Lin, H.-C., Tu, Y.-F., Hwang, G.-J., & Huang, H. (2021). From Precision Education to Precision Medicine: Factors Affecting Medical Staff's Intention to Learn to Use AI Applications in Hospitals. *Educational Technology & Society*, *24* (1), 123-137.

From Precision Education to Precision Medicine: Factors Affecting Medical Staff's Intention to Learn to Use AI Applications in Hospitals

Hui-Chen Lin[1], Yun-Fang Tu[2], Gwo-Jen Hwang[3*] and Hsin Huang[4]

[1]Department of Neurology, Tri-Service General Hospital National Defense Medical Center, Taiwan // [2]Department of Library and Information Science, Research and Development Center for Physical Education, Health, and Information Technology, Fu Jen Catholic University, Taiwan // [3]Graduate Institute of Digital Learning and Education, National Taiwan University of Science and Technology, Taiwan // [4]Department of Nursing, Tri-Service General Hospital National Defense Medical Center, Taiwan // ceciliatsgh@gmail.com // sandy0692@gmail.com // gjhwang.academic@gmail.com // jhshing1029@gmail.com

[*]Corresponding author

ABSTRACT: Precision medicine has become an essential issue in the medical community as the quality of medical care is being emphasized nowadays. The technological data analysis and predictions made by Artificial Intelligence (AI) technologies have assisted medical staff in designing personalized medicine for patients, making AI technologies an important path to precision medicine. During the implementation of the new emerging technology, medical staff's learning intentions will have a great influence on its effectiveness. With reference to the Technology Acceptance Model, this study explored medical staff's attitudes, intentions, and relevant influencing factors in relation to AI application learning. A total of 285 valid questionnaires were collected. Five major factors, perceived usefulness (PU), perceived ease of use (PEU), subjective norms (SN), attitude towards AI use (ATU), and behavioral intention (BI), were used for analyzing the AI learning of medical staff in a hospital. Based on the SEM analytical results and the research model, the four endogenous constructs of PU, PEU, SN, and ATU explained 37.4% of the changes in BI. In this model, SN and PEU were the determining factors of BI. The total effects of SN and PEU were 0.448 and 0.408 respectively, followed by PU, with a total effect of 0.244. As a result, the intentions of medical staff to learn to use AI applications to support precision medicine can be predicted by SN, PEU, PU, and ATU. Among them, subjective norms considering the influences of both supervisors and peers, such as encouragement, communication, and sharing, may assist precision education in supporting the learning attitudes and behavior regarding precision medicine. The research results can provide recommendations for examining medical staff's intention to use AI applications.

Keywords: Artificial intelligence, Subjective norms, Precision medicine, Precision education, Technology Acceptance Model

1. Introduction

The rapid advancement of computer technologies has provided new opportunities to facilitate medical services. Researchers have indicated that the ability of a computer to process a large amount of biological data and to calculate predicted models is becoming increasingly reliable, in particular for assisting doctors in making more accurate judgments (Alhashmi, Salloum, & Abdallah, 2018; Li, Hu, Li, & You, 2019). For instance, the advancement of AI (Artificial Intelligence) technologies enables computer systems to emulate medical experts' competences in analyzing, predicting and making judgments, as well as providing second opinions or support during the medical diagnosis process (Esteva et al., 2019; Williams et al., 2018). In the past, many studies have used computerized technologies to assist in medical diagnosis with positive results. For example, researchers have applied computerized technologies to radiology, pathology, and dermatology for image analysis. A combination of computerized calculation and the clinical diagnosis of doctors can greatly improve the accuracy and reliability of the diagnosis (Geras, Mann, & Moy, 2019; Nakata, 2019). Wearable devices can be used to assist and record the measurement of body health, and to collect physiological parameters (Yetisen, Martinez-Hurtado, Ünal, Khademhosseini, & Butt, 2018). The use of smartphone applications can provide a real-time risk assessment showing the possibility of having malignant melanoma (Chuchu et al., 2018). Applications of machine learning can assist doctors in improving the accuracy of cancer diagnosis and detection (Cruz & Wishart, 2006). Big data analysis and machine learning algorithms can be used to assist with clinical decision-making, successful-predictive surgical outcomes and medical treatment (Kanevsky et al., 2016; Senders et al., 2018).

The application of AI in clinical diagnosis has been gradually increasing. For example, it has been applied to improve the diagnostic accuracy of diabetic retinopathy (Poly et al., 2019); to have a fast test of ischemic stroke caused by large vessel occlusion (Murray, Unberath, Hager, & Hui, 2020); to improve the quality of fracture detection and its categorization (Langerhuizen et al., 2019); to improve the accuracy of valvular heart disease screening and congenital heart defects by AI auscultation (Thompson, Reinisch, Unterberger, & Schriefl, 2019); to assist the diagnosis and identification of liver masses (Azer, 2019) and mammography (Rodríguez-Ruiz et al., 2019); to assist the planning of Disease Risk Management (Marciniak, Kotas, Kamiński, & Ciota, 2014); different new emerging technologies, prescription, and treatments (Bassuk, Zheng, Li, Tsang, & Mahajan, 2016; Camarillo, Krummel, & Salisbury Jr, 2004); as well as to analyze the predicted treatment outcomes (Catto et al., 2003). Through using the technique of AI analysis, the big data of medical treatment provides precise data for making inferences. As a result, the effectiveness and accuracy of clinical diagnosis can be significantly increased. Such an application mode is of great help for improving the quality of medical treatments and ensuring the safety of patients (Hunter et al., 2012) as well as for implementing precision medicine, which emphasizes the importance of making precise analyses during the medical diagnosis process with the assistance of emerging technologies (Ho et al., 2020; Kosorok & Laber, 2019).

AI is becoming an important technology for precision medicine since it not only emulates the decision-making process of human experts, but can also make a detailed analysis and objective predictions based on a large set of data. From this perspective, it is important to train medical staff to employ AI applications to analyze medical data. Nursing staff would also need to be trained using a multidisciplinary approach to measure and analyze the critical factors of understanding precision medicine (Chen, Xie, Zou, & Hwang, 2020; Hwang, Sung, Chang, & Huang, 2020). Some studies have pointed out that, at this stage, active planning to cultivate AI professionals is an essential task in clinical education (Liao, Hsu, Chu, & Chu, 2015; Pepito & Locsin, 2019; Risling, 2017). Moreover, a study has shown that, in actual practice, the medical staff's understanding, attitudes, and behavioral intentions regarding AI applications are the key to determining whether AI technologies can support medical applications. Simultaneously, the promotion of AI applications to support precision medicine will be a great success if we understand the relevant factors that influence medical staff's learning of AI applications for medical treatment (Chiu & Tsai, 2014; Wu, Li, & Fu, 2011).

However, multiple factors influence medical staff's usage and learning of the technologies, for example, the personal beliefs and the expectations of peers, supervisors, and organizations (Alhashmi et al., 2019; Wu et al., 2011; Zhao, Ni, & Zhou, 2018). Several researchers have illustrated that subjective norms could be important determinants of medical staff's attitudes toward using technologies to learn or work; that is, subjective norms could directly influence the intention of medical staff to adopt technologies (Chiu & Tsai, 2014; Wang & Wang, 2009). Some previous studies have also reported the impacts of other factors that could affect medical staff's perceptions of using technologies; for example, Chiu and Tsai (2014) stated that when the social environment can encourage medical staff to adopt technologies for continuing learning, they will have more confidence in and positive attitudes towards using it. On the other hand, some studies have shown that medical staff's subjective norms would not significantly predict their behavioral intention to use technologies (Chiu, Tsai, & Chiang, 2013; Teo, Milutinović, & Zhou, 2016). As AI is an advanced technology, most medical staff may be unfamiliar with it; however, many medical institutes have started promoting AI in medical training or workplaces. Therefore, attention must be paid to medical staff's subjective norms when investigating the possibility of their use of AI applications to support medical applications (Ursavaş, Yalçın, & Bakır, 2019). More importantly, it is necessary to know the factors affecting their intention to learn AI applications. Those influential factors could be important parameters for developing adaptive or personalized training systems or approaches, which are the key issue in precision education (Hart, 2016). Therefore, this study aims to investigate the subjective norms as well as the learning perceptions, attitudes, and behavioral intentions of medical staff relating to the use of AI applications to support precision medicine, and the relationships among these factors in the workplace. The findings could be a good reference for those instructors and policymakers in medical schools or institutes.

2. Literature review and model development

2.1. Artificial intelligence and precision medicine

Artificial intelligence (AI) refers to the computer technologies that simulate human intelligence, such that computer systems are able to think and act like humans by making decisions and solving problems (Duan, Edwards, & Dwivedi, 2019; Simmons & Chappell, 1988). In the past decades, many AI applications have been reported by researchers, including in the areas of industrial design (Renzi, Leali, Cavazzuti, & Andrisano, 2014), smart buildings (Panchalingam & Chan, 2019), smart cars (Miles & Walker, 2006), factory automation (Özdemir & Hekim, 2018), medical diagnosis (Nakata, 2019; Park & Han, 2018) and education (Popenici & Kerr, 2017). Researchers have indicated several benefits of using AI technologies, such as improving the accuracy of decision making (Yang & Lin, 2019), enabling 24-hour service (Lilianira, Syah, Pusaka, & Ramdhani, 2020), and providing instant and personalized supports (Santos, 2019).

In the field of AI application, the issue of precision medicine has drawn the attention of researchers and practitioners in recent years (Collins & Varmus, 2015). Using personalized medicine as the foundation, precision medicine refers to the strategies used in treatments, such as targeted drug and cell therapy, through comparing the gene sequences and lifestyles of healthy people and patients after analyzing the computerized big data. According to the medical condition, precision medicine can provide the most suitable and precise treatments for each patient, or can effectively control diseases (Jameson & Longo, 2015). However, precise diagnosis and personalized medicine are the two main aspects of precision medicine to which AI has been applied. The purpose of precise diagnosis is to reduce the errors and to improve the accuracy of diagnosis; for instance, it provides reliable suggestions for diagnosis (Aerts, 2016; Giger, 2018) and predicts the possibility of a gene that causes cancer (Jamal-Hanjani et al., 2014; Nakagawa & Fujita, 2018). Regarding personalized medicine, it is used to not only conduct personal treatments based on patients' inherited genes, but also uses deep learning to improve the accuracy of drug development simulation and modeling, and hence shortens the development time and reduces the cost of developing new drugs (Bassuk et al., 2016). Several previous studies have reported the use of this approach in accelerating the development of cancer medicine (Denny, Van Driest, Wei, & Roden, 2018; Friedman, Letai, Fisher, & Flaherty, 2015). Furthermore, personalized medicine includes the use of an AI robot to operate more precise surgeries, resulting in a reduction in errors and cost (Camarillo et al., 2004).

Based on the above evidence, the use of AI and data analytics technologies to improve medical and health-care quality has been highly expected. However, some clinical professionals believe that there are potential uncertainties during the calculation of AI algorithms (Begoli, Bhattacharya, & Kusnezov, 2019). They are also concerned about the morals, social issues, and laws derived from AI medicine due to a lack of understanding (Cave & Dihal, 2019; Zou & Schiebinger, 2018). There is a trend of AI being introduced into medical care because of its positive impacts. However, it is necessary for medical staff who engage in AI-related work to attend training on the usage of AI equipment to carry out relevant inspections and treatments. The training content should not only include the fundamental understanding of AI, but also address the ethical norms and the standardized procedures of AI that practitioners should adhere to (Winfield, 2019). Furthermore, in the working field of assisting medical staff to learn and apply AI applications, the active cultivation of AI should be applied in precision medicine as it is one of the important tasks of medical education. The key to successful AI promotion is to understand the factors affecting medical staff's AI acceptance in precision medicine. Researchers have pointed out that the medical staff's behavior regarding technology adoption could be influenced by the usability and usefulness of the technologies (Chiu & Tsai, 2014; Chiu et al., 2013; Teo et al., 2016). When evaluating medical staff's behavioral intentions regarding new technology learning, the impact of important people's expectations around them should be considered (Fishbein & Ajzen, 1975; Chiu & Tsai, 2014). Therefore, the factors may be important variables to support the development of adaptive or personalized training systems or approaches (Hwang, Xie, Wah, & Gašević, 2020). Accordingly, this study proposed four factors from TAM (including perceived usefulness, perceived ease of use, attitude towards AI use, and behavioral intention), added a social factor (i.e., subjective norms), and explored the relationship between these factors.

2.2. Theoretical models related to the acceptance of new technologies

Several previous studies have reported that the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT) belong to the field of common theories and models (Chau & Hu, 2001; Holden & Karsh, 2010). Numerous studies have indicated that TAM, one of the most commonly used models, can be used to explore the technological acceptance of users and to explain the attitudes and behavioral intention of medical staff when using new technologies (Hsu & Wu, 2017; Kowitlawakul, 2011; Strudwick, 2015; Zhang, Cocosila, & Archer, 2010). It is concentrated on influencing users' intention or actual use of technologies (Al-Emran, Mezhuyev, & Kamaludin, 2018; Davis, Bagozzi, & Warshaw, 1989; Legris, Ingham, & Collerette, 2003). Perceived usefulness (PU) and perceived ease of use (PEU) are the two factors used to measure users' perceptions. If users believe such technology is useful, they will maintain a positive attitude. Moreover, if they believe that such technology can assist them in completing tasks in a relaxing and effective manner, they will have a strong intention to use it (Teo, 2019; Wang & Wang, 2009). Attitude towards technology use (ATU) and behavioral intention (BI) are the remaining factors in the TAM. Users' perceptions (i.e., PU and PEU) can influence their attitudes and behaviors regarding that technology (Sánchez-Prieto, Olmos-Migueláñez, & García-Peñalvo, 2017).

Despite TAM having been used in a variety of studies, some researchers have added other factors to extend the model, with the aim of understanding users' acceptance behavior (Kwateng, Atiemo, & Appiah, 2018; Ursavaş et al., 2019). For instance, researchers have applied the extended Technology Acceptance Model to explore healthcare students' acceptance of using electronic health records (EHR) in nursing education; researchers have indicated that it is important to cultivate students' positive attitudes and increase their practical perceptions of EHR (Kowitlawakul, Chan, Pulcini, & Wang, 2015). Apart from that, subjective norms, the social-external variable used in the extended TAM research, can assist in understanding an individual's acceptance and usage of the new technology (Yu et al., 2009). With the development of technology, it has been a trend for AI to support precision medicine and a goal for its implementation in medical education. It also highlights the importance of medical staff supporting and promoting AI applications in precision medicine (Hsu & Wu, 2017; Hwang, 2014; Shorey et al., 2019).

2.3. Subjective norms

Subjective norms are defined as the situation in which individuals are subjected to social pressure while taking certain kinds of actions. They include social norms, others' expectations, or the pressure given by organizations (Fishbein & Ajzen,1975). Many studies have indicated that subjective norms have been associated with issues relevant to organizations and to individuals. They have, furthermore, illustrated their influences on users' intentions to use technology-supported services, and that will be one of the important factors affecting users' acceptance of those technologies (Venkatesh & Davis, 2000). In addition to directly influencing medical staff's learning attitudes, subjective norms have been shown to have influences on their intention to use such technology through affecting perceived usefulness (PU) and perceived ease of use (PEU) (Alhashmi et al., 2019; Yu et al., 2009). Researchers have pointed out that nursing staff's subjective norms (e.g., colleague support) could influence their attitudes toward adopting technology to support continued learning (Chiu et al., 2013). However, some researchers have pointed out that users' subjective norms may not always significantly influence the use of that technology (Azizi & Khatony, 2019). This study therefore aimed at exploring the relationships between medical staff's subjective norms, perceptions, attitudes, and intention to use in terms of learning AI applications to support precision medicine in the workplace (Ketikidis, Dimitrovski, Lazuras, & Bath, 2012; Ursavaş et al., 2019).

3. Research model and hypotheses

Referencing the TAM as the foundation, this study explored medical staff's attitudes and intention to learn to use AI applications to support precision medicine in their workplace, in particular investigating the five factors of perceived usefulness (PU), perceived ease of use (PEU), subjective norms (SN), attitude towards AI use (ATU), and behavioral intention (BI). Figure 1 shows the research model for this study.

According to the literature, the medical staff's perceived ease of use, usefulness, subjective norms, and attitudes towards adopting technologies for learning could have effects on their behavioral intentions; their perceived usefulness and perceived ease of use also influence their attitudes toward adopting AI applications (Chiu & Tsai, 2014; Chiu et al., 2013; Teo et al., 2016; Teo, 2019; Wang & Wang, 2009). In addition, medical staff's perceived ease of use of AI applications could affect their perceptions of usefulness, attitudes and behavior (Ursavaş et al., 2019; Wang & Wang, 2009). Therefore, the following research hypotheses are proposed in the present study:

H1: PU has a significant positive effect on BI.
H2: PEU has a significant positive effect on BI.
H3: ATU has a significant positive effect on BI.
H4: SN has a significant positive effect on BI.
H5: PEU has a significant negative effect on PU.
H6: PU has a significant positive effect on ATU.
H7: PEU has a significant negative effect on ATU.

In this study, subjective norms refer to the medical staff's perceptions of their significant others' opinions or suggestions that relate to their acceptance of adopting AI applications. Some researchers have identified SN as an important variable in explaining medical staff's attitudes toward technology adoption, which directly affects the intention to use (Chiu & Tsai, 2014; Ursavaş et al., 2019; Wang & Wang, 2009). Researchers have also pointed out that SN directly links to perceived usefulness, perceived ease of use, and attitudes (Chiu & Tsai, 2014; Chiu et al., 2013; Ursavaş et al., 2019). Accordingly, the following research hypotheses are proposed:

H8: SN has a significant positive effect on PU.
H9: SN has a significant positive effect on ATU.

H10: SN has a significant positive effect on PEU.

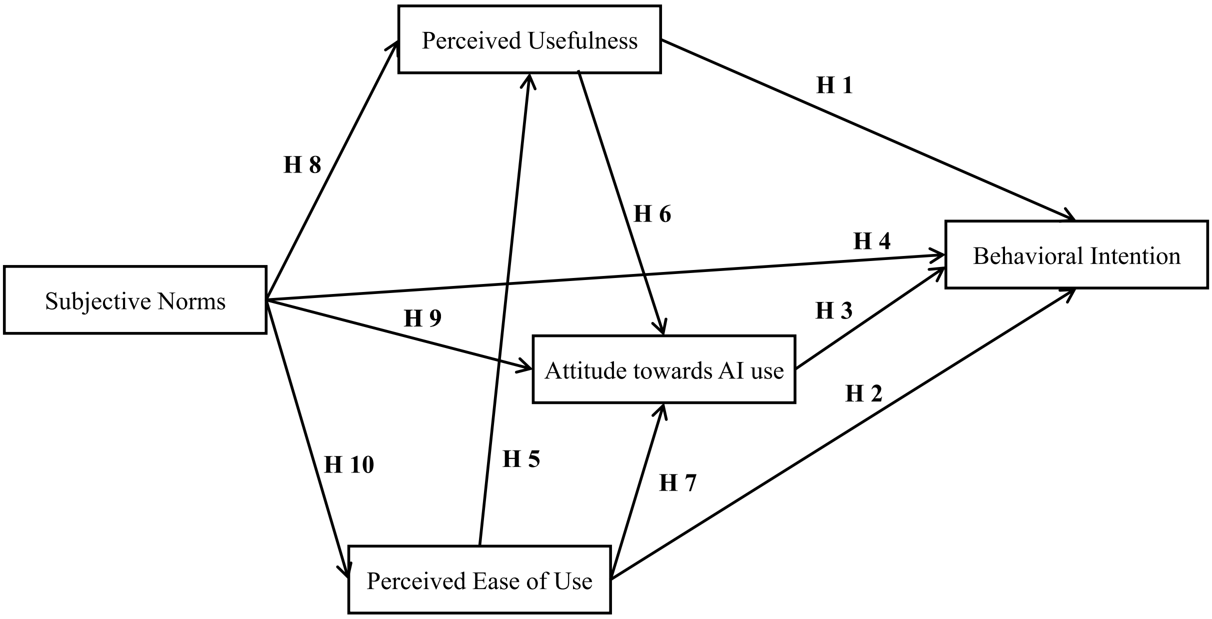

Figure 1. Proposed research model

4. Method

4.1. Participants

The participants of this study were medical staff working at a medical center in northern Taiwan. All participants were scheduled to complete two training modules, “AI and robotics in the New Health era” and “New era of medical education: AI-supported precision medicine” for 2 hours; following that, they were allowed to experience the use of an AI-based diagnosis system as shown in Figure 2 before completing the questionnaire. A total of 285 valid questionnaires were collected from 245 nursing staff and 40 physicians in this study.

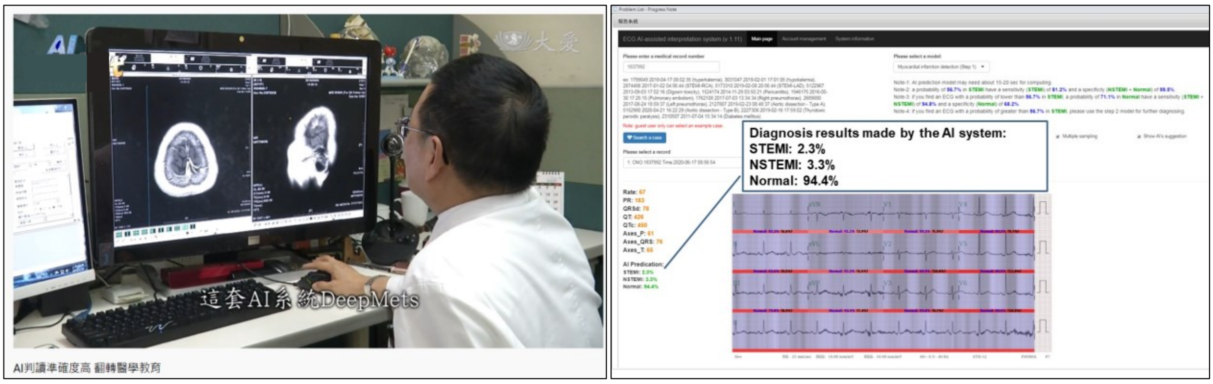

Figure 2. Learning materials and applications used in the training program

The demography of the sample is tabulated in Table 1. The gender distribution of participants was 13.3% male and 86.7% female. Regarding their age groups, 21-30 years old, 41-50 years old, and 31-40 years old constituted 30.2%, 29.8%, and 24.5% of total participants, respectively. Referring to their qualification levels, associate degrees, bachelor degrees, master degrees, and doctoral degrees constituted 58.2%, 23.5%, 15.4%, and 2.5%, respectively. Among them, the working experience of the medical staff was 2-5 years (29.1%), 6-10 years (21.4%), and above 10 years (49.5%).

All participants had experience of using the Internet, with 91.93% reporting that they used the Internet at least once a day. Furthermore, a majority of them reported that their average using time per day was approximately 3 to 5 hours (50.5%), 1 to 2 hours (32.6%), 0 to 1 hour (13%), and 6 hours and over (3.9%).

Table 1. Demography of the sample (N = 285)

Variable	Group	N	%
Sex	Female	247	86.7
	Male	38	13.3
Age	21-30 years	86	30.2
	31-40 years	70	24.5
	41-50 years	85	29.8
	51-60 years	35	12.3
	61 years and above	9	3.2
Educational qualification	Associate's degree	67	23.5
	Bachelor's degree	166	58.2
	Master's degree	44	15.4
	Doctoral degree	7	2.5
Working experience	2-5 years	83	29.1
	6-10 years	61	21.4
	11-15 years	34	11.9
	16-20 years	54	18.9
	21-25 years	24	8.4
	26 years and above	29	11.2
Frequency of using the Internet	at least once a day	262	91.9
	at least 3 times a week	22	7.7
	at least once a week	1	0.4
	less than once a week	0	0
Average time of using the Internet	0 to 1 hour per day	37	13.0
	1 to 2 hours per day	93	32.6
	3 to 5 hours per day	144	50.5
	6 hours and over per day	11	3.9

4.2. Instruments

The present study was based on Davis's study (1989) as the foundation and applied his scale items, which were adapted from published sources that reported a high degree of reliability (Chiu & Tsai, 2014; Teo & Zhou, 2014; Ursavaş et al., 2019; Wu et al., 2011). Four professionals were consulted during this study. Two are professors specializing in medical education and the other two are experts in scientific and technological education. The aim was to confirm that all items listed in the questionnaire could be used to completely understand medical staff's attitudes and intentions to learn to use AI applications to support precision medicine.

The instrument consists of participants' demographic information and 20 items, aiming at balancing their beliefs in five constructs with four items each. In terms of PU, participants will say "I believe that learning to use the AI-technology tools can better assist healthcare work"; in terms of PEU, they will say "Learning to use the AI-technology tools for healthcare is easy for me"; referring to the SN, they will mention "My supervisor or organization believes that I should employ the AI-technology tools to assist my healthcare work in the future"; referring to the ATU, they will mention "I have a generally favorable attitude toward learning the AI-technology tools"; referring to the BI, they will mention "I intend to learn the AI-technology tools for my healthcare 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 preliminary analysis indicated that four items (i.e., PU04, ATU03, ATU04, and BI04) had low factor loadings or had a higher correlation with other items used in the model. These items were, therefore, deleted from further analysis. Eventually, 16 items were selected for the subsequent analysis (Appendix A). The final structure showed an excellent internal consistency and reliability, with alpha values ranging from .819 to .922, as shown in Table 2.

4.3. Data analysis

The present study employed AMOS in SPSS for the analysis. Firstly, the descriptive statistics were conducted to verify the skewness and kurtosis of values and to establish the univariate normality of the data. The critical values were ±3.0 and ±10.0, respectively (Kline, 2010). Furthermore, we tested the multivariate normality using

Mardia’s normalized multivariate kurtosis (Mardia, 1970). The structure of the questionnaire was, thereafter, checked by confirmatory factor analysis (CFA) and the proposed hypotheses were verified, with the aim of exploring the relationships between PU, PEU, SN, ATU, and BI, in particular, influencing medical staff’s learning to use AI applications to support precision medicine.

5. Results

5.1. Descriptive statistics

In this study, the means of the other constructs were between 3.838 and 3.977, with standard deviations between 0.555 and 0.724. The values of the skewness and kurtosis for the items were between -0.568 and 0.17, and -0.839 and 0.535, respectively, indicating univariate normality in the data (Kline, 2010). In this study, Mardia’s coefficient was 68.548. According to the suggestion given by Bollen (1989), a multivariate normality will occur if Mardia’s coefficient is less than p (p +2), where p refers to the number of observed variables. This study used 16 observed variables, and Mardia’s coefficient was less than 288, indicating that the data had a multivariate normal distribution.

5.2. Test of the measurement model

The present study adopted the CFA as the measuring model. The estimation of overall model fit was made by $\chi 2$ 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 and 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 an acceptable fit to the sample data (χ^2 = 194.48; χ^2/df = 1.870; TLI = .967; CFI = .975; RMSEA = .053; SRMR = .037).

Table 2. Results of the Confirmatory Factor Analysis

Items	UE	*t*-value*	SE	CR	AVE	Alpha value	Mean	*SD*
PU				0.893	0.736	0.892	3.923	0.724
PU01#	1		0.901					
PU02	0.953	19.278	0.871					
PU03	0.924	16.958	0.798					
PEU				0.849	0.585	0.845	3.928	0.600
PEU01#	1		0.825					
PEU02	0.957	12.125	0.721					
PEU03	0.934	12.316	0.736					
PEU04	0.869	14.115	0.772					
SN				0.924	0.754	0.922	3.838	0.710
SN01#	1		0.894					
SN02	0.872	17.295	0.8					
SN03	0.937	20.757	0.879					
SN04	0.864	22.546	0.896					
ATU				0.820	0.695	0.819	3.977	0.656
ATU01	1		0.848					
ATU02#	1.044	13.196	0.819					
BI				0.827	0.616	0.824	3.860	0.555
BI01#	1		0.694					
BI02	1.042	11.937	0.806					
BI03	1.252	10.65	0.847					

Note. UE = unstandardized estimate; SE = standardized estimate, factor loadings; SN = subjective norms; PU = perceived usefulness; PEU = perceived ease of use; ATU = attitude towards AI use; BI = behavioral intention.
* p < .01; # this value was fixed at 1.000 for model identification purposes.

Table 2 describes the CFA result; all the factor loadings of the measured items are higher than the threshold value of 0.60 (ranging from 0.694 to 0.901). The values of Cronbach’s alpha of PU, PEU, SN, ATU, and BI were .892, .845, .922, .819, and .824, respectively. The overall reliability of the questionnaire was .912, indicating a sufficient internal consistency of the factor items. Moreover, the ranges of composite reliability (CR) were between 0.820 and 0.924, and the ranges of average variance extracted (AVE) were between 0.585 and 0.736, indicating that the present study had a good convergence validity of the adopted variables. Therefore, the convergence validity of all of the variables used in this study was confirmed (Fornell & Larcker, 1981).

Apart from the convergence validity, the square roots of the AVE of all variables used were greater than the correlation coefficient. Therefore, the variables used in this study have different validities (Farrell, 2010), as shown in Table 3.

Table 3. Correlation coefficient and discriminant validity

	PU	PEU	SN	ATU	BI
PU	(0.858)				
PEU	0.489	(0.765)			
SN	0.475	0.486	(0.868)		
ATU	0.754	0.490	0.489	(0.834)	
BI	0.486	0.530	0.448	0.472	(0.785)

Note. The diagonal value is the square root of AVE, the construct; SN= subjective norms; PU= perceived usefulness; PEU= perceived ease of use; ATU= attitude towards AI use; BI= behavioral intention.

5.3. Tests of direct and indirect effects

The results of the structural model showed a good model ($\chi^2 = 200.358$; $\chi^2/df = 2.131$; TLI = 0.952; CFI = 0.963; RMSEA = 0.063; SRMR = .044). Based on the hypotheses proposed in this study, the bootstrap method was performed for the evaluation. As shown in Table 4, six out of 10 hypotheses were supported by the data; except for H1, H3, H7, and H9, all other hypotheses were supported in this study (see Figure 3).

Table 4. Results of Hypothesis Testing.

Hypotheses	Path	Estimate	*t*-value	Bias-corrected		Sig	Result
				Lower	Upper	*p*	
H1	PU→BI	0.175	1.645	-0.063	0.418	0.136	Not supported
H2	PEU→BI	0.313	3.916	0.143	0.458	0.001	Supported
H3	ATU→BI	0.108	0.953	-0.161	0.357	0.395	Not supported
H4	SN→BI	0.161	2.225	0.014	0.305	0.032	Supported
H5	PEU→PU	0.339	4.73	0.189	0.476	0.001	Supported
H6	PU→ATU	0.636	9.179	0.503	0.755	0.001	Supported
H7	PEU→ATU	0.115	1.715	-0.017	0.251	0.09	Not supported
H8	SN→PU	0.31	4.599	0.174	0.445	0.001	Supported
H9	SN→ATU	0.131	2.087	-0.012	0.254	0.081	Not supported
H10	SN→PEU	0.486	7.575	0.366	0.584	0.001	Supported

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

Table 5 shows the standardized total effects, direct and indirect effects among each variable in the model. The addition of the direct effects and the indirect effects is equal to the total effects. In the model used in this study, the standardized total effects of predictor variables on the dependent variables ranged from 0.108 to 0.636.

According to the research model, four endogenous constructs were tested. The coefficient of variation of BI was determined by PU, PEU, SN, and ATU, and the explanatory power (R2) was 0.374. The changes of BI (37.4%) were explained by PU, PEU, SN, and ATU. Regarding the variations of other endogenous constructs, PU (31.3%), PEU (23.6%), and ATU (60%) were explained by their determinants.

Regarding these four endogenous constructs, the highest amount of variance (60%) was explained by the determinants of ATU. The most dominant determinant was PU and its total effect was 0.636. The second dominant determinant was SN and its total effect was 0.489. The total effect of PEU was 0.331. The explained variation of BI in this model was 0.374. It was mainly determined by SN and PEU, and their total effects were 0.448 and 0.408. Following this, the total effect of PU was 0.244. However, the total effect of ATU on BI was 0.108 and it was a statistically insignificant effect. The explained variation of PU was 0.313 and it was mainly determined by SN and PEU as their total effects were 0.474 and 0.339, respectively. The explained variation of PEU was 0.236, and it was mainly determined by SN with 0.486 as the total effect.

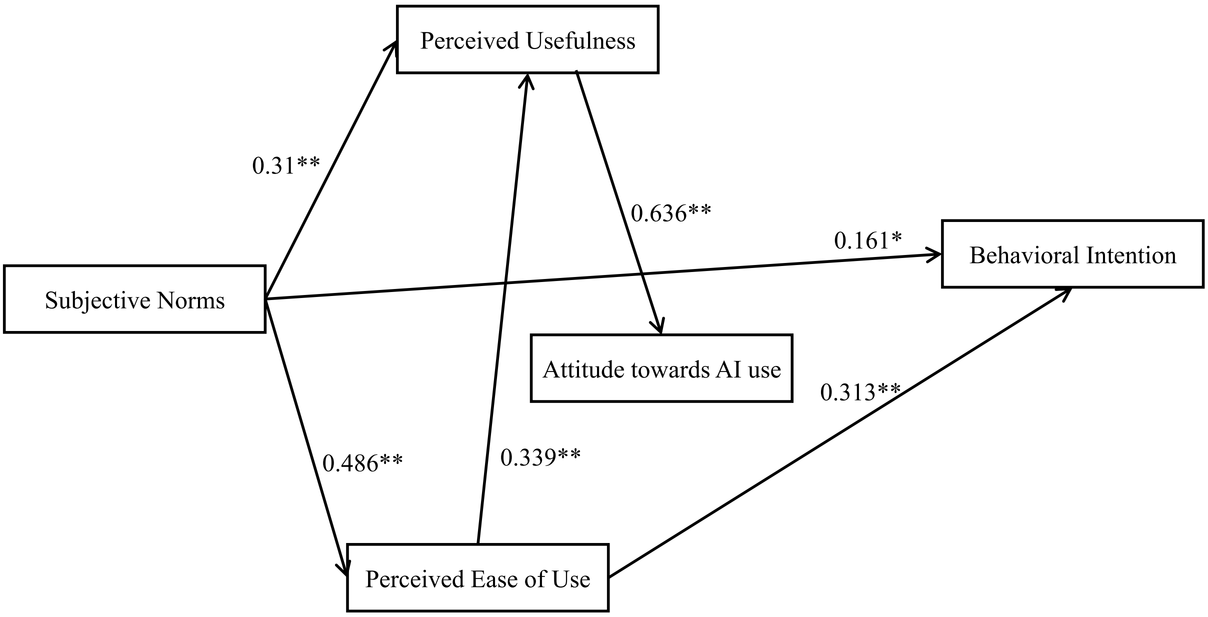

Figure 3. Results of the research model

Table 5. Direct, indirect and total effects of the research model

Endogenous variable	Determinant	Standardized estimates		
		Direct	Indirect	Total
PU (R^2 = 0.313)	PEU	0.339	-	0.339
	SN	0.310	0.164	0.474
PEU (R^2 = 0.236)	SN	0.486	-	0.486
ATU (R^2 = 0.600)	PU	0.636	-	0.636
	PEU	0.115	0.215	0.331
	SN	0.131	0.358	0.489
BI (R^2 = 0.374)	PU	0.175	0.069	0.244
	PEU	0.313	0.095	0.408
	SN	0.161	0.288	0.448
	ATU	0.108	-	0.108

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

6. Discussion and conclusions

The present study examined the relationship among subjective norms and PU, PEU, ATU and BI when medical staff learn to employ AI applications to support precision medicine. Firstly, this study adopted CFA to establish a five-factor structure. Based on the analytical results, this investigation was effective and reliable. Moreover, there were predictive relationships between PU, PEU, SN, ATU, and BI. The findings are consistent with the results of previous studies relating to medical staff's learning attitudes, use intention, and perceptions of technologies (Chiu & Tsai, 2014; Teo, 2019; Ursavaş et al., 2019; Wu et al., 2011). This study then adopted SEM for testing the proposed hypotheses, showing that medical staff's perceived usefulness of learning AI applications to support precision medicine would affect their learning attitude (H6). The medical staff's perceived ease of use of learning about AI applications to support precision medicine would affect their perceived usefulness (H5), which would also directly influence their behavioral intentions (H2). In other words, if the technology is not easy to operate, even if it is useful to users, they may remain in their original situation or choose other options (Teo, 2019).

Moreover, this study also found that medical staff's SN could predict their perceived usefulness (H8), perceived ease of use (H10), and behavioral intention (H4) to learn to use AI applications to support precision medicine. As SN represents the person or organization that has the power to determine and support specified events, it is important and interesting to know the role of SN in AI education (Li, Liu, & Rojas-Méndez, 2013). In particular, the 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. This could be the reason why subjective norms significantly influence the medical staff's behavior intention of adopting and learning AI applications (Chiu & Tsai, 2014; Chiu et al., 2013; Schmidt & Diestel, 2011). Some researchers have also indicated that subjective norms could be determined by the perceived pressure from social views or regulations to influence people's behaviors and manners to comply with the views or regulations (Ursavaş et al., 2019). In medical working environments, medical staff are trained to strictly follow the regulations in each step of the medical diagnosis and treatment process since failing to follow those regulations could endanger the patients (Chiu & Tsai, 2014).

Some of the hypotheses in this study are not significant. For instance, SN did not have a significant influence on ATU (H9). As medical staff generally work in a particular environment, which has a "problem orientation," they cooperate as a team to identify and solve problems. Therefore, SN would not be the main factor affecting their attitudes toward learning or working, although it would determine their behavioral intention. Similarly, ATU would not decide their behavioral intention either (H3). Medical staff might have their own attitudes toward learning AI applications; however, SN or missions generally outweigh their attitudes when making decisions related to their work. This finding is evidenced by several researchers who indicated the importance of a supportive organizational climate (i.e., the common value in an organization) to medical staff (Chiu & Tsai, 2014; Chiu et al., 2013; Schmidt & Diestel, 2011). Another important finding of the present study is that medical staff's subjective norms can further influence their attitudes towards learning to use AI applications through their perception of how AI applications can better assist healthcare. This also echoes the point that medical staff generally value the usefulness of a new technology to their work. If subjective norms deliver correct information to help them understand the usefulness of the new technology, they could change their attitudes toward learning or using it.

To sum up, subjective norms are an important factor influencing the adoption of AI applications in medical institutes for supporting precision medicine. In other words, medical institutes should consider the influences of supervisors and peers on medical staff. Positive opinions, for example encouragement, communication, and sharing, given by supervisors and peers can strengthen the expectations and confidence of medical staff. In turn, they may influence their perceptions and use intention regarding AI applications to support precision medicine (Chiu & Tsai, 2014; Zhao et al., 2018). As encouraging medical staff to learn AI applications is the basis for implementing precision medicine, based on the findings of this study, helping decision makers or management level staff to know the importance of promoting AI applications in their institutes is very important. Therefore, it is recommended that when trying to promote precision medicine, it is necessary to have a workshop or training program for those management level staff or relevant policymakers in the medical institutes. In the meantime, from the perspective of precision education, the findings of the present study could be a reference for those who intend to implement training programs for AI applications for medical staff. It has been found that, in addition to subjective norms, perceived ease of use is an important factor affecting medical staff's behavior intention. This implies that the development of adaptive learning systems needs to be considered from the perspective of the user interface in addition to the learning content or learning paths. As indicated by several previous studies, a proper user-interface design which takes into account individual learners' needs could significantly affect learning performances (Yang, Hwang, & Yang, 2013).

This study has some limitations. Regarding the samples, it focuses on medical staff from Taiwan, limiting the research inference. It is suggested that larger samples be used to explore the attitudes and behaviors of medical staff from different areas regarding learning to use AI applications to support precision medicine. It is also recommended that some external variables be considered when exploring their attitudes and behaviors. For example, facilitating conditions, anxiety, self-efficacy, training, and job relevance can all be considered as external variables. In the future, intervention experiments and interviews can be designed to investigate the teaching modes referencing the AI environment. They could provide a deeper understanding of medical staff's attitudes and explore relevant influencing factors and effectiveness in learning to use AI applications to support precision medicine.

Acknowledgement

This study is supported in part by the Ministry of Science and Technology of the Republic of China under contract numbers MOST-109-2511-H-011-002-MY3 and MOST-108-2511-H-011-005-MY3.

References

Aerts, H. J. (2016). The Potential of radiomic-based phenotyping in precision medicine: A Review. *JAMA Oncology, 2*(12), 1636-1642.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology acceptance model in m-learning context: A Systematic review. *Computers & Education*, *125*, 389-412.

Alhashmi, S. F., Salloum, S. A., & Abdallah, S. (2019). Critical success factors for implementing artificial intelligence (AI) projects in Dubai government United Arab Emirates (UAE) health sector: Applying the extended technology acceptance model (TAM). In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 393-405). doi:10.1007/978-3-030-31129-2_36

Azer, S. A. (2019). Deep learning with convolutional neural networks for identification of liver masses and hepatocellular carcinoma: A Systematic review. *World Journal of Gastrointestinal Oncology, 11*(12), 1218-1230.

Azizi, S. M., & Khatony, A. (2019). Investigating factors affecting on medical sciences students' intention to adopt mobile learning. *BMC Medical Education, 19*(1), 381. doi:10.1186/s12909-019-1831-4

Bassuk, A. G., Zheng, A., Li, Y., Tsang, S. H., & Mahajan, V. B. (2016). Precision medicine: genetic repair of retinitis pigmentosa in patient-derived stem cells. *Scientific Reports, 6*, 19969. doi:10.1038/srep19969

Begoli, E., Bhattacharya, T., & Kusnezov, D. (2019). The Need for uncertainty quantification in machine-assisted medical decision making. *Nature Machine Intelligence, 1*(1), 20-23.

Bollen, K. A. (1989). *Structural equations with latent variables*. New York, NY: John Wiley and Sons, Inc.

Camarillo, D. B., Krummel, T. M., & Salisbury Jr, J. K. (2004). Robotic technology in surgery: Past, present, and future. *The American Journal of Surgery, 188*(4), 2-15.

Catto, J. W., Linkens, D. A., Abbod, M. F., Chen, M., Burton, J. L., Feeley, K. M., & Hamdy, F. C. (2003). Artificial intelligence in predicting bladder cancer outcome: A Comparison of neuro-fuzzy modeling and artificial neural networks. *Clinical Cancer Research, 9*(11), 4172-4177.

Cave, S., & Dihal, K. (2019). Hopes and fears for intelligent machines in fiction and reality. *Nature Machine Intelligence, 1*(2), 74-78.

Chau, P. Y., & Hu, P. J. H. (2001). Information technology acceptance by individual professionals: A Model comparison approach. *Decision Sciences, 32*(4), 699-719.

Chen, X., Xie, H., Zou, D., & Hwang, G. J. (2020). Application and theory gaps during the rise of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence, 1*, 100002. doi:10.1016/j.caeai.2020.100002

Chiu, Y. L., & Tsai, C. C. (2014). The Roles of social factor and internet self-efficacy in nurses' web-based continuing learning. *Nurse Education Today, 34*(3), 446-450.

Chiu, Y. L., Tsai, C. C., & Chiang, C. Y. F. (2013). The Relationships among nurses' job characteristics and attitudes toward web-based continuing learning. *Nurse education today, 33*(4), 327-333.

Chuchu, N., Takwoingi, Y., Dinnes, J., Matin, R. N., Bassett, O., Moreau, J. F., Bayliss, S. E., Davenport, C., Godfrey, K., O'Connell, S., Jian, A., Walter, F. M., & Deeks, J. J. (2018). Smartphone applications for triaging adults with skin lesions that are suspicious for melanoma. *Cochrane Database of Systematic Reviews*(12), CD013192.

Collins, F. S., & Varmus, H. (2015). A New initiative on precision medicine. *New England Journal of Medicine, 372*(9), 793-795.

Cruz, J. A., & Wishart, D. S. (2006). Applications of machine learning in cancer prediction and prognosis. *Cancer Informatics, 2*, 59-78.

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A Comparison of two theoretical models. *Management Science, 35*(8), 982-1003.

Denny, J. C., Van Driest, S. L., Wei, W. Q., & Roden, D. M. (2018). The Influence of big (clinical) data and genomics on precision medicine and drug development. *Clinical Pharmacology & Therapeutics, 103*(3), 409-418.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48,* 63-71.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., & Dean, J. (2019). A Guide to deep learning in healthcare. *Nature Medicine, 25*(1), 24-29.

Farrell, A. M. (2010). Insufficient discriminant validity: A Comment on Bove, Pervan, Beatty, and Shiu (2009). *Journal of Business Research, 63*(3), 324-327.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An Introduction to theory and research*. Reading, MA: Addison-Wesley.

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Friedman, A. A., Letai, A., Fisher, D. E., & Flaherty, K. T. (2015). Precision medicine for cancer with next-generation functional diagnostics. *Nature Reviews Cancer, 15*(12), 747-756.

Geras, K. J., Mann, R. M., & Moy, L. (2019). Artificial intelligence for mammography and digital breast tomosynthesis: current concepts and future perspectives. *Radiology, 293*(2), 246-259.

Giger, M. L. (2018). Machine learning in medical imaging. *Journal of the American College of Radiology, 15*(3), 512-520.

Hart, S. A. (2016). Precision education initiative: moving toward personalized education. *Mind, Brain, and Education, 10*(4), 209-211.

Ho, D., Quake, S. R., McCabe, E. R., Chng, W. J., Chow, E. K., Ding, X., … Zarrinpar, A. (2020). Enabling technologies for personalized and precision medicine. *Trends in Biotechnology, 38*(5), 497-518.

Holden, R. J., & Karsh, B. T. (2010). The Technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics, 43*(1), 159-172.

Hsu, H. H., & Wu, Y. H. (2017). Investigation of the effects of a nursing information system by using the technology acceptance model. *CIN: Computers, Informatics, Nursing, 35*(6), 315-322.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55.

Hunter, J., Freer, Y., Gatt, A., Reiter, E., Sripada, S., & Sykes, C. (2012). Automatic generation of natural language nursing shift summaries in neonatal intensive care: BT-Nurse. *Artificial Intelligence in Medicine, 56*(3), 157-172.

Hwang, G. J. (2014). Definition, framework and research issues of smart learning environments-a context-aware ubiquitous learning perspective. *Smart Learning Environments, 1*(1), 4. doi:10.1186/s40561-014-0004-5

Hwang, G. J., Sung, H. Y., Chang, S. C., & Huang, X. C. (2020). A Fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors. *Computers and Education: Artificial Intelligence, 1*, 00003. doi:10.1016/j.caeai.2020.100003

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Computers & Education: Artificial Intelligence, 1*, 100001. doi:10.1016/j.caeai.2020.100001

Jamal-Hanjani, M., Hackshaw, A., Ngai, Y., Shaw, J., Dive, C., Quezada, S., … Swanton, C. (2014). Tracking genomic cancer evolution for precision medicine: The Lung TRACERx study. *PLoS Biology, 12*(7), e1001906. doi:10.1371/journal.pbio.1001906

Jameson, J. L., & Longo, D. L. (2015). Precision medicine—Personalized, problematic, and promising. *Obstetrical & gynecological Survey, 70*(10), 612-614.

Kanevsky, J., Corban, J., Gaster, R., Kanevsky, A., Lin, S., & Gilardino, M. (2016). Big data and machine learning in plastic surgery: A New frontier in surgical innovation. *Plastic and Reconstructive Surgery, 137*(5), 890e-897e. doi:10.1097/PRS.0000000000002088

Ketikidis, P., Dimitrovski, T., Lazuras, L., & Bath, P. A. (2012). Acceptance of health information technology in health professionals: An Application of the revised technology acceptance model. *Health Informatics Journal, 18*(2), 124-134.

Kline, R. B. (2010). *Principles and practice of structural equation modeling* (3rd ed.). New York, NY: Guilford Press.

Kosorok, M. R., & Laber, E. B. (2019). Precision medicine. *Annual Review of Statistics and Its Application, 6*, 263-286.

Kowitlawakul, Y. (2011). The Technology acceptance model: Predicting nurses' intention to use telemedicine technology (eICU). *CIN: Computers, Informatics, Nursing, 29*(7), 411-418.

Kowitlawakul, Y., Chan, S. W. C., Pulcini, J., & Wang, W. (2015). Factors influencing nursing students' acceptance of electronic health records for nursing education (EHRNE) software program. *Nurse Education Today, 35*(1), 189-194.

Kwateng, K. O., Atiemo, K. A. O., & Appiah, C. (2018). Acceptance and use of mobile banking: An Application of UTAUT2. *Journal of Enterprise Information Management, 32*(1), 118-151.

Langerhuizen, D. W., Janssen, S. J., Mallee, W. H., van den Bekerom, M. P., Ring, D., Kerkhoffs, G. M., … Doornberg, J. N. (2019). What are the applications and limitations of artificial intelligence for fracture detection and classification in orthopaedic trauma imaging? A Systematic review. *Clinical Orthopaedics and Related Research®, 477*(11), 2482-2491. doi:10.1097/CORR.0000000000000848

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A Critical review of the technology acceptance model. *Information & Management, 40*(3), 191-204.

Li, J., Liu, F., & Rojas-Méndez, J. I. (2013). How international students select offshore programs: The Influence of image, attitude, subject norm, and perceived behavioral control. *Asia Pacific Education Review, 14*(3), 381-390.

Li, X., Hu, B., Li, H., & You, B. (2019). Application of artificial intelligence in the diagnosis of multiple primary lung cancer. *Thoracic Cancer, 10*(11), 2168-2174.

Liao, P. H., Hsu, P. T., Chu, W., & Chu, W. C. (2015). Applying artificial intelligence technology to support decision-making in nursing: A case study in Taiwan. *Health Informatics Journal, 21*(2), 137-148.

Lilianira, F. T., Syah, T. Y. R., Pusaka, S., & Ramdhani, D. (2020). The Technology processing of "4 care" home care application based on artificial intelligence. *Journal of Multidisciplinary Academic, 4*(1), 6-9.

Marciniak, P., Kotas, R., Kamiński, M., & Ciota, Z. (2014). Implementation of artificial intelligence methods on example of cardiovascular diseases risk stratification. In *Proceedings of the 21st International Conference Mixed Design of Integrated Circuits and Systems (MIXDES)* (pp. 503-507). doi:10.1109/MIXDES.2014.6872251

Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika, 57*(3), 519-530.

Miles, J., & Walker, A. (2006). The Potential application of artificial intelligence in transport. *IEE Proceedings-Intelligent Transport Systems, 153*(3), 183-198. doi:10.1049/ip-its:20060014

Murray, N. M., Unberath, M., Hager, G. D., & Hui, F. K. (2020). Artificial intelligence to diagnose ischemic stroke and identify large vessel occlusions: A Systematic review. *Journal of NeuroInterventional Surgery, 12*(2), 156-164.

Nakagawa, H., & Fujita, M. (2018). Whole genome sequencing analysis for cancer genomics and precision medicine. *Cancer Science, 109*(3), 513-522.

Nakata, N. (2019). Recent technical development of artificial intelligence for diagnostic medical imaging. *Japanese journal of radiology, 37*(2), 103-108.

Özdemir, V., & Hekim, N. (2018). Birth of industry 5.0: Making sense of big data with artificial intelligence,"the internet of things" and next-generation technology policy. *Omics: A Journal of Integrative Biology, 22*(1), 65-76.

Panchalingam, R., & Chan, K. C. (2019). A state-of-the-art review on artificial intelligence for smart buildings. *Intelligent Buildings International*, 1-24.

Park, S. H., & Han, K. (2018). Methodologic guide for evaluating clinical performance and effect of artificial intelligence technology for medical diagnosis and prediction. *Radiology, 286*(3), 800-809.

Pepito, J. A., & Locsin, R. (2019). Can nurses remain relevant in a technologically advanced future?. *International Journal of Nursing Sciences, 6*(1), 106-110.

Poly, T. N., Islam, M. M., Yang, H. C., Nguyen, P. A., Wu, C. C., & Li, Y. C. J. (2019). Artificial intelligence in diabetic retinopathy: Insights from a meta-analysis of deep learning. *Studies in Health Technology and Informatics, 264*, 1556-1557.

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12*(1), 22.

Renzi, C., Leali, F., Cavazzuti, M., & Andrisano, A. O. (2014). A review on artificial intelligence applications to the optimal design of dedicated and reconfigurable manufacturing systems. *The International Journal of Advanced Manufacturing Technology, 72*(1-4), 403-418.

Risling, T. (2017). Educating the nurses of 2025: Technology trends of the next decade. *Nurse Education in Practice, 22*, 89-92.

Rodríguez-Ruiz, A., Krupinski, E., Mordang, J. J., Schilling, K., Heywang-Köbrunner, S. H., Sechopoulos, I., & Mann, R. M. (2019). Detection of breast cancer with mammography: Effect of an artificial intelligence support system. *Radiology, 290*(2), 305-314.

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2017). MLearning and pre-service teachers: An Assessment of the behavioral intention using an expanded TAM model. *Computers in Human Behavior, 72*, 644-654.

Santos, O. C. (2019). Artificial intelligence in psychomotor learning: Modeling human motion from inertial sensor data. *International Journal on Artificial Intelligence Tools, 28*(04), 1940006. doi:10.1142/S0218213019400062

Schmidt, K. H., & Diestel, S. (2011). Differential effects of decision latitude and control on the job demands–strain relationship: A Cross-sectional survey study among elderly care nursing staff. *International Journal of Nursing Studies, 48*(3), 307-317.

Senders, J. T., Staples, P. C., Karhade, A. V., Zaki, M. M., Gormley, W. B., Broekman, M. L. D., Smith, T. R., & Arnaout, O. (2018). Machine learning and neurosurgical outcome prediction: A Systematic review. *World Neurosurgery, 109*, 476-486. doi:10.1016/j.wneu.2017.09.149

Shorey, S., Ang, E., Yap, J., Ng, E. D., Lau, S. T., & Chui, C. K. (2019). A Virtual counseling application using artificial intelligence for communication skills training in nursing education: Development study. *Journal of Medical Internet Research, 21*(10), e14658. doi:10.2196/14658

Simmons, A. B., & Chappell, S. G. (1988). Artificial intelligence-definition and practice. *IEEE Journal of Oceanic Engineering, 13*(2), 14-42.

Strudwick, G. (2015). Predicting nurses' use of healthcare technology using the technology acceptance model: an integrative review. *CIN: Computers, Informatics, Nursing, 33*(5), 189-198.

Teo, T. (2019). Students and teachers' intention to use technology: Assessing their measurement equivalence and structural invariance. *Journal of Educational Computing Research, 57*(1), 201-225.

Teo, T., & Zhou, M. (2014). Explaining the intention to use technology among university students: A Structural equation modeling approach. *Journal of Computing in Higher education, 26*(2), 124-142.

Teo, T., Milutinović, V., & Zhou, M. (2016). Modelling Serbian pre-service teachers' attitudes towards computer use: A SEM and MIMIC approach. *Computers & Education*, *94*, 77-88.

Thompson, W. R., Reinisch, A. J., Unterberger, M. J., & Schriefl, A. J. (2019). Artificial intelligence-assisted auscultation of heart murmurs: Validation by virtual clinical trial. *Pediatric Cardiology, 40*(3), 623-629.

Ursavaş, Ö. F., Yalçın, Y., & Bakır, E. (2019). The Effect of subjective norms on preservice and in-service teachers' behavioural intentions to use technology: A Multigroup multimodel study. *British Journal of Educational Technology, 50*(5), 2501-2519.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204.

Wang, W. T., & Wang, C. C. (2009). An Empirical study of instructor adoption of web-based learning systems. *Computers & Education, 53*(3), 761-774.

Williams, A. M., Liu, Y., Regner, K. R., Jotterand, F., Liu, P., & Liang, M. (2018). Artificial intelligence, physiological genomics, and precision medicine. *Physiological Genomics, 50*(4), 237-243.

Winfield, A. (2019). Ethical standards in Robotics and AI. *Nature Electronics, 2*(2), 46-48.

Wu, L., Li, J. Y., & Fu, C. Y. (2011). The adoption of mobile healthcare by hospital's professionals: An Integrative perspective. *Decision Support Systems, 51*(3), 587-596.

Yang, T. C., Hwang, G. J., & Yang, S. J. H. (2013). Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles. *Educational Technology & Society, 16*(4), 185-200.

Yang, Z., & Lin, M. (2019). Intelligent fan system based on big data and artificial intelligence. In *Proceedings of the 6th International Conference on Systems and Informatics (ICSAI)* (pp. 637-642). doi:10.1109/ICSAI48974.2019.9010072

Yetisen, A. K., Martinez-Hurtado, J. L., Ünal, B., Khademhosseini, A., & Butt, H. (2018). Wearables in medicine. *Advanced Materials, 30*(33), 1706910. doi:10.1002/adma.201706910

Yu, P., Li, H., & Gagnon, M. P. (2009). Health IT acceptance factors in long-term care facilities: A Cross-sectional survey. *International Journal of Medical Informatics, 78*(4), 219-229.

Zhang, H., Cocosila, M., & Archer, N. (2010). Factors of adoption of mobile information technology by homecare nurses: A Technology acceptance model 2 approach. *CIN: Computers, Informatics, Nursing, 28*(1), 49-56.

Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A Meta-analysis and the moderating role of age. *International Journal of Information Management, 43*, 342-350.

Zou, J., & Schiebinger, L. (2018). AI can be sexist and racist- It's time to make it fair. *Nature, 559,* 324-326.

Appendix A

Questionnaire item

Intention	
PU01	I believe that learning to use the AI-technology tools can better assist healthcare work.
PU02	Using the AI-technology tools would increase my healthcare work productivity.
PU03	I believe that using the AI-technology tools would enhance my professional development.
PEU01	Learning to use the AI-technology tools for healthcare is easy for me.
PEU02	My interaction with the AI tools for healthcare is clear and understandable.
PEU03	Learning to operate the AI-technology tools in the healthcare field would be easy for me.
PEU04	Using the AI-technology tools would enhance the effectiveness of my healthcare work.
SN01	My supervisor or organization believes that I should employ the AI-technology tools to assist my healthcare work in the future.
SN02	I want to learn to use the AI-technology tools because my supervisor or organization requires it.
SN03	The support from my supervisors or organization in learning to use the AI-technology tools is important to me.
SN04	The opinion of my colleagues about learning to use the AI-technology tools is important to me.
ATU01	I have a generally favorable attitude toward learning to use the AI-technology tools.
ATU02	It is a good idea to learn to use the AI-technology tools for healthcare work and personal and professional development.
BI01	I intend to learn to use the AI-technology tools for my healthcare work in the future.
BI02	I intend to learn to use the AI-technology tools for my healthcare work frequently.
BI03	I intend to adapt the AI-technology tools for healthcare work and personal and professional development.