness, Perceived Ease of Use, Subjective Norms and Attitudes Towards AI Use compared to non-AI users 54.8%.

Figure 10 Direct effects of constructs for AI users

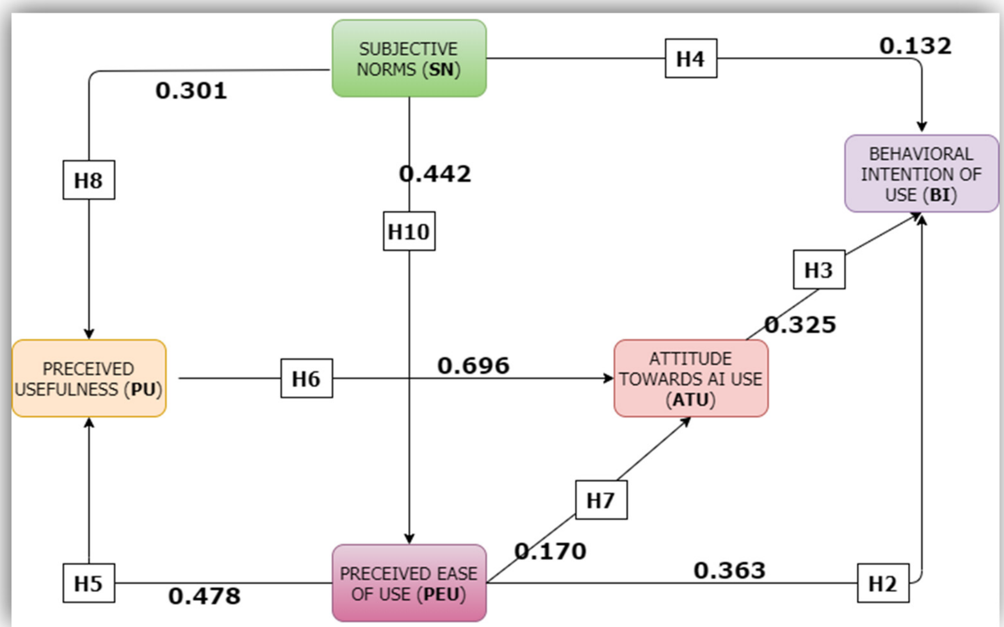


Table 8 Direct, Indirect, and Total effects of the research model for AI users

Endogenous Variable	Determinant	Standardized estimates		
		Direct	Indirect	Total
PU (R2 = 0.563)	PEU	0.478	-	0.478
	SN	0.301	0.212	0.513
PEU (R2 = 0.282)	SN	0.442	-	0.443
ATU (R2 = 0.713)	PU	0.696	-	0.696
	PEU	0.170	0.333	0.503
	SN	0.118	0.432	0.551
BI (R2 = 0.731)	PU	0.043	0.227	0.270
	PEU	0.326	-	0.326
	SN	0.363	0.185	0.548
	ATU	0.133	0.362	0.495

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

For AI users the highest amount of variance was explained by the determinants of Behavioural Intention (BI), 73.1% and Attitudes Towards AI Use (ATU), 71.3%. This follows the same pattern as for non-AI users, although less of the variation was explained: BI 54.8% and ATU 57.1%. Perhaps it is not surprising that telecom staff working with AI tools have attitudes towards AI use and a behavioural intention to use AI tools that are more closely correlated than for non-AI users.

For AI users, 73.1% of the variance of Behavioural Intention (BI) was explained by its determinants compared to 54.8% for non-AI users. For AI users, the dominant determinant of BI is Subjective Norms (SN) with total effect 0.548, followed by Attitudes Towards AI Use (ATU) 0.495 and Perceived Ease of Use (PEU) 0.326. Interestingly, the dominant determinants of the behavioural intention of AI users to use AI tools, SN and ATU, were not supported for direct effects by non-AI users. In addition, the dominant determinant for non-AI users Perceived Usefulness (PU) was not supported for direct effects by hypothesis testing for AI-users. Telecom staff with experience of AI tools use them mainly because of subjective norms and attitudes towards AI tools, while non-AI user's intention of using AI tools is determined mainly by perceived usefulness.

Similar to Behavioural Intention, a higher amount of variance was explained by the determinants of Attitudes Towards AI Use for AI users, 71.3% than for non-AI users, 57.1%. The dominant determinant of Attitudes Towards AI Use (ATU) for AI users is Perceived Usefulness with total effect 0.696 followed by Perceived Ease of Use 0.503 and indirect effects of Subjective Norms 0.432. In comparison, the dominant determinant of ATU for non-AI users is Perceived Ease of Use 0.577 followed by Subjective Norms 0.467 and Perceived Usefulness 0.355. It seems that for AI users the perceived usefulness of AI tools is more important than the perceived ease of use while for non-AI users the perceived ease of use of AI tools is more important than the perceived usefulness. Subjective norms are important to both AI users and non-AI users. This is because AI users focus on developing AI-technology tools which bring business value to end users, while non-AI users are mainly focused on whether the AI-technology tools are easy to use.

For AI users, the explained variance in Perceived Usefulness was 56.3%, only a little higher than for non-AI users 50.9%. Perceived Usefulness is determined almost equally by Perceived Ease of Use (PEU) with a total effect of 0.478 and Subjective Norms (SN) 0.513 for AI users. In contrast, direct effects of subjective norms are not supported for non-AI users. Finally, 28.2% of the variance of Perceived Ease of Use (PEU) was determined by Subjective Norms (SN) with total effect 0.443 for AI users, compared to 12.3% of the variance for non-AI users. Again, subjective norms are more important to AI users than non-AI users, concerning both Perceived Usefulness and Perceived Ease of Use.

6. Discussion and Conclusions

The aim of our study was to replicate the results in Lin et al. (2021) using data on the telecom sector. Our first research question (RQ 1.1) was to investigate if the general technology acceptance model with the constructs used (Perceived Usefulness, Perceived Ease of Use, Attitudes Towards AI Use, Behavioural Intention and Subjective Norms) for non-AI users in the medical sector in Lin et al. (2021) is applicable to non-AI-users in the telecom sector. Using Confirmatory Factor Analysis to investigate model fit, reliability and validity of the constructs we concluded that Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitudes Towards AI Use (ATU), Behavioural Intention (BI) and Subjective Norms (SN) are able to adequately measure the intention of both medical staff and telecom staff to use AI tools. This means that the general technology acceptance model is applicable to the telecom sector as well as in the medical sector, indicating good external validity of the technology acceptance model.

Our second research question (RQ 1.2) was to investigate if the final technology acceptance model with paths supported by hypothesis testing for non-AI users in the medical sector in Lin et al (2021) also is applicable to non-AI users in the telecom sector. Replicating the results using data on the telecom sector (i.e. similar factor loadings and model fit), would indicate that the model presented in Lin et al. (2021) also transfers to the telecom sector and expand the external validity in Lin et al. (2021) beyond the medical sector. Confirmatory Factor Analysis was used to develop our best model and structural equation modelling to check which hypotheses are supported by our data. We concluded that our model is specific to the telecom sector since the best model in Lin et al. (2021) supports different paths between the constructs PU, PEU, SN, ATU, and BI than our model. The model developed in Lin et al. (2021) does not transfer to the telecom sector, which limits the external validity of the model.

Our last research question (RQ 2) was to investigate if there is a difference between our final technology acceptance model with paths supported by hypothesis testing for non-AI users in the telecom sector and the final model with paths supported by hypothesis testing for AI users in the telecom sector? Again, Confirmatory Factor Analysis was used to develop our best model and structural equation modelling to check which hypotheses are supported by our data. We concluded that our best model for non-AI users is specific to non-AI users in the telecom sector since the best model for AI-users supports different paths between the constructs PU, PEU, SN, ATU, and BI than our model for non-AI users. Our model for non-AI users does not transfer to AI users, which limits the external validity of the model.

The contribution of our study is replicating the Technology Acceptance Model in Lin et al. (2021) into the telecom sector in Sweden. The general Technology Acceptance Model with constructs Perceived Usefulness, Perceived Ease of Use, Attitudes Towards AI Use, Behavioural Intention and Subjective Norms is applicable to our data on the telecom sector in Sweden as well as the data on the medical sector in Taiwan in Lin et al. (2021). However, we conclude that the results for the medical sector reported in Lin et al. (2021) do not directly transfer into the telecom sector. This indicates that the technology acceptance model is depending on the sector studied and needs to be fitted for each sector that is analyzed. In other words, the external validity regarding the results in one sector is low.

7. Extension, limitations and future research

The original plan for our study, was to extend the technology acceptance model with two additional constructs, *Resistance to Change* and *Trust.* Questions on these constructs were included in our survey (appendix 9.1) and we have a confirmatory factor analysis including these constructs. For users' intention to use AI applications, it would be interesting to investigate how resistance to change and trust affect the other constructs, PU, PEU, SN, ATU, and BI. We hope that other studies would consider extending our study with resistance to change and trust. Description and the initial analysis can be found in these sections in appendix 10.

The data for this study was mainly collected from one of the largest telecom firms in Sweden. The results may be firm specific and not necessarily representative for the entire telecom sector in Sweden. It is possible that the external validity of the models increases as more data is collected, including responses from other firms with different sizes in the Swedish telecom sector. Our current models would be more effective if a large dataset is collected and likely model fit, reliability and validity of the models would increase. Data collected from many different telecom firms would provide more generalized insights into our research questions on the comparison between the industry sectors and AI and non-AI users. We also hope that other studies would consider collecting more data on the Swedish telecom sector to refine our study.

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9. Appendix

9.1. Questionnaire

INDEX	CATEGORY	QUESTIONs for non-AI users
PU01	Perceived Usefulness	I believe that using AI-technology tools can assist my professional work.
PU02	Perceived Usefulness	As a user, AI-technology tools would enhance the productivity of my professional work.
PU03	Perceived Usefulness	I believe that using the AI-technology tools would enhance my professional development.
PEU01	Perceived Ease of Use	Learning to use AI-technology tools for professional work is easy for me.
PEU02	Perceived Ease of Use	My interaction with AI-technology tools for professional work would be clear and understandable.
PEU03	Perceived Ease of Use	Learning to operate AI-technology tools in my industry is easy for me.
PEU04	Perceived Ease of Use	Using AI-technology tools would enhance the effectiveness of my professional work.
SN01	Subjective Norm	My supervisor or organization believes that I should employ the AI-technology tools to assist my professional work in the future.
SN02	Subjective Norm	I want to learn to use AI-technology tools because my supervisor or organization requires it.
SN03	Subjective Norm	The support from my supervisors or organization in learning to use the AI-technology tools is important to me.
SN04	Subjective Norm	The opinion of my colleagues about learning to use AI-technology tools is important to me.
ATU01	Attitude towards AI use	I have a generally favourable attitude toward learning to use AI-technology tools.
ATU02	Attitude towards AI use	I think it is a good idea to learn to use AI-technology tools for professional work.
BI01	Behavioural Intention	I intend to learn to use AI-technology tools for my professional work in the future.
BI02	Behavioural Intention	I intend to learn to use the AI-technology tools for my professional work frequently.
BI03	Behavioural Intention	I intend to adapt AI-technology tools for professional work or professional development.
RC01*	Resistance to Change	I do not want AI-technology tools to change the way I do my professional work.
RC02*	Resistance to Change	I do not want AI-technology tools to change the way work is done in my industry.
TR01*	Trust	I trust the information provided by AI-technology tools in my professional work.

TR02*	Trust	I trust that AI-technology tools in professional work correctly even when not monitored.
TR03*	Trust	Overall, I believe AI-technology tools for professional work are trustworthy.

**Item not included in data analysis*

INDEX	CATEGORY	QUESTIONs for AI users
PU01	Perceived Usefulness	I believe that using AI-technology tools can assist my professional work.
PU02	Perceived Usefulness	As a user, AI-technology tools enhance the productivity of my professional work.
PU03	Perceived Usefulness	I believe that using AI-technology tools enhances my professional development.
PEU01	Perceived Ease of Use	Using AI-technology tools for professional work is easy for me.
PEU02	Perceived Ease of Use	My interaction with AI-technology tools for professional work is clear and understandable.
PEU03	Perceived Ease of Use	Learning to operate AI-technology tools in my industry is easy for me.
PEU04	Perceived Usefulness	Using AI-technology tools enhances the effectiveness of my professional work.
SN01	Subjective Norm	My supervisor or organization believes that I should employ the AI-technology tools to assist my professional work in the future.
SN02	Subjective Norm	I'm using AI-technology tools because my supervisor or organization requires them.
SN03	Subjective Norm	The support from my supervisors or organization in using AI-technology tools is important to me.
SN04	Subjective Norm	The opinion of my colleagues about using AI-technology tools is important to me.
ATU01	Attitude towards AI use	I have a generally favourable attitude toward using AI-technology tools.
ATU02	Attitude towards AI use	I think it is a good idea to use AI-technology tools for professional work.
BI01	Behavioural Intention	I intend to use AI-technology tools for my professional work in the future.
BI02	Behavioural Intention	I intend to use the AI-technology tools for my professional work frequently.
BI03	Behavioural Intention	I intend to adapt AI-technology tools for professional work or professional development.
RC01*	Resistance to Change	I do not want AI-technology tools to change the way I do my professional work.
RC02*	Resistance to Change	I do not want AI-technology tools to change the way work is done in my industry.

TR01*	Trust	I trust the information provided by AI-technology tools in my professional work.
TR02*	Trust	I trust that AI-technology tools in professional work correctly even when not monitored.
TR03*	Trust	Overall, I believe AI-technology tools for professional work are trustworthy.

*Item not included in data analysis

9.2. The general TAM model – non-AI users

9.2.1. Descriptive statistics

Starting with analysing the data for non-AI users to match the group surveyed by Lin et al (2021), the means of the constructs were between 3.290 and 4.196, with standard deviations between 0.701 and 0.889.

9.2.2. Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was used as measuring model. The estimation of overall model fit was made by χ2, the Tucker-Lewis index (TLI), the comparative fit index (CFI) and the root mean square error of approximation (RMSEA). (Hu & Bentler, 1999) indicate that the TLI and CFI show a good model fit if their statistics are greater than 0.95. They also report that RMSEA values less than .06 are acceptable.
The measurement model displayed a less than satisfactory fit to the sample data compared to the indications by (Hu & Bentler, 1999): (χ_2 = 218.249; χ_2/df = 2.322; TLI = 0.775; CFI = 0.823; RMSEA = 0.121).

Table 9 Results of the Confirmatory Factor Analysis for non-AI users

Items	Unstandardized Estimates	t-value (Coefficient /standard error)	Standardized Estimates (factor loadings)	Composite Reliability	Average Variance Extracted	Cronbach's Alpha	Mean	Standard deviation
PU				0.7905	0.5598	0.767	4.036	.701
PU01#	1		.704					
PU02	1.294	6.88	.853					
PU03	1.103	5.64	.674					
PEU				0.6254	0.3097	0.718	3.563	.722
PEU01#	1		.398					
PEU02	1.222	3.25	.514					
PEU03	1.171	3.11	.455					
PEU04	1.590	3.69	.781					
SN				0.8049	0.5082	0.762	3.290	.889
SN01#	1		.717					
SN02	.926	5.53	.702					
SN03	.956	5.65	.779					
SN04	.640	3.98	.486					
ATU				0.6480	0.4794	0.6433	4.196	.756
ATU01 #	1		.686					
ATU02	1.048	5.94	.699					
BI				0.8473	0.6494	0.853	3.882	.823
BI01#	1		.845					
BI02	.955	7.50	.766					
BI03	1.134	8.03	.805					

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.* # value fixed at 1.000 for model identification purposes.

Table 17 describes the CFA results. Most of the factor loadings (standardized estimates) of the measured items are higher than the threshold value of 0.60, but not all (ranging from 0.398 to 0.853). Factor loadings below 0.40 should be removed, i. e. PEU01 at .398. The values of Cronbach's alpha of PU, PEU, SN, ATU, and BI were .767, .718, .762, .643 and .853, respectively, with values above 0.70 indicating a good internal consistency (reliability) of the constructs. The ranges of composite reliability (CR) were between 0.625 and 0.847, with values above 0.70 indicating a good CR. The average variance extracted (AVE) was mostly above an acceptable value of 0.5, ranging from 0.310 to 0.649, indicating that our survey had an acceptable convergence validity of the adopted constructs (Ab Hamid, Sami, & Mohmad Sidek, 2017).

Finally, to check if the constructs PU, PEU, SN, ATU, and BI differ from each other, discriminant validity is measured. The square roots of the average variance extracted (AVE) of the constructs (shown in parenthesis in the table below) should be greater than the correlation coefficients between constructs, shown without parenthesis in Table 18. This indicates that the constructs explain the variance of their own items better than the variance of other constructs. Since all square roots of AVE are greater than almost all correlation coefficients, we can conclude that the constructs PU, PEU, SN, ATU, and BI differ from each other (Ab Hamid, Sami, & Mohmad Sidek, 2017). E. g. the square root of AVE for PU (0.748) is greater than all correlation coefficients in the same column, showing correlation with PEU, SN, ATU and BI.

Table 10 Correlation coefficients and square root of AVE shown in parenthesis for non-AI users

	PU	**PEU**	**SN**	**ATU**	**BI**
PU	(0.748)				
PEU	0.573	(0.556)			
SN	0.413	0.337	(0.713)		
ATU	0.681	0.641	0.468	(0.692)	
BI	0.674	0.615	0.414	0.651	(0.806)

Note. ***PU*** = *perceived usefulness;* ***PEU*** = *perceived ease of use;* ***SN*** = *subjective norms;* ***ATU*** = *attitude towards AI use;* ***BI*** = behavioural *intention.*

9.3. Telecom specific model – non-AI users

Several low factor loadings and the poor model fit indicated by the fit indexes point towards several items in our questionnaire which do not measure Perceived Ease of Use (items PEU01 and PEU03) and Subjective norms (item SN04) for telecom staff as well as for medical staff by Lin et al (2021). We will now try to improve our model to test if our best model is similar to the best model by Lin et al. (2021).

Checking the covariances of the construct items, item PEU01 turned out to be correlated to item PEU03 since their covariance was higher than all other covariances. Both items were excluded from further analysis along with item SN04 with factor loading below 0.40. A new CFA was performed without items PEU01, PEU03 and SN04, presented below. This means that our best model seems to be different from the best model in Lin et al. (2021).

9.3.1. Confirmatory Factor Analysis

Performing a new CFA without items PEU01, PEU03 and SN04, the measurement model this time displayed a more satisfactory fit to the sample data compared to the indications by (Hu & Bentler, 1999): TLI and CFI show a good model fit if their statistics are greater than 0.95. RMSEA values less than 0.06 are acceptable. (χ_2 = 100.829; χ_2/df = 1.833; TLI = 0.887; CFI = 0.921; RMSEA = 0.096).

Table 11 Results of the Confirmatory Factor Analysis for non-AI users

Items	Unstandardized Estimates	t-value (Coefficient /standard error)	Standardized Estimates (factor loadings)	Composite Reliability	Average Variance Extracted	Cronbach's Alpha	Mean	Standard deviation
PU				0.7904	0.5600	0.767	4.036	.701
PU01#	1		.710					
PU02	1.290	7.03	.859					
PU03	1.074	5.64	.662					
PEU				0.5382	0.3787	0.513	3.755	.747
PEU02#	1		.472					
PEU04	1.325	4.87	.731					
SN				0.7775	0.5384	0.772	3.328	.976
SN01#	1		.735					
SN02	.893	5.25	.695					
SN03	.924	5.20	.770					
ATU				0.6838	0.5200	0.709	4.196	.756
ATU01#	1		.664					
ATU02	1.118	5.88	.721					
BI				0.8500	0.6542	0.833	3.882	.823
BI01#	1		.829					
BI02	.981	7.43	.771					
BI03	1.184	8.06	.825					

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.* # value fixed at 1.000 for model identification purposes.

Table 19 describes the CFA result; all the factor loadings of the measured items are now higher than the threshold value of 0.60 apart from PEU02 (ranging from 0.472 to 0.859). The values of Cronbach's alpha of PU, PEU, SN, ATU, and BI were .787, .512, .772, .709 and .833, respectively, with values above 0,70 indicating a good internal consistency (reliability) of the constructs. This is slightly lower than before. The ranges of composite reliability (CR) were between 0.538 and 0.850 with values above 0.70 indicating a good CR, also slightly lower than before. The ranges of average variance extracted (AVE) increased to between 0.379 and 0.654, mostly above an acceptable value of 0.5 and indicating that our survey had an acceptable convergence validity of the adopted constructs (Ab Hamid, Sami, & Mohmad Sidek, 2017).

To check if the constructs PU, PEU, SN, ATU, and BI differ from each other, discriminant validity is measured. The square roots of the average variance extracted (AVE) of the constructs (shown in parenthesis in the table below) should be greater than the correlation coefficients between constructs, shown without parenthesis in Table 20. This indicates that the constructs explain the variance of their own items better than the variance of other constructs. Since all square roots of AVE are greater than almost all correlation coefficients, we can conclude that the constructs PU, PEU, SN, ATU, and BI differ from each other (Ab Hamid, Sami, & Mohmad Sidek, 2017).

Table 12 Correlation coefficients and square root of AVE shown in parenthesis for non-AI users

	PU	**PEU**	**SN**	**ATU**	**BI**
PU	(0.748)				
PEU	0.692	(0.615)			
SN	0.407	0.351	(0.734)		
ATU	0.681	0.670	0.467	(0.721)	
BI	0.674	0.640	0.378	0.651	(0.809)

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.*

In summary, the model fit and factor loadings improved. Reliability decreased slightly but validity remained unchanged. This is our best model for non-AI users.

Comparing our improved model to the model in Lin et al. (2021), our model has removed some items, has lower factor loadings and not as good model fit. This indicates that a telecom specific model may be needed and that the model in Lin et al. (2021) does not transfer to the telecom sector, limiting the model's external validity. To investigate which paths between constructs are supported by the data on the telecom sector, hypothesis testing using structured equation modelling (SEM) is carried out.

9.3.2. Hypotheses testing using SEM for non-AI users

Structured equation modelling (SEM) is used to estimate the relationships between multiple dependent variables. In our study, SEM is used to estimate the regression coefficients for each pair of constructs (variables) among PU, PEU, SN, ATU, and BI and test if the relationship between the constructs is significant at the 95% confidence level. Since we have hypothesized that all constructs are related to each other (hypotheses H1 through H10), this test will show which relationships between constructs are supported at the 95% confidence level and contribute to technology acceptance model specific to our data. This model is then compared to the model in Lin et al. (2021) to answer research question 1.2. on model transfer from medical sector to telecom sector. The bootstrap method is a non-parametric way of estimating the standard errors by creating sub samples of the original data, in our case 1000 subsamples. Bootstrapping does not assume that all constructs are normally distributed.

The result of the using SEM (including the bootstrap method, 1000 iterations) on the relationships between the constructs (the structural model) displayed a satisfactory fit to the sample data compared to the indications by (Hu & Bentler, 1999): TLI and CFI show a good model fit if their statistics are greater than 0.95. RMSEA values less than 0.06 are acceptable. (x^2 = 100.829; x^2/df = 1.833; TLI = 0.887; CFI = 0.921; RMSEA = 0.096).

Figure 11 Structural model (general model) with the supported and unsupported paths for non-AI users

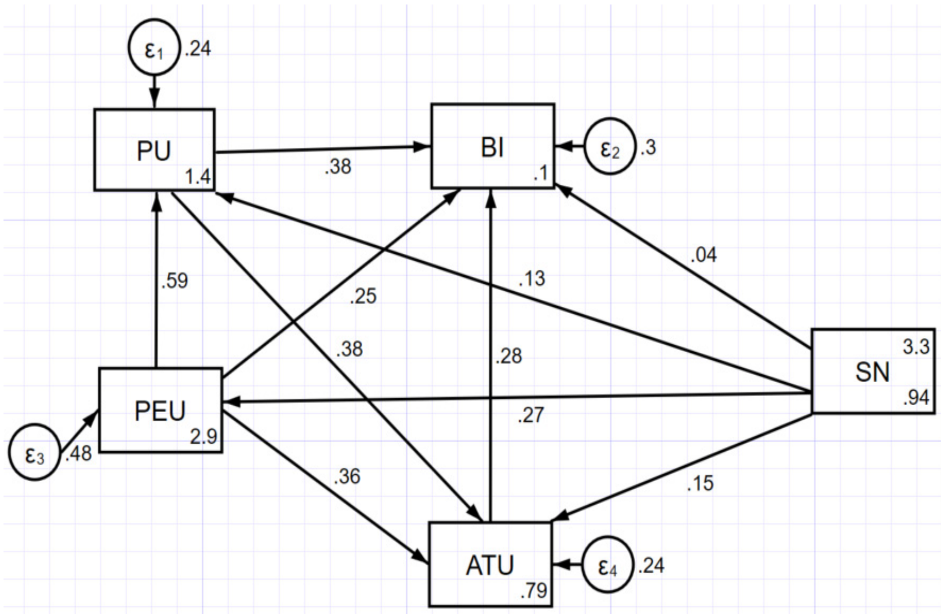


Table 8 shows the results of the hypotheses testing and which hypotheses that are supported by our data on non-AI users in the telecom sector.

Table 13 Hypotheses testing results for non-AI users

	Path		t-value	Bias-corrected		

Hypotheses		Estimate		Lower	Upper	Significant p level	Result (95% CL)
H1	PU --> BI	0.378	2.06	0.019	0.737	0.045	Supported
H2	PEU --> BI	0.253	1.98	0.004	0.503	0.052	Not Supported
H3	ATU --> BI	0.278	1.63	0.063	0.620	0.117	Not Supported
H4	SN --> BI	0.039	0.59	0.000	0.170	0.558	Not Supported
H5	PEU -->PU	0.588	6.60	0.416	0.759	0.000	Supported
H6	PU --> ATU	0.382	3.41	0.158	0.606	0.001	Supported
H7	PEU --> ATU	0.359	3.67	0.159	0.606	0.000	Supported
H8	SN --> PU	0.134	1.84	0.000	0.276	0.065	Not Supported
H9	SN --> ATU	0.153	2.46	0.0288	0.277	0.014	Supported
H10	SN --> PEU	0.268	2.72	0.071	0.466	0.006	Supported

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.*

Figure 12 Supported model paths for non-AI users in the telecom sector

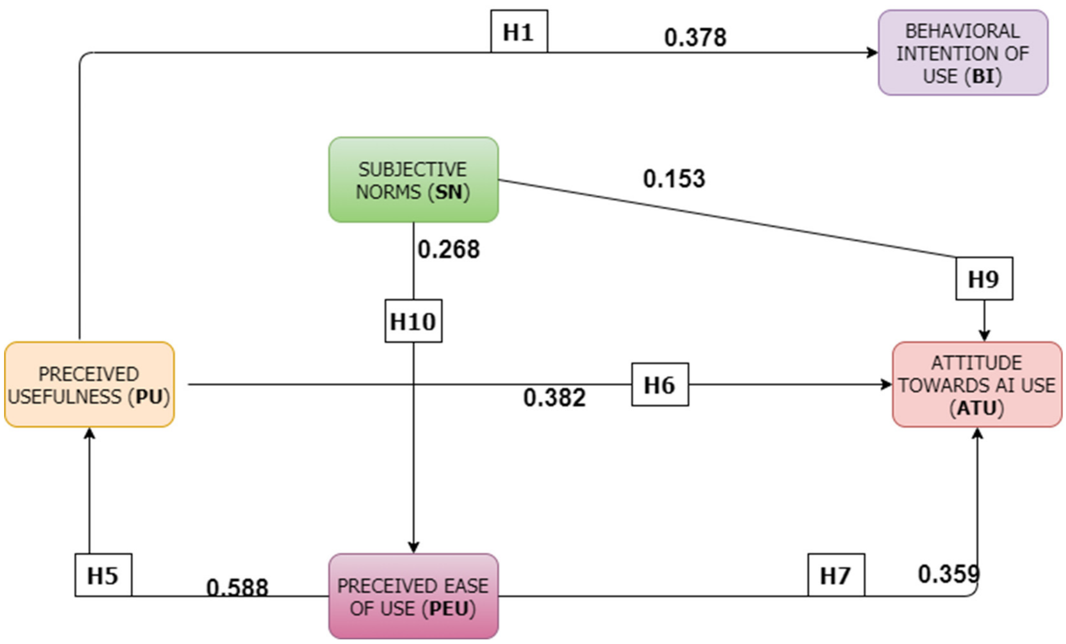


Figure 12 shows our best model with all model paths that are supported. Direct effects of the constructs are shown along the paths. As shown in Table 4, all hypotheses were supported by our data except H2, H3, H4 and H8. Our best model is telecom specific. The best model in Lin et al. (2021) supports different paths between the constructs PU, PEU, SN, ATU, and BI than our model. We can therefore conclude that the model developed in Lin et al. (2021) does not transfer to the telecom sector, which limits the external validity of the model.

Table 19 Shows direct, indirect and total effects for the different constructs and their determinants. The direct effect is the estimated regression coefficient in the structural equation modelling. E. g. Perceived Ease of Use explains 0.588 of the variance of Perceived Usefulness (direct effect). Subjective Norms has a direct effect on Perceived Ease of Use of 0.269 and therefore an indirect effect on Perceived Usefulness of 0.588 · 0.269 = 0.158. The total effect is used to estimate the relative importance of the different constructs.

Table 14 Direct, Indirect, and Total effects of the research model for non-AI users

Endogenous Variable	Determinant	Standardized estimates		
		Direct	Indirect	Total
PU (R2 = 0,509)	PEU	0.588	0.000	0.588
	SN	0.134	0.158	0.292
PEU (R2 = 0,123)	SN	0.269	0.000	0.269
ATU (R2 = 0,571)	PU	0.382	0.000	0.382
	PEU	0.359	0.225	0.584
	SN	0.153	0.208	0.362
BI (R2 = 0,548)	PU	0.378	0.107	0.485
	PEU	0.279	0.000	0.279
	SN	0.254	0.385	0.639
	ATU	0.040	0.279	0.319

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

9.4. The general TAM model – AI users

9.4.1. Descriptive statistics

The means of the constructs were between 3.716 and 4.260 (higher than non-AI users), with standard deviations between 0.668 and 0.800 (lower than non-AI users).

9.4.2. Confirmatory Factor Analysis

Performing a CFA using only AI user data, the measurement model displayed a satisfactory fit to the sample data compared to the indications by (Hu & Bentler, 1999): TLI and CFI show a good model fit if their statistics are greater than 0.95. RMSEA values less than 0.06 are acceptable. (x^2 = 160.906; x^2= $/df$ = 1.712; TLI = 0.900; CFI = 0.922; RMSEA = 0.086). This model fit is already better than the model fit of the best model for non-AI users.

Table 15 Results of the Confirmatory Factor Analysis for AI users

Items	Unstandardized Estimates	t-value (Coefficient /standard error)	Standardized Estimates (factor loadings)	Composite Reliability	Average Variance Extracted	Cronbach's Alpha	Mean	Standard deviation
PU				0.8003	0.5722	0.801	4.224	.705
PU01#	1		.738					
PU02	1.232	7.90	.790					

PU03	1.111	7.35	.740					
PEU				0.8231	0.5412	0.829	3.751	.718
PEU01#	1		.766					
PEU02	.837	6.81	.675					
PEU03	.768	6.31	.629					
PEU04	.930	8.10	.853					
SN				0.6821	0.3664	0.686	3.716	.800
SN01#	1		.691					
SN02	.626	3.17	.365					
SN03	.934	5.87	.782					
SN04	.766	4.11	.494					
ATU				0.8209	0.6966	0.777	4.260	.771
ATU01#	1		.800					
ATU02	1.064	9.64	.868					
BI				0.7994	0.5707	0.789	4.185	.668
BI01#	1		.759					
BI02	1.251	7.44	.731					
BI03	.956	8.01	.775					

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.* # value fixed at 1.000 for model identification purposes.

Table 15 describes the CFA results. Most of the factor loadings (standardized estimates) of the measured items are higher than the threshold value of 0.60, but not all (ranging from 0.365 to 0.868). Factor loadings below 0.40 should be removed, i. e. SN02 at 0.365. The values of Cronbach's alpha of PU, PEU, SN, ATU, and BI were 0.801, 0.829, 0.686, 0.777 and 0.789, respectively, with values above 0.70 indicating a good internal consistency (reliability) of the constructs. The ranges of composite reliability (CR) were between 0.682 and 0.821, with values above 0.70 indicating a good CR. The average variance extracted (AVE) was mostly above an acceptable value of 0.5, ranging from 0.366 to 0.697, indicating that our survey had an acceptable convergence validity of the adopted constructs (Ab Hamid, Sami, & Mohmad Sidek, 2017).

To check if the constructs PU, PEU, SN, ATU, and BI differ from each other, discriminant validity is measured. The square roots of the average variance extracted (AVE) of the constructs (shown in parenthesis in the

Table 16) should be greater than the correlation coefficients between constructs, shown without parenthesis in

Table 16. This indicates that the constructs explain the variance of their own items better than the variance of other constructs. Since all square roots of AVE are greater than almost all correlation coefficients, we can conclude that the constructs PU, PEU, SN, ATU, and BI differ from each other (Ab Hamid, Sami, & Mohmad Sidek, 2017).

Table 16 Correlation coefficients and square root of AVE shown in parenthesis for AI users

	PU	PEU	SN	ATU	BI
PU	(0.756)				
PEU	0.683	(0.736)			
SN	0.531	0.481	(0.605)		
ATU	0.828	0.663	0.513	(0.835)	
BI	0.730	0.762	0.521	0.778	(0.755)

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

9.4.3. Confirmatory Factor Analysis of telecom-specific model for AI users

Trying to improve model fit by checking the covariances of the construct items, no correlations were found. Items SN02 and SN04 were excluded from further analysis since their factor loadings are low. A new CFA was performed without items SN02 and SN04, presented below. This model excludes different items than the best model for non-AI users (which excludes items PEU01, PEU03 and SN04), which means that our best model for AI users will be different from our best model for non-AI users.

Performing a new CFA without items SN02 and SN04, the measurement model this time displayed a more satisfactory fit to the sample data compared to the indications by (Hu & Bentler, 1999): TLI and CFI show a good model fit if their statistics are greater than 0.95. RMSEA values less than 0.06 are acceptable. (x^2= 113.090; x^2/df = 1.688; TLI = 0.922; CFI = 0.943; RMSEA = 0.084).

Table 17 Results of the Confirmatory Factor Analysis for AI users

Items	Unstandardized Estimates	t-value (Coefficient /standard error)	Standardized Estimates (factor loadings)	Composite Reliability	Average Variance Extracted	Cronbach's Alpha	Mean	Standard deviation
PU				0.8005	0.5725	0.801	4.224	.705
PU01#	1		.742					
PU02	1.224	7.95	.790					
PU03	1.101	7.36	.737					
PEU				0.8230	0.5410	0.829	3.751	.718
PEU01#	1		.766					
PEU02	0.837	6.81	.675					
PEU03	0.767	6.30	.628					
PEU04	0.931	8.15	.853					
SN				0.6811	0.5169	0.672	4.102	.861
SN01#	1		.689					
SN03	.895	5.86	.748					
ATU				0.8209	0.6965	0.777	4.260	.771
ATU01 #	1		.801					
ATU02	1.062	9.62	.866					

BI				0.7992	0.5703	0.789	4.185	.668
BI01#	1		.758					
BI02	1.258	7.49	.734					
BI03	0.954	7.99	.773					

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.* # value fixed at 1.000 for model identification purposes.

Table 17 describes the CFA results. All the factor loadings of the measured items are now higher than the threshold value of 0.60 (ranging from 0.628 to 0.866). The values of Cronbach's alpha of PU, PEU, SN, ATU, and BI are almost unchanged: 0.801, 0.829, 0.672, 0.777 and 0.789, respectively, with values above 0.70 indicating a good internal consistency (reliability) of the constructs. The ranges of composite reliability (CR) were also unchanged, between 0.681 and 0.823, with values above 0.70 indicating a good CR. The average variance extracted (AVE) increased, now all AVE are larger than an acceptable value of 0.5, ranging from 0.517 to 0.697, indicating that our study had an acceptable convergence validity of the adopted constructs (Ab Hamid, Sami, & Mohmad Sidek, 2017).

To check if the constructs PU, PEU, SN, ATU, and BI differ from each other, discriminant validity is measured. The square roots of the average variance extracted (AVE) of the constructs (shown in parenthesis in the table below) should be greater than the correlation coefficients between constructs, shown without parenthesis in Table 18. This indicates that the constructs explain the variance of their own items better than the variance of other constructs. Since all square roots of AVE are greater than almost all correlation coefficients, we can conclude that the constructs PU, PEU, SN, ATU, and BI differ from each other (Ab Hamid, Sami, & Mohmad Sidek, 2017).

Table 18 Correlation coefficients and square root of AVE shown in parenthesis for *AI users*

	PU	**PEU**	**SN**	**ATU**	**BI**
PU	(0.757)				
PEU	0.683	(0.735)			
SN	0.627	0.531	(0.719)		
ATU	0.828	0.663	0.616	(0.835)	
BI	0.730	0.762	0.638	0.778	(0.755)

Note. ***PU*** *= perceived usefulness;* ***PEU*** *= perceived ease of use;* ***SN*** *= subjective norms;* ***ATU*** *= attitude towards AI use;* ***BI*** *= behavioural intention.*

In summary, model fit, factor loadings and average variance extracted (AVE) improved. Reliability and validity remained unchanged. This is our best model for AI users.

Comparing our best model for AI users to our best model for non-AI users, our model for AI users has removed different items, has higher factor loadings and better model fit. This indicates that the best model for AI users may be different to the best model for non-AI users, limiting the model's external validity. To investigate which paths between constructs are supported by the data on AI users in the telecom sector, hypothesis testing using structured equation modelling (SEM) is carried out.

9.4.4. Hypotheses testing using SEM for the telecom-specific model for AI users:

The result of the using SEM (including the bootstrap method, 1000 iterations) on the relationships between the constructs (the structural model) displayed a satisfactory fit to the sample data compared to the indications by (Hu & Bentler, 1999): TLI and CFI show a good model fit if their statistics are greater than 0.95. RMSEA values less than 0.06 are acceptable.

The result of the structural model showed (x^2= 113.090; x^2/df= 1.688; TLI = 0.922; CFI = 0.943; RMSEA = 0.084). Bootstrap method has been used for the hypothesis's analysis.

Figure 13 Structural model (general model) with the supported and unsupported paths for AI users

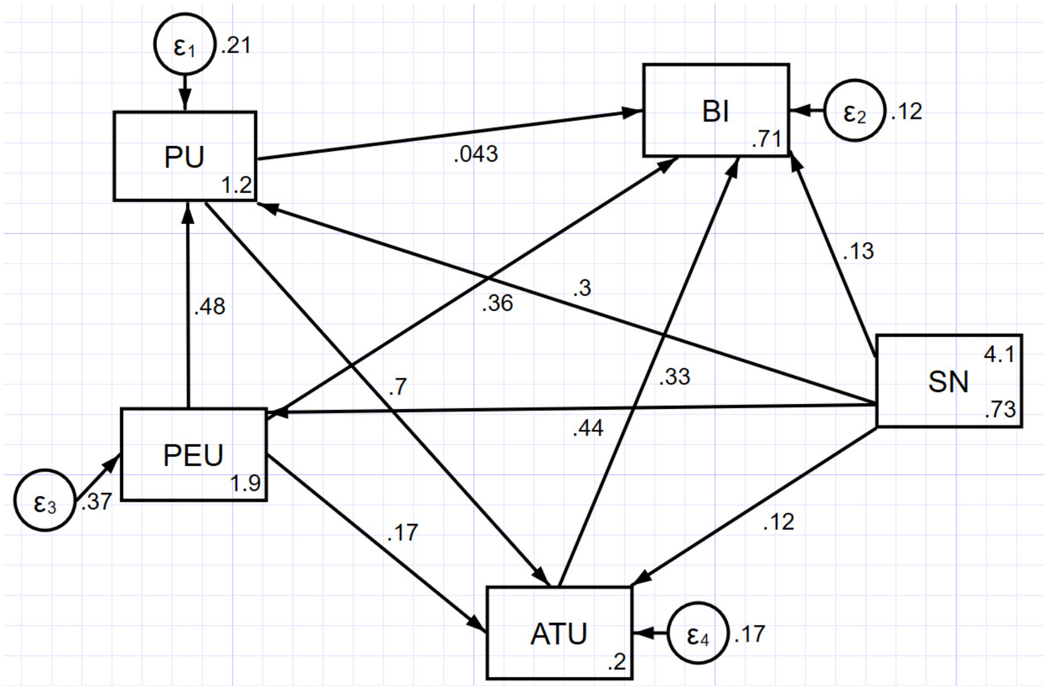


Table 11 shows the results of the hypotheses testing and which hypotheses that are supported by our data on AI users in the telecom sector.

Table 19 Hypotheses testing results for AI users

Hypotheses	Path	Estimate	t-value	Bias-corrected		Significant p level	Result (95% CL)
				Lower	Upper		
H1	PU --> BI	0.043	0.357	0.000	0.280	0.722	Not Supported
H2	PEU --> BI	0.363	5.04	0.222	0.504	0.000	Supported
H3	ATU --> BI	0.325	3.36	0.136	0.516	0.000	Supported
H4	SN --> BI	0.132	2.22	0.016	0.249	0.026	Supported
H5	PEU -->PU	0.478	5.63	0.312	0.644	0.000	Supported
H6	PU --> ATU	0.696	6.58	0.489	0.903	0.000	Supported

H7	PEU --> ATU	0.170	2.28	0.024	0.315	0.024	Supported
H8	SN --> PU	0.301	4.19	0.160	0.441	0.000	Supported
H9	SN --> ATU	0.118	1. 81	0.000	0.246	0.080	Not Supported
H10	SN --> PEU	0.442	5.58	0.287	0.598	0.000	Supported

***Note*. *PU* = *perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

Figure 14 Supported model paths for AI users in the telecom sector

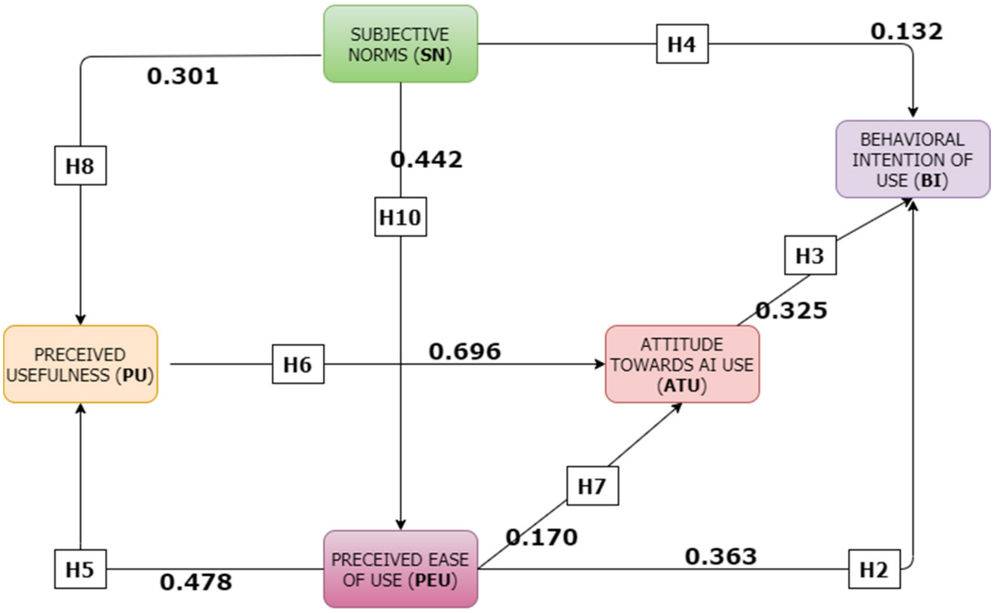


Figure 14 shows our best model with all model paths that are supported at 95% confidence level. Direct effects of the constructs are shown along the paths. As shown in Table 11, all hypotheses were supported by our data except H1 and H9. Our best model for non-AI users supports different paths between the constructs PU, PEU, SN, ATU, and BI than our best model for AI-users. We can therefore conclude that our model for non-AI users does not transfer to AI users, which limits the external validity of the model.

Table 20 Shows direct, indirect and total effects for the different constructs and their determinants.

Table 20 Direct, Indirect, and Total effects of the research model (AI users)

Endogenous Variable	Determinant	Standardized estimates		
		Direct	Indirect	Total
PU (R2 = 0,563)	PEU	0.478	-	0.478
	SN	0.301	0.212	0.513
PEU (R2 = 0,282)	SN	0.442	-	0.443
ATU (R2 = 0,713)	PU	0.696	-	0.696
	PEU	0.170	0.333	0.503
	SN	0.118	0.432	0.551
BI (R2 = 0,731)	PU	0.043	0.227	0.270
	PEU	0.326	-	0.326
	SN	0.363	0.185	0.548

	ATU	0.133	0.362	0.495

***Note**. **PU** = perceived usefulness; **PEU** = perceived ease of use; **SN** = subjective norms; **ATU** = attitude towards AI use; **BI** = behavioural intention.*

9.5. Confirmatory Factor Analysis and Structural Equation Modelling

Confirmatory factor analysis, developed by Karl J; Oreskog in the 1960s, is extremely important in SEM applications as it is used to test the measurement model. That's why measurement model in SEM can be considered as a confirmatory factor analysis tool. We have used direct effect of one variable on another variable when doing the analysis. (Ramlall, 2016)

SEM is used for covariance structure and study relationships among both observed and latent variables. SEM incorporates various statistical models such as regression analysis, factor analysis and variance/covariance analysis. SEM is also known as other names like "Simultaneous equation modelling, path analysis and latent variable analysis". (Ramlall, 2016)

SEM is mostly used in real datasets. In that respect, there is the need to use data to generate covariance/correlation matrix. Consequently, prior to deriving these covariance/correlation matrices, it is of paramount significance to have recourse towards data screening to remove outliers, ensure that normality conditions are being fulfilled and that there is no missing data. Data imputation techniques can be used to deal with missing data, but we have not used in our study. (Ramlall, 2016)

Degrees of freedom approach is widely used to assess model identification under SEM. An over-identified model has positive degrees of freedom, whereas an under-identified model has negative degrees of freedom. (Ramlall, 2016)

There are two types of parameters: namely, fixed, and free. Fixed parameters are never estimated from the data since their values are fixed to be either zero or one. To set up a scale for each latent variable, there is the need to fix the variance of each latent variable to one or fix the value to one of one parameter. Free parameters are estimated from the data.

SEM can deal with multiple dependent variables and able to estimate all effects in the model as compared to regression analysis has only one independent variable and able to estimate parts of an overall model. That is the reason for opting SEM model. This study uses this model with the aim of exploring the relationships between PU, PEU, SN, ATU and BI influencing telecom staff's learning to use AI applications. GSEM has been used in our study to generates quasimaximum likelihood (QML) which deals with nonnormality by adjusting the standard errors. GSEM adheres to the QML method when vce (robust) option to estimate the standard errors. ML works well in the case of marginal violation of multivariate normality. This study uses the 'Bootstrap' method in the data analysis.

"A widely reported Goodness-of-Fit index in SEM analysis is the x^2 test which provides a test of the null hypothesis that the theoretical model fits the data. If the model fits the data well, the x^2 values should be small, and the p-value associated with the 'chisquare' should be relatively large (non-significant)." (Ramlall, 2016)

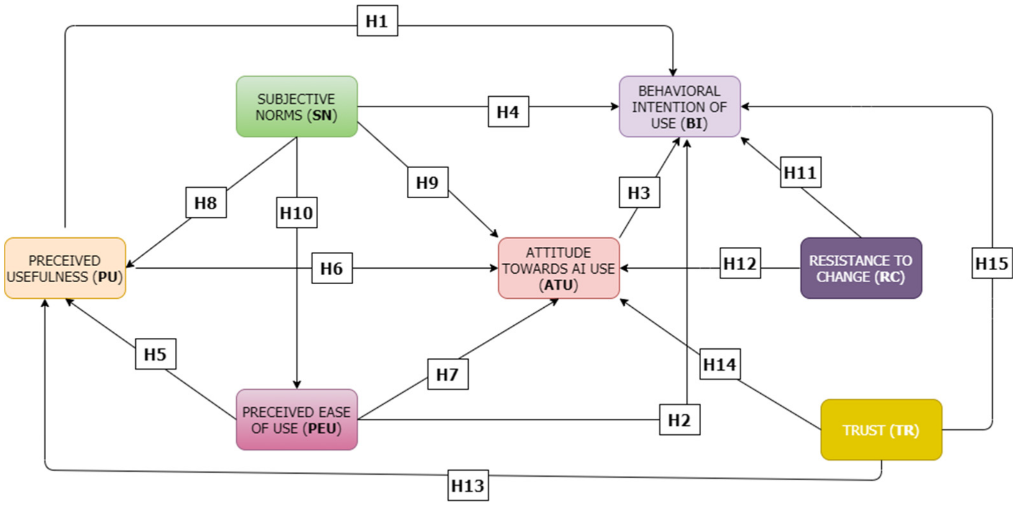
10. Extended factors.

Accordingly, the following extended research hypotheses are proposed:

1) Resistance to change (RC)
2) Trust (TR)

H11: Resistance to change (RC) has a significant negative effect on behavioural intention (BI).
H12: Resistance to change (RC) has a significant negative effect on Attitude towards AI use (ATU).
H13. Trust (TR) has a significant positive effect on perceived usefulness (PU).
H14. Trust (TR) has a significant positive effect on attitude towards AI use (ATU).
H15. Trust (TR) has a significant positive effect on behavioural intention (BI).

Figure 15 Extended proposed model including TR and RC



10.1. Trust (TR)

Trust (TR) is a construct originated in the field of social psychology (Shao, Zhang, Li, & Guo, 2019) and defined as the willingness of the individual to rely on the other party (Flavián, Guinalíu, & Torres, 2006). This variable has been recognized as a critical element that determines human-automation interaction having a persuasive or dissuasive effect on the use of AI-assisted technologies such as automated vehicles (Zhang, et al., 2019).

10.2. Resistance to Change (RC)

Resistance to Change refers to the feeling of stress or discomfort experienced by the individuals when they have to face changes (Guo, 2013) and is deemed to have an adverse effect on their technology adoption (Cenfetelli, 2004). The incorporation of AI-driven assessment on eLearning courses entails profound changes in the teaching-learning process including the increase of the human-computer interaction and the decrease of involvement of teachers in assessment activities. These changes may face resistance from the student that may affect their perception of the usefulness of the technology, their feelings towards its use and their subjective probability of participation in AI-driven assessment activities (Bhattacherjee, 2007).

From chapter 3.2: and 5 additional items added by this study. The additional five items aim at investigating the participants beliefs in two additional constructs. In terms of Resistance to Change (RC), participants will say "I do not want AI-technology tools to change the way I do my professional work" and referring to Trust (TR) they will mention "I trust the information provided by AI-technology tools in my professional work".

10.3. Test of the measurement model – non-AI users including RTC and TR

Confirmatory Factor Analysis (CFA) was used as measuring model. The estimation of overall model fit was made by x^2 and other fit indices, including the Tucker-Lewis index (TLI), the comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). (Hu & Bentler, 1999) indicated that the TLI and CFI show a good model fit if their statistics are greater than 0.95. They reported that RMSEA and SRMR values less than .06 and .08, respectively, are acceptable. From the results, the measurement model displayed a less than satisfactory fit to the sample data (x^2 = 350.437; x^2/df = 2.086; TLI = .760; CFI = .808; RMSEA = .109).

Table 21 Results of the Confirmatory Factor Analysis

Items	Unstandardized Estimates	t-value Coefficient /stand err	Standardized Estimates	Composite Reliability	Average Variance Extracted	Cronbach's Alpha	Mean	Standard deviation
PU						0.767	4.133	.708
PU01#	1		.726					
PU02	1.232	7.06	.841					
PU03	1.036	5.62	.652					
PEU						0.718	3.660	.724
PEU01#	1		.386					
PEU02	1.296	3.26	.529					
PEU03	1.317	3.17	.497					
PEU04	1.599	3.59	.762					
SN						0.762	3.510	.869
SN01#	1		.717					
SN02	.913	5.49	.693					
SN03	.938	5.70	.766					
SN04	.679	4.15	.516					
ATU						0.643	4.229	.762
ATU01#	1		.691					
ATU02	1.036	6.28	.697					
BI						0.853	4.039	.761
BI01#	1		.838					
BI02	.975	7.48	.775					
BI03	1.148	7.88	.807					
RTC						0.798	2.136	1.112
RTC01#	1		.762					
RTC02	1.036	5.60	.867					
TR						0.733	3.435	.773
TR01#	1		.873					
TR02	.800	4.14	.509					
TR03	.879	5.83	.748					

***Note**. PU = perceived usefulness; PEU = perceived ease of use; SN = subjective norms; ATU = attitude towards AI use; BI = behavioural intention.*

Table 21 describes the CFA result; all the factor loadings (standardized estimates) of the measured items are not all higher than the threshold value of 0.60 (ranging from 0.531 to 0.815), but all factor loadings are meaningful according to Ghauri et al if their absolute values are greater than 0.40. The values of Cronbach's alpha of PU, PEU, SN, ATU, and BI were 0.787, 0.776, 0.739, 0.709, and 0.833, respectively, with values above 0.70 indicating a good internal consistency of the factor items. Moreover, the ranges of composite reliability (CR) were between 0.730 and 0.830, and the ranges of average variance extracted (AVE) were between 0.422 and 0.620, indicating that the present study had an acceptable convergence validity of the adopted variables.