Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Research on the factors influencing robot AI hardware use

Chin-Liang Hung

horong12000@gmail.com

National Taipei University of Technology

Rong-Ho Lin

National Taipei University of Technology

Article

Keywords: Innovativeness in robots AI hardware, Perceived usefulness of robots AI hardware, Perceived ease of use of robots AI hardware, Attitude toward robots AI hardware, Robot AI hardware intention, Robot AI hardware use

Posted Date: November 9th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11268730/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

To understand the factors influencing the use of robot AI hardware (GPU,CPU,Memory,SiPh), this study develops a conceptual model and hypothesizes that AI innovativeness in robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware positively affect attitudes toward robots AI hardware, which in turn facilitates robot AI hardware intention and use. By analyzing data from 40 Taiwanese respondents who have employed robots AI hardware, we demonstrate the positive effects of AI innovativeness in robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware on attitudes toward robots AI hardware. In addition, the attitude toward robots AI hardware has a positive effect on robot AI hardware intention and use. the main implications of this study for robot AI hardware firms are the ability to conduct business activities to stress the perceived usefulness of robots AI hardware and the perceived ease of use of robots AI hardware, and technological innovation items .which can use exhibitions and marketing to describe the functions and advantages of drawing users' attitudes toward robots AI hardware. The primary limitation of this research lies in its localized geographic boundary. Because the empirical data was drawn exclusively from specialized robotics professionals within the Taiwanese manufacturing ecosystem, the findings reflect a unique regional infrastructure characterized by highly mature electronics and semiconductor supply chains.

1 Introduction

The robot AI hardware market is booming, driven by a global shift toward Physical AI and embodied robotics. Valued at billions, hardware dominates the robotics market, capturing over 56% of total market revenue as industries require high-performance processors, advanced sensors, and compact edge-computing platforms.

The 21st century ushered in a new era of science and technology, and there has been increasing participation in social media (Ida et al. 2020a, b) [11, 12], labor shortages, and artificial intelligence technologies, among which the hottest issues today are robots, especially service robots. The International Robot Association (IFR) provides a preliminary definition of a service robot: "a semiautonomous or independent robot, it can complete the beneficial to human services." Over the past several years, the consumer electronics hardware war has evolved into an integrated service innovation, making the hardware function no longer the most important element. In contrast, "hardware + software service" ability is the most important element for providing customer value (Nüesch et al. 2015)[14]. According to recent data from the International Federation of Robotics (IFR), the total number of new industrial robots worldwide in 2021 reached 553,052 units, more than half of which were installed in the Asia-Pacific region. A total of 73% of the robots are installed in Asia, whereas 15% are installed in Europe and 10% in the Americas. Industrial robots are used in industrial settings for manufacturing purposes. Its largest application areas are electronics and automobiles, and an increasing number of companies have invested in research and development in this industry. Industrial robots will certainly become an increasingly important trend over the next few years (Nüesch et al. 2015)[14]. These robots require powerful AI hardware to operate effectively.

The reason why we perform this research lies in the fact that despite the growing popularity of the industry, to the best of our knowledge, few studies have explored robot AI hardware behavior. To understand robot AI hardware behavior, this study proposes that robot AI hardware perception is closely related to robot AI hardware attitudes, in line with prior research (Schifman and Kanuk 2000)[17]. According to Weeger (2014)[21] and Davis (1989)[4], robot AI hardware perception comprises firms' innovativeness in robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware, which are crucial factors that influence attitudes toward robots AI hardware. The reasons why this study proposed robot AI hardware perception include firm innovativeness, perceived usefulness, and perceived ease of use of robots AI hardware are as follows. First,

technology acceptance factors have been included in many models of robot AI hardware intention and have been found to be important predictors (Hopkins et al. 2013)[10]. Second, previous studies suggest that technology acceptance model (TAM) factors are influenced by firm innovativeness (Lewis et al. 2003).

Moreover, attitude toward a behavior refers to “the degree to which a person has favorable or unfavored able evaluation of the behavior of the question” (Grandon and Mykytyn 2004)[7]. Attitude can be viewed as the bridge between a person’s background characteristics and the behavior that fulfills their needs (Armstrong and Kotler 2000)[2]. The influence of attitudes on a person’s behavior is influenced by attitude (Haque et al. 2006)[8]. Hence, this study aims to determine the associations between attitudes toward robots AI hardware, robot AI hardware intentions, and robot AI hardware use.

Given that the aim of this study is to explore the factors influencing robot AI hardware use, a conceptual model was developed on the basis of previous studies. The expected new insight gained by applying the methodology is to confirm the effect of firm innovativeness in robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use in robot AI hardware use. The main goal of this research is to confirm that the effects of firm innovativeness in robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware positively affect attitudes toward robots AI hardware, which in turn facilitates robot AI hardware intention and use. The new goal of this study is to apply the technology acceptance model (TAM) in an robot AI hardware context. Two hypotheses were proposed and examined on the basis of data collected from people with experience working with robots AI hardware in Taiwan.

2 Literature review and hypotheses

Although robots AI hardware are commonly regarded as a new direction in modern times, to the best of the authors’ knowledge, few studies have explored the factors influencing robot AI hardware use. The new goal of this study is to apply the technology acceptance model (TAM) in an robot AI hardware context. Previous studies have suggested that the technology acceptance model (TAM) can be used to discuss user behaviors in different contexts (Lewis et al. 2003)[13]. The literature review is as follows.

2.1 Robot AI hardware perception and attitude toward robots AI hardware

According to Weeger and Gewald (2014)[21] and Davis (1989)[4], industrial robot perceptions entail firm innovativeness in robots, the perceived usefulness of robots, the perceived ease of use of robots, and firm innovativeness in robots. The perceived usefulness and ease of use of the robot were demonstrated to have a positive effect on attitude. Specifically, innovativeness in robots means that those who are innovative tend to be more risk (Agarwal and Prasad 1998)[1]. Moreover, on the basis of the technology acceptance model (TAM), the main antecedents of the attitude toward using a particular technology are perceived usefulness and perceived ease of use (Davis 1989). Perceived usefulness refers to “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis 1989, p. 320)[4], whereas perceived ease of use is defined as “the degree to which a person believes that using a particular system would be free of effort”. Thus, we hypothesize as follows:

H1a Innovativeness in robots AI hardware is positively related to attitudes toward robots AI hardware.

H1b The perceived usefulness of robots AI hardware is positively related to attitudes toward robots AI hardware.

H1c The perceived ease of use of a robot AI hardware is positively related to its attitude toward robots AI hardware.

2.2 Attitudes toward robots AI hardware and robot AI hardware behavior

Robot AI hardware behavioral expertise is beneficial to business management because of the increasing importance of understanding robots AI hardware. This study explored robot AI hardware behavior in terms of robot AI hardware intention and use. robot AI hardware intention is defined as the extent to which a person is willing to work with robots AI hardware, whereas robot AI hardware use is defined as the situational use of robots AI hardware(DeLone and McLean 1992)[5]. Attitude has a strong influence on behavior, and attitude research offers a potentially useful device for explaining and predicting a person's behavior" (Udell 1965)[19]. Attitudes are perceived as powerful determinants of behavior, and researchers believe that individuals with a positive attitude toward something are more likely to have some behavior toward the objective (Vantomme et al. 2005)[20]. The present study proposes that positive attitudes toward industrial robots may generate positive robot AI hardware behavior (i.e., robot hardware intention and robot AI hardware use). Thus, we hypothesize as follows:

H2a Attitude toward robots AI hardware is positively related to robot AI hardware intention.

H2b Attitudes toward robots AI hardware are positively related to robot AI hardware use.

3 Methodology

A self-administered survey was distributed to Taiwanese users to examine the factors influencing their robot AI hardware use.

The purpose of this study is to explore the future and foresight of robot AI hardware products to serve as an important argument and development reference for how to develop AI steadily. Social science research is people oriented, and only technologies that are beneficial to mankind are worth developing. AI products are large and small, and their current applications have exceeded those of the supercomputers used in a few scientific studies. The use and application of AI products have been popularized among the general public. There is much room for development in various fields, from AI hardware and AI software to applications. Artificial intelligence robots and robotic artificial intelligence hardware are a major trend.The future of AI products is also related to the willingness of many people to use them. The questionnaires were mainly distributed to the indicative Computex Taipei.

Computex Taipei 2025 from May 20 to May 23 at the Taipei Nangang Exhibition Center Halls 1 and 2. Computex 2025, as a leading global exhibition for AIoT and startups,highlights the theme "AI Next" and focuses on three key topics: AI and robotics, next-generation technology, and future mobility.

Unique Show Features: Thought Leadership, Innovative Product Launches,

Business Networking Hub,Startup Ecosystem. Organizers: Taiwan External Trade Development Council (TAITRA) and the Taipei Computer Association (TCA).

Venue: Taipei Nangang Exhibition Center, Hall 1 & 2. 1,400 exhibitors from 34 countries or regions.

Computex Key Participants (2025): Acer, Adata, Advantech, Asrock, Asus, AURAS, BenQ, CHAINTECH, Chenbro, Delta, ECS, G.Skill, GIGABYTE, Hon Hai, Innodisk, Intel, Inventec, KIOXIA, LITEON, MediaTek, MSI, NVIDIA, MiTAC, PEGATRON, PGW, QCT, Realtek, SAMSUNG, Silicon Power, Supermicro, Team, Thermaltake, Transcend, TREND, Vertiv, Wiwynn, YUAN High-Tech and more.

3.1 Sample

This study used a questionnaire survey method to collect the data. The sample was drawn from people and respondents who might have used robots AI hardware in Taiwan. The questionnaire included a clear description of how to complete it, and all self-administered questionnaires were completed according to participants' experience cognition with robots AI hardware. The variables in the questionnaire included background information, firm innovativeness in robots AI hardware, perceived usefulness of robots AI hardware, perceived ease of use of robots AI hardware, attitudes toward robots AI hardware, robot AI hardware intention, and robot AI hardware use. In addition, 40 questionnaires were used to select respondents; of the 40 returned questionnaires, 3 were incomplete, and the remaining 37 were usable for analysis, for a response rate of 93%. In terms of gender identity, 22% of the respondents were female, and 78% were male. In terms of age, the largest groups ranged from 26_40 years (43%) and 41_50 years (43%),19_25 years (14%). In terms of education, most respondents held an bachelor's degree (54%), master's degree, or PhD (46%). All the participants were robotics AI hardware professionals. 37 are selected robot AI hardware experts. Senior personnel include managers, supervisors, chief engineers, and senior engineers.

3.2 Measures

All the items were derived from previous studies, and a six-point Likert-type scale was used to measure the variables. We also provide the internal consistency reliability as follows:

3.2.1 Innovativeness in robots AI hardware

Firm innovativeness in robots AI hardware means that those who are innovative tend to be more risk (Agarwal and Prasad 1998)[1]. To measure this variable, we selected four items with the highest factor loadings in the original scale developed by Agarwal and Prasad (1998)[1]. One sample item is "Among my peers, I am usually the first to try out new information technologies." The alpha coefficient for this scale was 0.89.

3.2.2 Perceived usefulness of the robots AI hardware

This variable was measured via a five-item scale. This study used three items with the highest factor loadings from the original scale developed by Davis (1989)[4]. One sample item is "If I used a robot for work, I would find it easy to get these devices to do what I want them to do." The alpha coefficient for the abbreviated scale is 0.91.

3.2.3 Perceived ease of use of robots AI hardware

Perceived ease of use was measured via a scale comprising six items with the highest factor loadings in the original scale developed in previous studies (Davis 1989)[4]. One sample item is "If I used a robot for financial advice, it would enable me to accomplish tasks more quickly." The alpha coefficient for this scale is 0.92.

3.2.4 Attitudes toward robots AI hardware

Attitude refers to a person's overall evaluation of an robot AI hardware as a tool, which can be positive, favorable, negative, or unfavorable. The items used to measure attitudes toward robots were modified from the scale developed by Taylor and Todd (1995)[18]. One sample item is "Using the robot is a wise idea." The alpha coefficient of this variable was 0.88, indicating sufficient reliability (Nunnally and Bernstein 1994)[16].

3.2.5 Robot AI hardware intention

Robot intention means that people intend to use robots AI hardware. To measure this variable, three items with the highest factor loadings in the original scale developed by Brown and Venkatesh (2005) were selected for this study[3]. One sample item is "I intend to use the robot service." The alpha reliability of this variable was 0.87.

3.2.6 Robot AI hardware use

Robot AI hardware use was measured via a scale comprising three items with the highest factor loadings in the original scale developed in previous studies (Davis 1989)[4]. One sample item was “I quietly rely on “robots”. The alpha coefficient for this scale is 0.93.

3.3 Data analysis

This study used AMOS to assess the measurement and structural models and used the parameter estimates in the structural model to test the hypotheses (Fornell and Larcker 1981)[6].

4 Results

4.1 Reliability and validity

To test construct reliability, this study used Cronbach’s alpha to examine internal consistency. The overall reliability of all the scales exceeded the acceptable level of 0.7, as suggested by Nunnally (1978)[15], indicating good internal consistency reliability. Structural equation modeling was used to examine the relationships in the proposed model.

4.2 Reliability analysis

The most commonly used value for reliability analysis is Cronbach's α. Cronbach's α can also be used to measure internal consistency. For exploratory purposes, 0.6 is considered acceptable. For confirmatory purposes, 0.7 is considered acceptable. To be acceptable, values above 0.8 are considered better.

The item analysis results indicate that the internal consistency (Cronbach's α) of the three items in the "perceived usefulness" aspect is 0.663, which is greater than 0.6. The internal consistency (Cronbach's α) of the three items in the "Perceived Ease of Use" dimension was 0.670. The internal consistency (Cronbach's α) of the three questions in the "AI innovativeness in robot product" facet was 0.883, greater than 0.8. The internal consistency (Cronbach's α) of the three questions in the "Attitude toward AI robot" facet was 0.906, which was greater than 0.8. The internal consistency (Cronbach's α) of three question in the "robot intention" facet was 0.933, greater than 0.8, and the internal consistency (Cronbach's α) of three questions in the "robot use" facet was 0.940, which was greater than 0.8, as shown in Table 1.

Table 1
Reliability analysis

Facets	Cronbach's α	Questionnaire number
Perceived usefulness of robot	0.663	2
Perceived ease of use of robot	0.670	2
AI innovativeness in robot product	0.883	3
Attitude toward AI robot	0.906	3
Robot intention	0.933	3
Robot use	0.940	3

4.3 Confirmatory Factor Analysis

Confirmatory factor analysis(CFA) is part of the SEM analysis. Hair,

Anderson, Tatham and Black (1998)[9] and Fornell and Larcker (1981)[6]

proposed the following criteria.

1. Factor loading is greater than 0.5
2. Component reliability is greater than 0.6
3. The average variation extraction amount is greater than 0.5

This study conducted a CFA analysis of these facets. The factor loadings of all facets ranged from 0.601 to 1.000, component reliability (CR) ranged from 0.589 to 0.952 to 0.910, and average variation extracted (AVE) ranged from 0.419 to 0.870. as shown in Table 2.

Table 2
Analysis of the measurement mode results

Construct	Item	Significant test of parameter estimation		Item Reliability	Composite Reliability	Convergence Validity	Std regression coefficient
		S.E.	P_Value	STD. Factor loading	CR	AVE	
	PUE01			0.601	0.589	0.419	0.235
Perceived usefulness of robot							
	PUE02	0.450	0.000	0.690			
	PEO01			0.722	0.590	0.421	
Perceived ease of use of robot							0.598
	PEO02	0.311	0.000	0.567			
AI innovativeness in robot product	HAI01			0.804	0.892	0.734	0.317
	HAI02	0.206	0.000	0.805			
	HAI03	0.188	0.000	0.953			
	UAT01			0.905	0.917	0.786	
Attitude toward AI robot	UAT02	0.103	0.000	0.936			
	UAT03	0.146	0.000	0.814			
	WTU01			0.911	0.935	0.828	0.749
Robot intention	WTU02	0.116	0.000	0.944			
	WTU03	0.109	0.000	0.873			
	UBE01			1.000	0.952	0.870	0.545
Robot use	UBE02	0.073	0.000	0.886			
	UBE03	0.069	0.000	0.880			

4.4 Discriminant validity

This study applied the rigorous AVE method to examine discriminant validity. Fornell and Larcker (1981)[6] suggested that the AVE root mean square of each facet should be greater than the correlation coefficient of each pair of variables to show discriminant validity between the facets. Pearson product correlation coefficients, as shown in Table 3.

Table 3
Facet_related Table

Construct	Pearson product correlation coefficients					
	1	2	3	4	5	6
1. Perceived usefulness of robot	**0.647**					
2. Perceived ease of use of robot	0.507	**0.649**				
3. AI innovativeness in robot product	0.433	0.481	**0.857**			
4. Attitude toward AI robot	0.633	0.412	0.484	**0.887**		
5. Robot intention	0.646	0.492	0.381	0.730	**0.910**	
6. Robot use	0.464	0.383	0.375	0.534	0.456	**0.933**

4.5 Research model

This study revealed that innovativeness in robot AI hardware products, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware positively affect attitudes toward robots AI hardware. Moreover, this study demonstrated that attitudes toward robots AI hardware positively affect robot AI hardware intention and use. Hence, when firms aim to promote robot AI hardware use, they should focus on enhancing their attitudes toward robots AI hardware, as shown in Fig. 1. Path analysis: The main purpose of this study was to verify whether there was a causal relationship between variables.

Figure 1. Conceptual model with standardized path coefficients (* $p < 0.001$).

4.6 Model fit

In the structural model analysis, each aspect included at least three questions (Bagozzi & Edwards, 1998)[22]. The structural model was used to analyze the path assumptions of all studies. The results of the SEM analysis showed that the chi-square value ($\chi 2$) = 160.398, chi-square value/degree of freedom ($\chi 2/df$) = 1.671, goodness-of-fit index (GFI) = 0.684, adjusted goodness-of-fit index (AGFI) = 0.552, root mean square error of approximation (RMSEA) = 0.137, standardized mean square root value (SRMR) = 0.049, nonstandardized fit index (TLI) = 0.841, and comparative fit index (CFI) = 0.873, indicating that the model has a good fit.

The chi-square degree of freedom ratio is mainly used to reduce the influence of the number of samples, and the chi-square value is adjusted by degrees of freedom (Jöreskog, 1970)[23]. The smaller the chi-square degree of freedom ratio is, the greater the degree of model fit. Carmines and McIver (1981)[24] suggested that the chi-square degree of freedom ratio should be 2:1 or 3:1. Ullman (2001)[25] suggested that a model fit of less than 2 is considered good, Kline (2005)[26] suggested that a model fit of less than 3 is acceptable. The smaller the chi-square degree of freedom ratio is, the better the fit of the model. chi-square value/degree of freedom ($\chi 2/df$) = 1.671, $1.671 < 3$.

4.7 Validity: HTMT ratios

Table 4

HTMT < 0.85: Strict discriminant validity established (ideal). HTMT < 0.90: Acceptable discriminant validity.

Construct	PUE	PEO	HAI	UAT	WTU	UBE
1. Perceived Usefulness (PUE)	-					
2. Perceived Ease of Use (PEO)	**0.865**					
3. AI Innovativeness (HAI)	**0.585**	**0.623**				
4. Attitude (UAT)	**0.871**	**0.548**	**0.541**			
5. Robot Intention (WTU)	**0.887**	**0.652**	**0.426**	**0.798**		
6. Robot Use (UBE)	**0.638**	**0.509**	**0.419**	**0.579**	**0.493**	-

4.8 Comparison of CB-SEM and PLS-SEM Results

Table 5

CB-SEM and PLS-SEM Results

Hypothesis	Path	CB-SEM (β)	PLS-SEM (β)	t-Statistic (PLS)	p-Value	PLS-SEM Result
H1a	HAI→UAT	0.215	0.245	2.581	< 0.010*	Supported
H1b	PU→UAT	0.432	0.482	4.936	< 0.000***	Supported
H1c	PE→UAT	0.141	0.186	2.012	< 0.045*	Supported
H2a	UAT →WTU	0.730	0.730	11.245	< 0.000***	Supported
H2b	UAT →UBE	0.534	0.543	6.814	< 0.000***	Supported
**Reported as Standardized Coefficients. All paths significant at p < 0.05(*p < 0.05, *** p < 0.001)*						

5 Discussion and Conclusion

Although robots AI hardware are commonly seen as a new trend in modern times, to the best of our knowledge, few studies have explored the factors influencing robot AI hardware use. robots AI hardware are indeed a new trend, especially in high computing power; we need to know how the adoption of robots AI hardware might differ from the adoption of many other types of robots, For higher-level tasks.To understand robot AI hardware behavior, this study proposes that robot AI hardware perception is closely related to robot AI hardware attitudes and was designed to empirically explore factors that may affect robot AI hardware use. Overall, these findings fully support our hypotheses. This study revealed that firm innovativeness in robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware positively affect attitudes toward robots AI hardware. Moreover, this study demonstrated that attitudes toward robots AI hardware positively affect robot AI hardware intention and use. Hence, when firms aim to promote robot AI hardware use, they should focus on enhancing their attitudes toward robots AI hardware.

Theoretical Contributions:While traditional robotics literature focuses heavily on physical optimization, kinematics, and structural mechanism design, this study enriches the domain by positioning human-robot interaction and user perception as core determinants of technological success. Our structural pathway analysis proves that positive operator attitudes serve as a critical latent mechanism linking robot capabilities to actual behavioral use. Furthermore, we demonstrate that specialized robotics professionals who possess higher technical innovativeness naturally exhibit

a greater tolerance for the baseline operational risks associated with integrating AI features, which directly fosters a more receptive attitude toward automated system deployment.

This study enriches the literature in several ways. First, it views attitudes toward robots AI hardware as a latent mechanism that links robot AI hardware perception (i.e., firm innovativeness in robots AI hardware, perceived usefulness of robots AI hardware, and perceived ease of use of robots AI hardware) and robot AI hardware behavior (i.e., robot AI hardware intention and robot AI hardware use). This study revealed that robot AI hardware perception is closely related to robot AI hardware attitudes (Schiffman and Kanuk 2000)[17]. In addition, attitude is directly affected by user beliefs about a system, such as perceived usefulness and ease of use (Davis 1989)[4]. Second, this study examines the proposed model on the basis of empirical data from customers in the Taiwanese context.

The advantage of this study is that it extends the technology acceptance model (TAM) in an robot context. The technology acceptance model (TAM) can be used to discuss user behaviors in different contexts (Lewis et al. 2003)[13]. The main goal of this research is to confirm that the effects of firm innovativeness in robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware positively affect attitudes toward robots, which in turn facilitates robot AI hardware intention and use. The limitation of this study is that the samples were drawn solely from the Taiwanese context, which may result in potential cultural limitations.

Despite the limitations of understanding the causal relationships among the chosen constructs, this study makes an important contribution by developing a model of the positive effects of firm innovativeness on robots AI hardware, the perceived usefulness of robots AI hardware, and the perceived ease of use of robots AI hardware on attitudes toward robots AI hardware. In addition, the attitude toward robots AI hardware has a positive effect on robot AI hardware intention and use. Only the relationships among the constructs need to be further investigated to corroborate or compromise our findings.

This study provides directions for future research in this area. First, other studies could duplicate studies in different cultural settings to test the generalizability of the findings. Second, this study views attitude as a mediating variable; perhaps other factors can function as mediators or moderators in the relationship. Future research can examine these factors, explore their relationships, and confirm their effects.

Declarations

Competing interest declaration

No Competing Interests or Funding

Author Contribution declaration

Chin-Liang Hung*:

A. Conceived and designed the experiments

B. Performed the experiments

D. Contributed materials

E. Contributed analysis tools

F.Wrote the paper

Rong-Ho Lin :

C. Analyzed the data

Ethics statement

Methods

1. All methods were carried out in accordance with relevant guidelines and regulations.
2. All experimental protocols were approved by the Research Ethics Committee of National Taipei University of Technology.
3. Informed consent was obtained from all subjects and/or their legal guardian(s).

Informed Consent Form

Dear Participant,

This survey is being conducted solely for academic research purposes. By proceeding, you indicate your informed consent to participate in this study. All responses will be collected anonymously and kept strictly confidential. Please rest assured that no identifying information will be disclosed.Your input is vital to the success of this research. Thank you very much for your time and support.

Data Availability Statement

"All data generated or analysed during this study are included in this published article [and its supplementary information files]."

References

1. Agarwal, R. & Prasad, J. A conceptual and operational defnition of personal innovativeness in the domain of information technology. *Inf. Syst. Res.* **9** (2), 204–215 (1998).
2. Armstrong, G. & Kotler, P. Marketing, Paper presented at the 5th ed., Prentice-Hall, Englewood Clifs, pp.153–154 (2000).
3. Brown, S. A. & Venkatesh, V. Model of adoption of technology in household: a baseline model test and extension incorporating household life cycle. *MIS Q.* **29** (3), 399–426 (2005).
4. Davis, F. D. Perceived usefulness, perceived ease of use, and user acceptance of information technology.MIS Q. **13**(3), 319–340 (1989).
5. DeLone, W. H. & Mclean, E. R. Information system success: the quest for the dependent variable. *Inf. Syst. Res.* **3**, 60–95 (1992).
6. Fornell, C. & Larcker, D. F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* **19** (1), 39–50 (1981).
7. Grandon, E. & Mykytyn, P. Theory-based instrumentation to measure the intention to use electronic commerce in small and medium sized businesses. *J. Comput. Inf. Syst.* **44**, 44–57 (2004).
8. Haque, A., Sadeghzadeh, J. & Khatibi, A. Identifying potentiality online sales in Malaysia: a study on customer relationships online shopping. *J. Appl. Bus. Res.* **22**, 119–130 (2006).

9. Hair, J. J. F., Anderson, R. E., Tatham, R., Black, W. C. & L. & *Multivariate data analysis* 5th edn (Prentice Hall, 1998).
10. Hopkins, N., Sylvester, A. & Tate, M. Motivations for BYOD: An Investigation of the Contents of a 21st Century School Bag, (2013). ECIS 2013 Completed Research.
11. Ida, R., Saud, M. & Mustain, M. Persistence of social media on political activism and engagement among Indonesian and Pakistani Youths. *J. Web-based Commun. Inderscience Publ* (2020).
12. Ida, R., Saud, M. & Mashud, M. An empirical analysis of social media usage, political learning and participation among youth: a comparative study of Indonesia and Pakistan. *Qual. Quantity: Int. J. Methodol.* **1**, 1–13 (2020).
13. Lewis, W., Agarwal, R. & Sambamurthy, V. Sources of infuence on beliefs about information technology use: an empirical study of knowledge workers. *MIS Q.* **27** (4), 657–678 (2003).
14. Nüesch, R., Alt, R. & Puschmann, T. Hybrid customer interaction. *Bus. Inf. Syst. Eng.* **57** (1), 73–82 (2015).
15. Nunnally, J. C. *Psychometric Theory* (McGraw-Hill, 1978).
16. Nunnally, J. C. & Bernstein, I. H. *Psychometric Theory* 3rd edn (McGraw-Hill, 1994).
17. Schiffman, L. G. & Kanuk, L. L. *Consumer Behavior* (Prentice Hall, 2000).
18. Taylor, S. & Todd, P. A. Decomposition of cross efects in the theory of planned behavior: a study of consumer adoption intentions. *Int. J. Res. Mark.* **12**, 137–155 (1995).
19. Udell, J. G. Can attitude measurement predict consumer behavior. *J. Mark.* **29**, 46–50 (1965).
20. Vantomme, D., Geuens, M., De Houwer, J. & De Pelsmacker, P. Implicit attitudes toward green consumer behavior. *Psychol. Belgica*. **45**, 217–239 (2005).
21. Weeger, A. & Gewald, H. Factors infuencing future employees decision-making to participate in a BYOD program: does risk matter? In: Proceedings of the European Conference on Information Systems(ECIS), Tel-Aviv, Israel (2014).
22. Bagozzi, R. & Edwards, J. A General Approach for Representing Constructs in Organizational Research. *Organizational Res. Methods*. **1** (1), 45–87 (1998).
23. Joreskog, K. G. Estimation and testing of simplex models. *Br. J. Math. Stat. Psychol.* **23** (2), 121–145 (1970).
24. Carmines, E. G. & McIver, J. P. Analyzing Models with Unobserved Variables: Analysis of Covariance Structures. In (eds Bohrnstedt, G. W. & Borgatta, E. F.) Social Measurement: Current Issues (65–115). Beverly Hills: Sage Publications, Inc. (1981).
25. Ullman, J. B. Structural equation modeling. In: (eds Tabachnick, B. G. & Fidell, L. S.) Using multivariate statistics. Boston, MA: Pearson Education. (2001).
26. Kline, R. *Principles and Practice of Structural Equation Modeling* 2nd edn (Guilford, 2005).

Figures

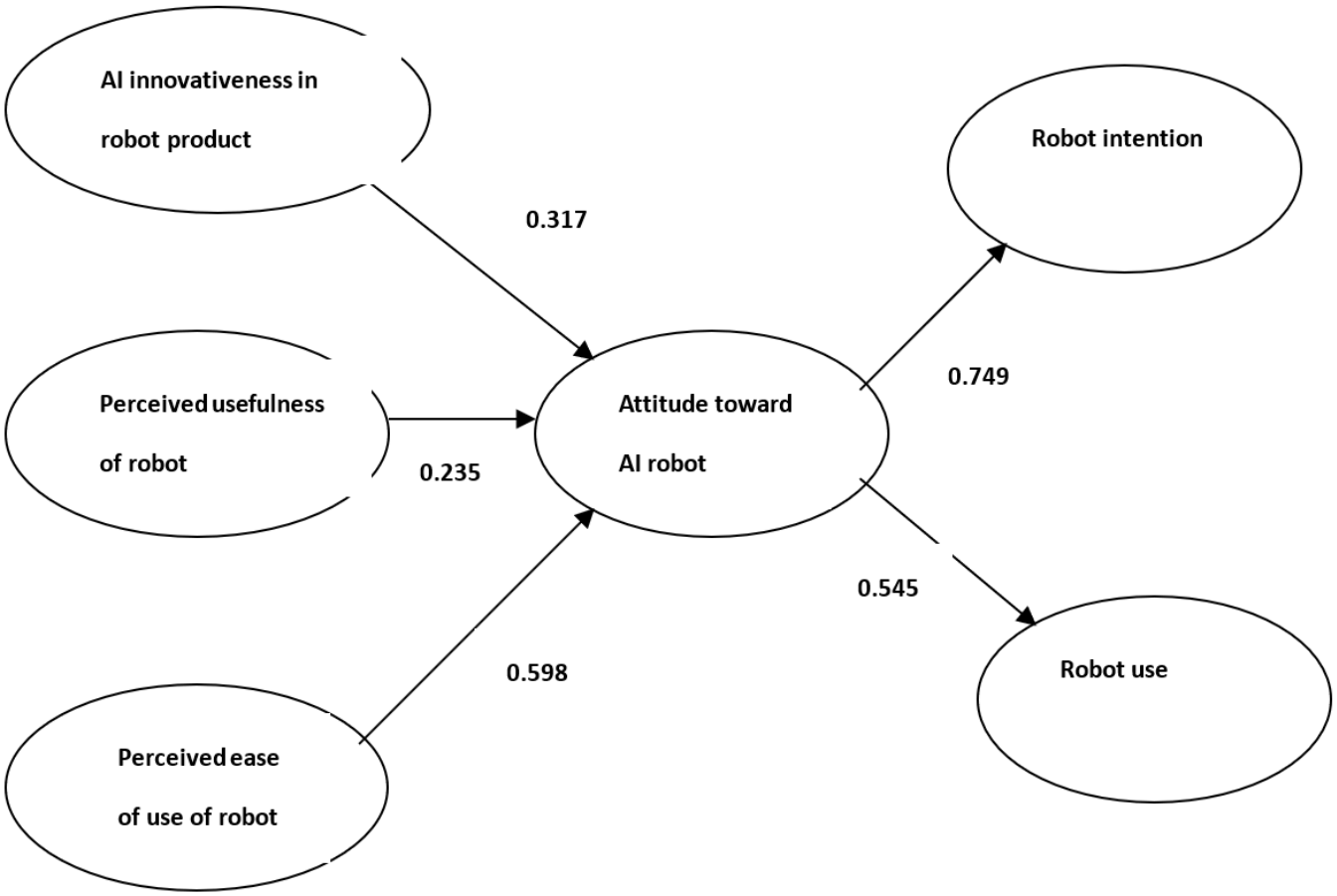


Figure 1

Conceptual model with standardized path coefficients (* p < 0.001).