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Assessing acceptance of AI nurses for outpatients with chronic diseases: From nurses' perspective

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ABSTRACT

The primary objective of this article is to investigate and forecast nurses' attitudes toward using AI nurses for outpatients with chronic diseases. AI technology is used in hospitals in a disease-centric manner. However, it is desired by healthcare regulators to be used in an individual-centric and holistic manner. The research model was developed based on the Unified Theory of Accepting and Using Technology. In determining the causes and consequences of the attitudes, actions, ideas, and beliefs of the nurses, the screening technique of causal comparison was used. Research data was collected from registered nurses who work in research hospitals and use intelligent health technologies for inpatients. Based on 494 responses, this study conducted a dual-phase assessment using Partial Least Squares Structural Equation Modeling as well as the creation of an AI method known as deep learning (artificial neural network). According to the results, nurses are convinced that AI is a suitable tool for their nursing tasks and increases their efficiency and productivity. It has been determined that nurses have intentions to use AI nurses for outpatients with chronic diseases. However, nurses have concerns about the reliability of ambulatory patient data. The policies and strategies of regulators will affect the acceptance of AI technology, not only for nurses but for all healthcare professionals and patients.

Keywords: artificial intelligence; health informatics; nursing care; deep learning; artificial neural network; partial least squares-structural equation modeling

1. Introduction

Nursing is a noble profession, and a nurse is a trained professional in the field of healthcare who is licensed and either works independently or under the direction of a doctor. In nursing, autonomous and team-based care is given to patients of all ages, groups, and communities, whether or not they are sick, anywhere their location might be[1]. Based on these definitions, we see that the job description of the nurse job position covers vital activities and a very wide workload. In many countries, nurses account for half of all healthcare professionals[2]. They play a crucial role in how health activities are planned and implemented, both at the

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administrative and front-line levels. The quality of their initial assessment and ongoing treatment is crucial for better health outcomes since they are usually the first and the only healthcare professional a patient may see. Because the availability of adequate physicians and nurses in a nation does not guarantee that everyone has access to healthcare. The high cost of healthcare and the unequal distribution of hospitals, doctors, and nurses throughout areas are the main causes of this predicament[3].

Today, we have the technologies at our disposal that were impossible a couple of decades ago. We can measure almost everything instantly at the micro level and transform the data into information to be used in decision-making. As a result of the substitution of the human factor by technology, many services have become available to many people faster and at a lower cost and more effectively.

Artificial Intelligence technology (AI) has also been used extensively in the health sector[4–9] by integrating AI into healthcare, it is expected that health services can be expanded, and improved. The extension of the AI healthcare system aims to provide contextually relevant and informed healthcare as well as illness prevention, detection, diagnosis, error reduction, individualized disease treatment, patient follow-up, and cost-effective healthcare.

Around fifty percent of Americans currently have a chronic condition, chronic disease-related expenses account for eighty-six percent of all medical expenses[10]. More than fifty percent of fatalities globally are caused by chronic illnesses, mainly cardiovascular disease, type 2 diabetes, cancer, and chronic respiratory disorders[11]. Globally, noncommunicable diseases account for seventy-four of fatalities, or 41 million people every year[12]. The main risk factors for this disease burden are tobacco smoking, a poor diet, and a lack of physical activity[11].

AI, which is used in hospitals as disease-centric, is desired to be used in an individual-centric and holistic manner by health sector regulators[8,9]. Outpatients who can be cared for by AI nurses, especially in disease prevention and chronic disease management, are a good starting point in managing healthcare workload and expenses. Because AI may handle the health activities of outpatients[6,8,9,13]. For example, companies such as Omada, Glooko, Virta, Living, and Lark offer AI health coaching to their customers (who are patients) who have diabetes, hypertension, and obesity[7,14].

The human-human aspect of nursing cannot be eliminated, but some of the nursing duties and activities are performed by AI technology. In particular, the monitoring of inpatients, recording, and processing of electronic health records, implementation and follow-up of the treatment process, monitoring the daily routines of patients, and arranging their daily movements according to the necessity of their health are carried out by AI nurses[15].

The use of AI in healthcare seems inevitable to some scientists[7]. This study explores nurses' attitudes toward their intention to utilize and collaborate with AI nurses for outpatients with chronic diseases. As a bias, attitude can be used to predict future behaviors. A well-researched attitude study is a valuable tool for the future[8,9,16,17]. The results lead outpatients, health professionals, and sector regulators to develop new policies and strategies. In the coming years, we will witness the desire for and use of AI more effectively. To manage the inevitable, health technologies must be developed and adapted, considering the needs and concerns of all stakeholders.

AI technology in nursing

AI is referred to as "computational intelligence" or the "science and engineering of building intelligent machines"[18] and is a fast-developing field that models cognition and humanoid behaviors in machines. The "Turing test," which was created by the early pioneer of AI, Alan Turing, in 1950, was based on the notion of building a machine that perceives and decides like a human[19]. In the 1970s, Shortliffe built the MYCIN, which was a computer-based consultation system created to help doctors diagnose patients with bacterial infections and choose the best course of treatment[20]. Since then, the primary uses of AI in healthcare have been diagnosis and treatment[21]. In 1985, Evans emphasized the usefulness of AI to other health professionals; assumptions in the literature that are based on the restricted experience of doctors (mostly in diagnostic and pharmacologic therapy) must be updated[22].

According to World Bank estimates, 13 million nurses are needed globally[23]. In nations with fifty percent of the world's population, eighty percent of the nursing workforce is employed. Alternatively, the African continent accounts for 25% of the world's illness burden but accounts for just 1% of the world's healthcare workers, the majority of whom are nurses[24]. Training time and costs associated with nursing degrees might be frightening, though. In actuality, total tuition fees can range from six thousand USD for a nursing associate's degree to more than 100 thousand USD for a graduate degree[25]. For a person who wants to be a nurse, it is costly and requires many years of training. Unfortunately, there are not enough educational institutions, resources, and time to train nurses who can meet the present and ever-growing needs worldwide. Also, the imbalance in the geographical distribution of nurses makes it more difficult for some individuals to access healthcare services[3]. Since the nurse shortage cannot be met in the short term due to the reasons mentioned above, health sector regulators are to expand the use of technology in healthcare services to use the existing human resources more effectively and efficiently[26].

A global strategy document on digital health has been published by the World Health Organization (WHO) as a part of its "health for everyone, everywhere" goal. The utilization of wearable health technology, patient record systems, and mobile health apps to improve health is referred to in this research as AI[2]. Not only the WHO but also health ministries[21,27], companies[7], and professionals[28–31] throughout the world are interested in developing and implementing strategies to expand AI in the healthcare system.

The availability of patient health records has increased along with technological advancements. Machine-learning methods that are data-centric and designed to detect complex relationships in a patient's medical records have become more prevalent due to advances in AI[32]. AI is now being utilized in healthcare to advance the care of patients by speeding up processes and achieving higher levels of accuracy, leading ways for better healthcare[33]. AI, for instance, is used to evaluate radiological images and pathology slides, and it helps clinicians diagnose and treat patients while also enhancing their skills[34–36]. AI is now being applied in healthcare to improve patient care by speeding up operations and attaining a higher level of accuracy, opening the path for a better healthcare system[33].

A change from a disease-centric to an individual-centric perspective of AI's value has been underway in recent years[8,9,37,38]. AI is now being utilized for managing people's health in daily activities as well as by medical personnel[9,14,39]. These efforts are not aimed at the level of disease but rather at the level of evaluation of everyone as a single event. Moreover, some companies have also created AI-powered physicians, nurses, and coaches[40–42]. While this is going on, patients benefit from individualized healthcare services, the supply and sharing of medical data and healthcare services are encouraged, and the digitization of healthcare is accelerated[13,15]. Comparable healthcare attempts like CareMore, Iora, and Humana have proved that they decreased expenses per patient by reducing patients' visits to the hospital[7].

One of the primary goals of AI's expansion is to facilitate access to healthcare services and reduce costs with methods of managing chronic diseases, preventing diseases, and promoting a healthy life[39]. The second important goal is to minimize the need for patients and healthcare professionals' geographic proximity. The third one is to reduce the workload of healthcare professionals, especially nurses, who are the backbone of healthcare services, and to restructure their work activities more effectively and efficiently.

Nearly fifty percent of the global health workforce are nurses[43]. At the same time, the time and workload of nurses in the follow-up process of patients' treatment are high. The introduction of AI-based technologies into healthcare has sparked debate and worries. Some people worry that AI will replace nurses[44,45], and doctors[46]. The human-human aspect of nursing cannot be eliminated, but some of the nursing duties and activities can be managed and performed by an AI nurse, thereby increasing the effectiveness and efficiency of human nurses. Using AI in healthcare thus increases the efficiency and productivity of not only nurses but also all healthcare workers. However, eighty-six percent of them expressed doubt that robots would take on the job of nurses[41]. To manage the inevitable, health technologies must be developed and adapted, considering the needs and concerns of both nurses and patients.

2. Research methodology

This study's conceptual framework is based on the Unified Theory of Acceptance and the Use of Technology (UTAUT2) model developed by Venkatesh and colleagues[47]. UTAUT2 is designed to measure how people intend to use and behave with technology. The study design utilized the causal comparison screening technique, which is utilized when it is required to discover the causes and effects of individuals' attitudes, behaviors, ideas, and beliefs[48].

2.1. Hypotheses development

Considering nurses' intention to utilize AI nurses for outpatients with chronic diseases, as seen in **Figure 1** the research model and the following hypotheses have been developed.

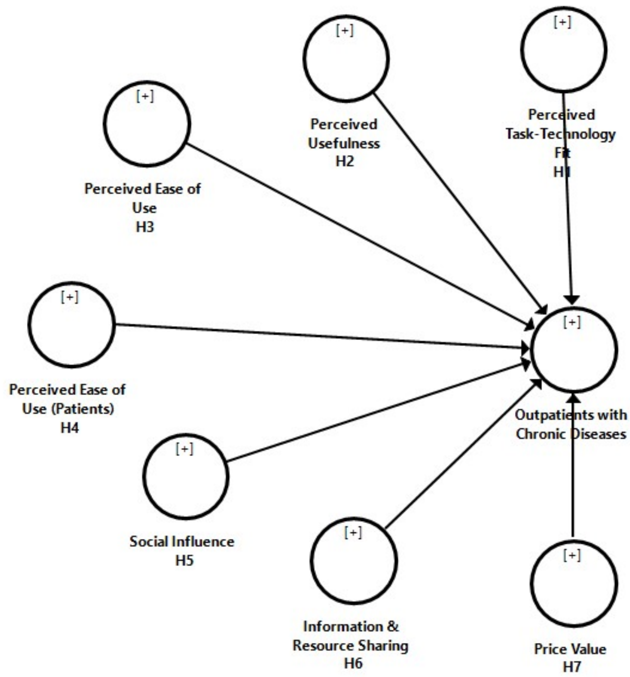

Figure 1. Research model.

2.1.1. Perceived task-technology fit-PTTF

This study has assessed how proper AI is for nursing in the perceived task-technology fit dimension. The technology acceptance model asserts that perceived task-technology fit and perceived usefulness serve as the primary driving forces for accepting and utilizing new technology[49]. AI nurses collect and analyze real-time patient health data and can make decisions and share the status of the patients with themselves, human nurses, and doctors.

H_1: Perceived task-technology fit affects nurses' intention to utilize AI nurses for outpatients with chronic diseases.

2.1.2. Perceived usefulness-PU

Perceived usefulness can be described as the extent to which a person thinks that using a specific system would improve work performance. It is essential in both voluntary as well as required circumstances, and it is the most reliable indicator of usage purpose[49,50].

H_2: Perceived usefulness affects nurses' intention to utilize AI nurses for outpatients with chronic diseases.

2.1.3. Perceived ease of use-PEOU

Perceived ease of use describes the extent to which an individual thinks that utilizing a specific device or method would not require any physical or intellectual effort[49].

H_3: Perceived ease of use affects nurses' intention to utilize AI nurses for outpatients with chronic diseases.

2.1.4. Perceived ease of use for patients-PEOUP

AI is now being utilized by ordinary people to manage their medical conditions in everyday activities, alongside physicians and nurses[37]. For AI nurses to work at the targeted level, it must also be user-friendly. Patients also need to use AI technology according to health professionals' needs. For AI nurses to work properly, it must also be user-friendly[51] for patients, as patients are the primary data source.

H_4: Perceived ease of use for patients affects nurses' intention to utilize AI nurses for outpatients with chronic diseases.

2.1.5. Social influence-SI

The degree to which a person is behaving under the sway of another person, or a group is known as social influence[47,52].

H_5: Social influence affects nurses' intention to utilize AI nurses for outpatients with chronic diseases.

2.1.6. Information and resources sharing-IRS

For AI to work properly, the validity and reliability of the data must be ensured[53]. AI may manage an individual's daily routines, the important thing here is the collection of data that shapes the AI[7]. In addition to obtaining permission to share personal data, a system should be established in the health management system that can be accessed by respective authorities[54].

H_6 Information & resources sharing affects nurses' intention to utilize AI nurses for outpatients with chronic diseases.

2.1.7. Price value-PV

Price value can be defined as a state where the advantages of a technology exceed the expenses a user must pay to use it[47]. The desire to pay the costs associated with utilizing the technology is shown by the customer's opinion of the device or technology as "good value for money"[52]. Within the scope of this study, price value for nurses is the investment that the organization must make to build an AI nurses system. The second is the cost and benefit for the patient to use AI nurses.

H_7 Price value affects nurses' intention to utilize AI nurses for outpatients with chronic diseases.

2.2. Research methodology

On 494 responses, this study conducted a double-phase assessment, utilizing structural equation modeling (Partial Least Squares PLS-SEM) as well as creating an AI method, known as deep learning (ANN-Artificial Neural Network). The hypotheses were first assessed using SEM. The SEM analysis method was used to explore the linear relationships between the constructs stated in the research model. SEM analyzes through defined relationships, hence it could be able to dismiss the study model's unexpected relations[55–57]. The nonlinear relations between the constructs have been studied utilizing ANN as an additional step to address the SEM's limitation. A more sophisticated kind of machine learning called ANN is an analytical approach that takes cues from the human nervous system. The inputs, outputs, and variable weights that connect inputs and outputs are the basis for ANN's approach to problems[21,58]. ANN can be used to verify the SEM findings. A hybrid model is advised rather than just ANN because in ANN, formulating hypotheses is difficult[56,57,59,60]. SmartPLS 3.3.2 for SEM analysis; SPSS 24 statistic programs were used for analyses.

2.3. Measurement of variables

In the study, previously tested measurements have been customized to fit within the AI nurses' framework. The perceived task technology fit was adapted from Lu and Yang[61]. Perceived usefulness and perceived ease of use; information, and resource sharing were adapted from Park et al.[49,50,62]. Social influence; price value; and the behavioral intention to use AI nurses for outpatients with chronic diseases were adapted from Venkatesh et al.[47]. In this study, indicators were assessed on a five-point Likert scale between 1 (strongly disagree) and 5 (strongly agree).

2.4. Sample and data collection

Registered nurses' data was gathered via paper and online. The measurement was made available online, and the link was sent to the participants' business email. The convenience sampling approach was chosen for data collection on paper. The research data was collected online from 128 of the participants and on paper from the rest of the participants. 33 participants were not included in the analysis because they had a single value for the rating of all statements. The analysis of the study has been made on the data which was collected from 494 registered nurses who work at research hospitals. The sample included 364 females and 130 males. In terms of educational characteristics of the participants, 424 participants have a bachelor, thirty-two participants have a graduate, twenty-one participants have a college (two-year degree), and twelve participants have a high school degree. In terms of age characteristics of the participants, 67 people are between the ages of 21–25, 157 participants are between the ages of 26–30; 134 people are between the ages of 31–35, 54 people are between the ages of 36–40, 77 people are over the age of 40.

3. Empirical evidence

3.1. Research model SEM analysis and results

3.1.1. Initial assessments of the research model

According to Hair and his associates' suggestions[63], an initial assessment of the research model has been carried out in the study (**Table 1** shows). Initially, the outer loadings of the indicators, Cronbach's alpha, and composite reliabilities (CRs) values of constructs are above the cutoff of 0.70; average variance extracted (AVEs) values are greater than 0.50. The minimal conditions for maintaining construct and indicator reliability, internal consistency reliability, convergent validity, and divergent validity are satisfied.

Table 1. Research model constructs' reliability, validity analysis results.

					Reliability		Validity		
					Indicator reliability		Internal consistency reliability		Conv. validity
	Mean	SD	Kurtosis +/– 7	Skewness +/– 2	construct loading ≥ 0.70	VIF < 5	Cronbach's alpha α ≥ 0.70	Composite reliability CR ≥ 0.70	AVE ≥ 0.50
Perceived task-technology fit (PTTF)	3.49	1.05				2.25	0.77	0.85	0.60
I think that using AI nurses is well–suited to the way to do nursing practices	3.395	1.063	–0.442	–0.251	0.814	1.811			
AI Nurses are a good medium to provide a way to manage nursing practices.	3.433	1.051	–0.383	–0.222	0.874	2.162			
Using AI nurses fits well with the way to manage healthcare services.	3.603	1.034	–0.160	–0.427	0.606	1.222			
I think that using AI nurses is a good way to manage healthcare for patients.	3.540	1.036	–0.405	–0.240	0.764	1.492			
Price value (PV)	3.86	1.01				2.45	0.80	0.87	0.63
AI nurses must be reasonably priced for outpatients with chronic diseases.	3.605	1.006	–0.680	–0.129	0.645	1.195			
AI nurses are a reasonable investment for outpatients with chronic diseases.	3.838	1.033	–0.220	–0.589	0.863	3.070			
An AI technology healthcare system would be a good value for the money.	3.945	0.995	0.123	–0.730	0.897	3.269			
At the current high technologies budget, AI nurses' system would provide good value for outpatients with chronic diseases.	4.028	0.991	0.342	–0.882	0.741	1.560			
Information & resources sharing (IRS)	4.23	0.96				2.48	0.85	0.90	0.69
Sharing information/knowledge of AI Tech. with other departments is a normal thing.	4.071	0.959	0.238	–0.819	0.771	1.643			
Sharing information/knowledge of AI nurses with health professionals (doctors, paramedics) is a good idea.	4.047	0.895	–0.193	–0.601	0.871	2.368			
Sharing information/knowledge of AI nurses with a healthcare system is a wise move.	4.000	0.959	0.260	–0.761	0.865	2.403			
Sharing information/knowledge of AI nurses with relevant institutions and organizations is a positive step.	3.974	1.003	0.253	–0.805	0.801	1.660			
Perceived usefulness (PU)	4.16	0.92				3.45	0.90	0.92	0.71
Using AI nurses in my job enables me to accomplish tasks more quickly.	4.239	0.902	0.891	–1.153	0.860	3.202			
Using AI nurses is improving my job performance.	4.204	0.893	0.604	–0.994	0.880	3.346			
Using AI nurses is enhancing my effectiveness on the job.	4.259	0.857	1.224	–1.144	0.869	2.811			
Using AI nurses is making it easier to do my job.	4.113	0.965	0.059	–0.880	0.795	2.035			
I find AI nurses useful in my job.	3.955	0.981	–0.541	–0.557	0.812	1.809			

Table 1. (*Continued*).

	Mean	SD	Kurtosis +/– 7	Skewness +/– 2	Reliability: Indicator reliability construct loading ≥ 0.70	VIF < 5	Validity: Internal consistency reliability: Cronbach's alpha α ≥ 0.70	Composite reliability CR ≥ 0.70	Conv. validity: AVE ≥ 0.50
Perceived task-technology fit (PTTF)	3.49	1.05				2.25	0.77	0.85	0.60
Perceived ease of use (PEOU)	3.93	0.96				3.78	0.84	0.89	0.61
My interaction with the AI nurse is clear and understandable.	3.646	1.013	–0.492	–0.289	0.768	1.663			
I find AI nurses to be flexible to interact with.	3.945	0.899	0.335	–0.680	0.849	2.225			
I find it easy for an AI nurse to do what I want it to do.	4.061	0.940	0.610	–0.914	0.771	1.803			
Learning to operate an AI nurse is easy for me.	4.223	0.939	0.963	–1.178	0.725	1.616			
It is easy for me to become skilled at using AI nurses.	3.785	1.017	–0.190	–0.544	0.773	1.612			
Perceived ease of use for patients (PEOUP)	2.53	1.21				1.45	0.91	0.94	0.79
Outpatients' interaction with AI nurses would be clear and understandable.	2.342	1.262	–0.563	0.661	0.878	2.991			
Outpatients would find AI nurses to be flexible to interact with.	2.443	1.237	–0.543	0.610	0.913	4.096			
Outpatients would find it easy to AI nurses to do what they want them to do.	2.555	1.173	–0.614	0.423	0.906	3.659			
Learning to operate AI nurses is easy for outpatients with chronic diseases.	2.775	1.184	–0.725	0.200	0.862	2.051			
Social influence (SI)	3.66	0.95				2.83	0.85	0.89	0.63
People who are important to me think that I should use AI nurses.	3.543	0.961	–0.363	–0.114	0.721	1.552			
People who influence my behavior think that I should use AI nurses.	3.755	0.977	–0.440	–0.395	0.822	1.990			
People whose opinions I value prefer that I use AI nurses.	3.713	0.975	–0.173	–0.372	0.808	1.910			
Patients whose opinions I value prefer that I use AI nurses.	3.433	1.100	–0.407	–0.334	0.774	1.694			
The government that influences my behavior think that I should use AI nurse.	3.840	0.957	0.023	–0.565	0.832	2.044			
Behavioral intention to use for outpatients with chronic diseases (OutP)	3.72	1.06					0.84	0.88	0.56
I intend to use an AI nurse for outpatients with chronic diseases to prevent diseases.	3.709	1.044	–0.257	–0.510	0.792	2.244			
I always try to use an AI nurse for distance nursing practices.	3.743	1.006	–0.316	–0.412	0.763	2.010			
I plan to use an AI nurse to follow outpatients with chronic diseases.	3.559	1.173	–0.542	–0.477	0.707	1.725			
I always try to use an AI nurse for chronic outpatients to promote their health.	3.887	0.977	–0.191	–0.620	0.789	2.083			
I plan to use an AI nurse to follow chronic outpatients with chronic diseases.	3.605	1.108	–0.512	–0.375	0.774	2.197			
I will use an AI nurse to control outpatients with chronic diseases.	3.789	1.040	–0.306	–0.546	0.659	1.424			

As seen **Table 2**, the Heterotrait-Monotrait (HTMT)[64] correlation ratios are below 0.95, and the AVEs are greater than squared inter-construct correlations[65]. The HTMT ratio and Fornell-Larcker criteria for discriminant validity have been met by these outcomes.

Before initiating the analysis of the research model, the Variance Inflation Factor (VIF) values were evaluated for collinearity between the indicators. If the VIF values are more than 5, this indicates that the research model may have been compromised by common method bias[63,66]. In this study, the collinearity between the indicators of the research model is unproblematic, and **Table 1** shows that the indicators' VIF values range between 1.195 and 4.096.

Table 2. The fornell-larcker discriminant validity and the HTMT correlation matrix.

	Fornell_larcker								**HTMT**							
	IRS	**OutP**	**PEOU**	**PEOUP**	**PTTF**	**PU**	**PV**	**SI**	**IRS**	**OutP**	**PEOU**	**PEOUP**	**PTTF**	**PU**	**PV**	**SI**
IRS	0.828															
OutP	0.652	0.749							0.764							
PEOU	0.735	0.774	0.778						0.876	0.906						
PEOUP	0.060	0.342	0.231	0.890					0.073	0.382	0.243					
PTTF	0.518	0.689	0.652	0.441	0.771				0.646	0.853	0.810	0.529				
PU	0.661	0.793	0.856	0.301	0.660	0.803			0.744	0.890	0.902	0.322	0.788			
PV	0.597	0.688	0.746	0.232	0.589	0.741	0.793		0.726	0.825	0.909	0.265	0.743	0.864		
SI	0.611	0.761	0.709	0.437	0.649	0.737	0.570	0.792	0.707	0.893	0.824	0.496	0.804	0.827	0.684	

IRS: Information & Resource Sharing; **OutP**: Behavioral intention to use AI nurses for outpatients with chronic diseases; **PEOU**: Perceived Ease of Use, **PEOUP**: Perceived Ease of Use for Patients, **PTTF**: Perceived Task-Technology Fit; **PU**: Perceived Usefulness, **PV**: Price Value; **SI**: Social Influence.

3.1.2. Research model path analysis

The hypotheses have been examined using the bootstrapping approach (10.000 resamples), as described by Hair and colleagues[63], with a significance level of 0.05. **Figure 2** and **Table 3** provide the outcomes of the bootstrapping method. From perceived task-technology fit to behavioral intention to use AI nurses for outpatients with chronic diseases (β = 0.150; t value = 4.127; p < 0.000); from perceived usefulness to behavioral intention to use AI nurses for outpatients with chronic diseases (β = 0.233; t value = 4.561; p < 0.000); from perceived ease of use to behavioral intention to use AI nurses for outpatients with chronic diseases (β = 0.120; t value = 2.332; p < 0.020); from social influence to behavioral intention to use AI nurses for outpatients with chronic diseases (β = 0.268; t value = 5.341; p < 0.000); from price value to behavioral intention to use AI nurses for outpatients with chronic diseases (β = 0.122; t value = 3.197; p < 0.001); from information & resources sharing to behavioral intention to use AI nurses for outpatients with chronic diseases (β = 0.094; t value = 2.212; p < 0.027) have positive and significant influences have been indicated. H_1, H_2, H_3, H_5, H_6, and H_7 hypotheses have been supported. The H_4 hypothesis has not been statistically supported.

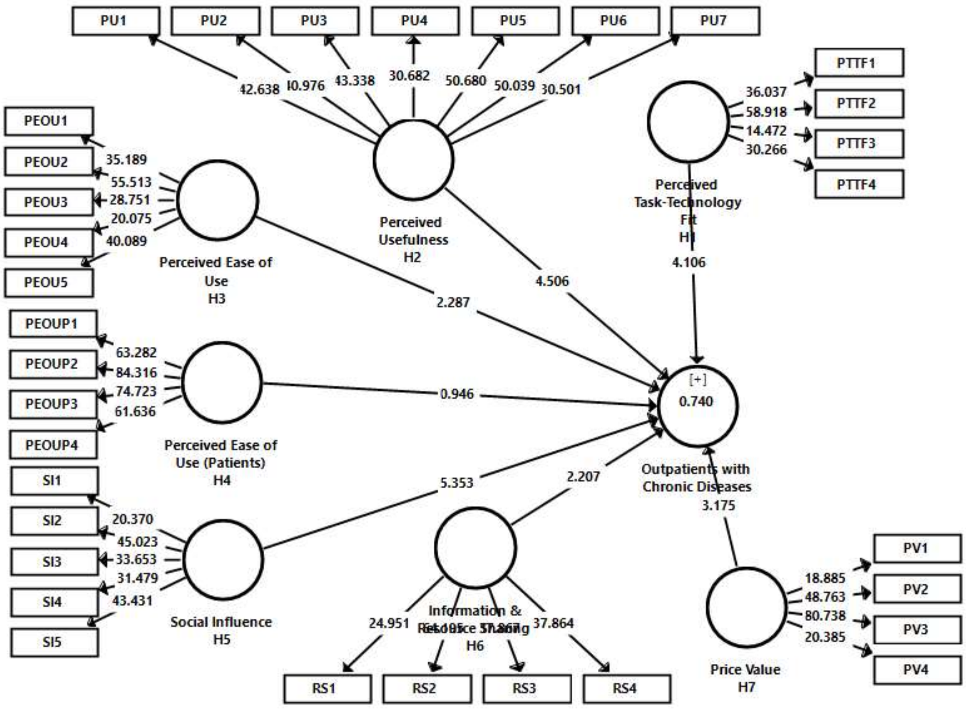

Figure 2. Research model path coefficients.

Table 3. Results of research model path analysis and hypothesis testing.

Hypothesized paths		R^2	β coefficients org. sample	β coefficients boots. sample	T statistics	*P* values	H	
Perceived task-technology Fit ->	Behavioral intention to use AI nurses for outpatients with chronic diseases.	0.732	0.150	0.151	4.127	0.000	H_1	Supported
Perceived usefulness ->			0.233	0.233	4.561	0.000	H_2	Supported
Perceived ease of use ->			0.120	0.118	2.332	0.020	H_3	Supported
Perceived ease of use for patients ->			0.027	0.027	0.953	0.341	H_4	Not supported
Social influence ->			0.268	0.267	5.341	0.000	H_5	Supported
Information & resource Sharing ->			0.094	0.096	2.212	0.027	H_6	Supported
Price value ->			0.122	0.122	3.197	0.001	H_7	Supported

To prevent model misspecification, the Standardized Root Mean Square Residual (SRMR) which is the recommended cut-off value of 0.08, is the preliminary measure created. The SRMR of the research model is 0.076, which is less than the literature's recommended cut-off value. Another criterion, known as Root Mean Square Residual (RMStheta), assesses "how closely the outer model residuals correlate." The result shows a good model fit if RMStheta is less than 0.12[63]. RMStheta for the research model is 0.12. In terms of misspecification, the results of the research model analysis are satisfactory.

3.1.3. PLS predict analysis

To estimate the research model's capability for out-of-sample forecasting, a PLS prediction assessment has been performed according to the recommended parameters which are 10 folds and 10 repetitions[63]. The mean absolute error (MAE), the root-mean-square error (RMSE), and the Q^2 values of the PLS prediction. As seen in **Table 4**, if all the Q^2 values are higher than zero, the PLS-SEM findings indicated smaller prediction errors than when using mean values alone. In terms of MAE values at the indicator level, there is also an appropriate amount of out-of-sample predictive potential.

Table 4. PLS predict analysis of the research model.

	PLS				LM				PLS–LM			
	RMSE	MAE	MAPE	Q²_predict	RMSE	MAE	MAPE	Q²_predict	RMSE	MAE	MAPE	Q²_predict
OutP1	0.677	0.521	17.118	0.549	0.711	0.559	18.453	0.502	–0.034	–0.038	–1.335	0.047
OutP2	0.909	0.695	27.651	0.403	0.943	0.715	30.112	0.357	–0.034	–0.020	–2.461	0.046
OutP3	0.776	0.581	18.326	0.372	0.797	0.624	19.690	0.338	–0.021	–0.043	–1.364	0.034
OutP4	0.822	0.616	23.211	0.451	0.833	0.626	23.865	0.436	–0.011	–0.010	–0.654	0.015
OutP5	0.702	0.543	17.702	0.547	0.729	0.556	18.662	0.510	–0.027	–0.013	–0.960	0.037
OutP6	0.849	0.676	23.459	0.357	0.895	0.708	25.225	0.286	–0.046	–0.032	–1.766	0.071

OutP: Behavioral intention to use AI nurses for outpatients with chronic diseases.

3.2. Analysis of artificial neural network (ANN)

ANN is an algorithm intended to imitate the operation of the brain of a human being[67,68]. When a dependent construct is connected with independent constructs, ANN analysis behaves feed-forward, back-propagation, and multi-layer perception performances to understand, explain, and make predictions about the dependent construct[59,60,69]. ANN is made up of three layers: the input layer, the hidden layer, and the output layer. It is a simulation of the human brain neurons and their pre-existing synaptic connections made by computer software. Throughout the process of learning, neurons connect in many ways to form networks. These networks can learn, remember, and link many constructs to one another[67]. The knowledge acquired during learning is stored in synaptic weights[55].

Beyond the benefits of a linear model, a deep ANN (with more than two layers; **Figure 3**) has exceptional nonlinear fitting capabilities and strong extrapolative potential. The input layer of the model in **Figure 3** shows that the outpatients' model has seven neurons. The dependent construct nurses' intention to utilize AI nurses for outpatients with chronic diseases has been reflected by one neuron (outpatient) in the output layer. In **Figure 3**, and **Table 5**, H (1:1), and H (1:2) are shown as the ANN's hidden layers. Without assuming anything about the research model, **Table 6** and **Figure 3** show that the ANN model has been trained ten times. Training can create connections between independent and dependent constructs, as illustrated in **Figure 3**[70]. A ten-fold cross-validation method has been utilized to avoid overfitting [56,57,59,60,67]. 90% of the data was utilized for training processes and 10% was used for testing using the SPSS 24 Neural Network Algorithm.

Table 5. The contribution of the hidden layer.

Parameter estimates									
Predictor		Predicted							
		Hidden layer 1				Hidden layer 2			Output layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(2:1)	H(2:2)	H(2:3)	Outpatients
Input Layer	(Bias)	1.816	0.806	–0.470	–0.338				
	PU	–0.170	–0.382	2.091	–1.614				
	PEOU	–0.560	–0.519	2.395	–1.953				
	PV	–0.126	–0.540	1.824	–1.470				
	PTTF	–0.736	0.079	1.799	–1.057				
	PEOUP	–0.259	0.016	1.362	–1.217				
	SI	–0.817	–0.629	2.154	–1.417				
	IRS	–0.227	–0.253	2.177	–1.510				
Hidden Layer 1	(Bias)					–0.726	–0.166	–0.604	
	H(1:1)					–4.105	–2.639	–0.598	
	H(1:2)					–2.463	–2.470	–0.333	
	H(1:3)					2.345	1.829	0.112	
	H(1:4)					–0.852	–0.332	0.358	
Hidden Layer 2	(Bias)								–1.730
	H(2:1)								2.721
	H(2:2)								4.830
	H(2:3)								–0.451

IRS: Information & Resource Sharing; **PEOU**: Perceived Ease of Use; **PEOUP**: Perceived Ease of Use for Patients; **PTTF**: Perceived Task-Technology Fit; **PU**: Perceived Usefulness; **PV**: Price Value; **SI**: Social Influence.

Table 6. ANN analysis RMSE and R2 values.

Outpatients						
Training			**Testing**			
n	**SSE**	**RMSE**	**n**	**SSE**	**RMSE**	**R^2**
441	2.973	0.082	53	0.350	0.081	0.993
443	2.662	0.078	51	0.251	0.070	0.994
440	2.515	0.076	54	0.326	0.078	0.994
432	2.649	0.078	62	0.377	0.078	0.994
438	2.775	0.080	56	0.406	0.085	0.994
448	2.701	0.078	46	0.171	0.061	0.994
440	2.595	0.077	54	0.327	0.078	0.994
446	2.765	0.079	48	0.225	0.068	0.994
437	2.665	0.078	57	0.373	0.081	0.994
442	2.592	0.077	52	0.312	0.077	0.994
Average		0.078			0.080	0.994

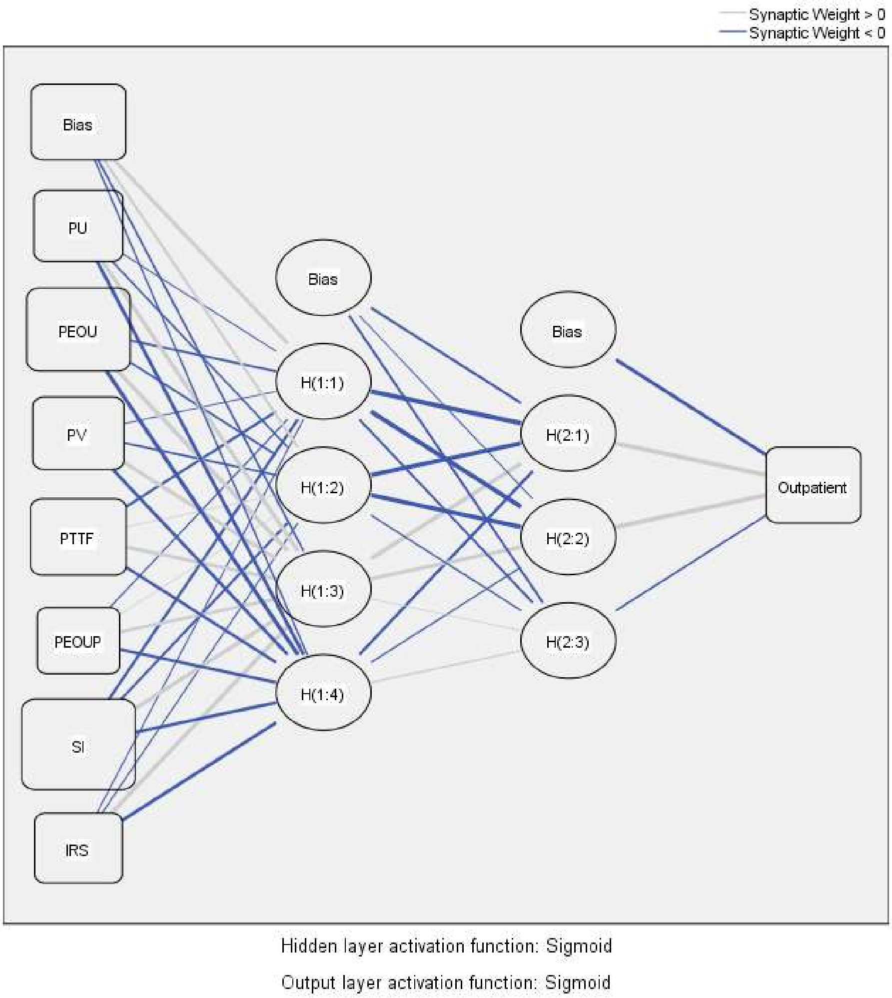

Figure 3. ANN research model.

RMSE values are employed to assess the results of the ANN model. The minimal and similar RMSE mean values indicate the high model fit and forecast accuracy[59]. As shown in **Table 6**, the model's RMSE values are low, and the ANN model is very precise and effective. The inquiry of the R^2 coefficient revealed[55] that the ANN model explains 0.94% of the variance of utilizing an AI nurse.

A sensitivity analysis is used to order the input neurons of the ANN model based on their normalized significance (NI). Sensitivity analysis is used to evaluate the variables' normalized relevance and importance[60]. As can be seen in **Table 7**, the constructs, social influence, perceived usefulness, perceived task-technology fit, and perceived ease of use have been ordered in order of relevance for the behavioral intention to utilize AI nurses for outpatients with chronic diseases.

Table 7. ANN research model independent variables importance.

	Outpatients	
	I	**NI**
Perceived usefulness	0.099	35.0%
Perceived ease of use	0.210	73.9%
Price value	0.114	40.3%
Perceived task-technology fit	0.150	52.8%
Perceived ease of use for patients	0.053	18.5%
Social influence	0.284	100.0%
Information and resources sharing	0.090	31.7%

4. Results

The most significant constructs influencing the behavioral intention to utilize AI nurses for outpatients with chronic conditions, according to the output of the SEM analysis, are social influence, perceived usefulness, and perceived task-technology fit. The Nurses have the conviction that they can achieve their defined tasks and goals for outpatients with chronic diseases by using AI nurse technology. The perceived task-technology fit is a statistically significant construct. Nurses are of the view that nursing activities can be done with AI technology. Social influence is a statistically significant construct. Nurses have stated that if the government, patients, and people who are important to them advise using an AI nurse in healthcare, they will. The perceived ease of use is a statistically significant construct for outpatients.

The second important output of this study is information and resources sharing. Nurses believe in the necessity of collecting valid and reliable data and AI systems for health services. At the same time, they believe that an AI infrastructure that can be accessed by the relevant people, and organizations, both as data and information, is required.

ANN results agree with SEM results. In order of importance for outpatients, the order is social influence, perceived ease of use, perceived task-technology fit, price value, and perceived usefulness. These results and SEM findings are also in conformity.

Perceived ease of use for patients and the behavioral intention to utilize AI nurses for outpatients with chronic diseases did not have a significant relationship, according to the analysis's findings.

When the research results were examined, it was seen that the information & resources sharing is not high, and the perceived ease of use for patients is not an important construct for outpatients with chronic diseases. These results do not support the goals of healthcare sector regulators. Although the study is not qualitative research, results have been evaluated with 5 nurses from the research sample. The opinion of Nurse-I is that "Patients have a perception that they can do anything or eat and drink when they take the medicine. Inpatients do things they shouldn't do; they don't do things they should. For example, they bring food from outside and eat it secretly. Outpatients are difficult to control. Patients with chronic diseases need to be educated about healthy living. Because lifestyle and daily routines are also important for managing chronic diseases. Patients need to learn to live healthy despite their chronic diseases".

Nurse-II has said "Inpatients are in the nurses' control zone, but outpatients are in their control. One patient said, 'I would rather die by eating than die by not eating.' To be able to do what they want, be sure, they either turn off the AI device or even let someone else use it. 'How is the validity and reliability of the data collected by AI ensured?' The answer to this question is important".

Nurse-III thinks that "The AI system is a reliable and lasting technology. Instead of being mandatory, first, volunteers should be included in the AI system. Benefits and results should be reported regularly. Because the AI system will be oriented toward preventing diseases and promoting healthy living. The workload and costs for all stakeholders will be reduced, excluding pharmaceutical companies. It will help protect the health of those who want to use it and make their lives easier. Everything depends on the patients".

Nurse-IV has shared that "Before the use of AI, training must be given, just like when getting a driver's license. Having forms that end with sentences such as 'I have read and understood', 'shared with me' or 'all responsibility is my own' is not the solution".

Nurse-V thinks that "We currently have a system in which all health data and records of each patient are shared, accessible to stakeholders if consented by the patient. AI already gives us insights into possible situations based on each patient's previous illness and treatment. In the AI nurse system, primarily, patients should be guided according to their health status. Doctors, nurses, and other related professionals should have access to these records and information at any time."

5. Discussion

Governments, insurance, technology research and development companies, device manufacturers, hospitals, and medical professionals—all significant players in the healthcare system—are already searching for ways to increase access to AI healthcare services. Disease prevention, detection, and diagnosis, personalized disease treatment, medical imaging, clinical trial efficiency, mistake reduction, lowering costs of care, and offering contextually relevant and educated healthcare are the goals of the expansion of the AI healthcare system. Additionally, the results gained with the use of AI technology are encouraging, and the analysis of the data is far superior to human ability, both of which reinforce the tendency to extend the use of AI in healthcare. The big data aspect of the data that is gathered naturally calls for the usage of AI, and AI may make better diagnoses and provide treatments in many areas than a human health professional.

According to the results of this study, nurses have been convinced that AI is suitable for nursing tasks and that AI nurses are suitable for managing the health of outpatients with chronic diseases. The AI system will increase nurses' efficiency and productivity. Some scientists consider the utilization of AI in the healthcare system inevitable[7,8]. AI is now being used by individuals to manage their health in everyday activities[37,39,71]. AI may also provide daily counseling, and act as a nurse to prevent diseases and manage chronic conditions.

Perceived usefulness and perceived task-technology fit are important constructs which means nurses are aware of AI's ability and it is a powerful tool to care for outpatients with chronic diseases. AI can collect a lot of data about the individual simultaneously and analyze the relationships between them instantly at the individual level.

The health of individuals will be protected, the workload of medical professionals will be reduced, and state and insurance company costs will go down, particularly with chronic patient follow-up, health protection, and disease prevention strategies[8].

Regarding the assessment of the findings of the research involving nurses; it has been determined that nurses have been convinced that AI nurses are a useful tool for outpatients with chronic diseases and healthcare professionals but they have concerns about the behaviors of patients, and the data that AI nurses will collect from outpatients, and these anxieties are caused by the behavior of the patients[72,73], not the AI technology. As a result of the behavioral risk analysis related to the disease, patients can be divided into risk categories, just like credit risk management. For a well-functioning AI healthcare system, it is recommended to develop incentive practices such as lower insurance premiums for patients who are non-risky.

The reliability of the data is important for both the health of the patient and the operation of the AI system. Other studies have emphasized the importance of valid and reliable data necessary for the operation of AI[7–9,74–76]. Social influence is an important construct. Within the scope of social influence, it is foreseen that the government, insurance companies, and/or hospital management are the key policy-makers in the engagement of AI technology.

Also, AI devices must be user-friendly. The result of the research shows that people want an AI doctor to be used in health services to communicate with themselves like human doctors[77,78]. It is predicted that this feature is also valid for AI nurses, and it will have an affirmative effect on the utilization of AI nurses.

5.1. Implications for stakeholders

The outcome of this study contributes to healthcare professionals, technology developers, insurance companies, and governments.

Firstly, nurses are convinced that AI nurses will contribute to their performance and the health of outpatients with chronic diseases. Outpatients can use smart healthcare tools connected to an AI system, manage their health with the help of AI, and manage their chronic diseases by getting support from healthcare professionals when they need it.

Health technology developers are recommended to develop AI nurses' applications and devices for outpatients with chronic diseases. Also, it is recommended to establish a system that provides a holistic service that can both protect the health, prevent chronic diseases, and perform risk analysis and reporting on the health status of patients.

For governments and health sector organizations and professionals, a strong AI healthcare system will reduce the workload of health professionals, they will be able to engage in more value-added and important activities. Indisputably, the AI health system will not only make access to health services easier and cheaper but will also reduce the workload of healthcare professionals.

AI nurses provide the opportunity to provide healthcare services for outpatients and even people who live in rural areas. At the same time, because of this study, it was determined that additional user control features should be developed for the reliable operation of the AI nurse developed for outpatients. Perhaps the reliable patient may be considered less risky, and the cost of using AI nurses may be lower.

The acceptability of AI in healthcare will increase if there are systems that can communicate like a real nurse or doctor instead of only alerting people with numbers, colors, or noises. However, when healthcare professionals enhance the accuracy of their decisions by using AI will be welcomed by patients.

The policies and strategies of industry regulators will affect the acceptance of AI, not only for nurses but for all healthcare professionals and patients.

5.2. Future studies

This is the first study on the adoption of AI nurses for outpatients with chronic diseases at the nursing level. The research data used in this study was collected from registered nurses. It is advised that new research be undertaken using data gathered from physicians, people of all ages with chronic illnesses, senior citizens, and their families.

Governments, insurance companies, and healthcare companies want to utilize AI more widely in medical services to decrease costs. Soon, the costs of AI and human services are supposed to be differentiated. It is recommended to examine the cost/benefit analysis in terms of outpatients with chronic diseases.

Apprehensions regarding the privacy of personal data and information are widespread. In the use of AI in the health sector, it is necessary to examine the ethical and legal regulations in terms of both healthcare providers and users.

Qualitative research is thought to be necessary to fully comprehend how AI is used in the healthcare industry.

5.3. Limitations

This study examines nurses' attitudes toward AI nurses for outpatients. Well-studied attitude research is a valuable resource for behavior prediction. It is important to note that attitudes do not necessarily translate into or reflect behavior.

The study was designed in terms of the attitudes of nurses working in the hospital in terms of the management of chronic outpatients. It does not cover all nursing activities and tasks.

This study very briefly covers a certain period; it is not long-term research. It is important to remember that attitudes can alter with time.

The participants stated their self-reported use intentions. By assuming that their claims were accurate, the study has been conducted.

Ethics statement

The university's Human Sciences Scientific Research and Publication Ethics Committee has supplied its clearance (reference number E-70561447-050.01.04- 35758).

Research data

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Author contributions

Conceptualization, AOU, PU, and YA; methodology, AOU, PU, and YA; validation, AOU, PU, and YA; formal analysis, AOU, and YA; investigation, AOU, PU, and YA; resources, AOU, PU, and YA; data curation, AOU, PU, and YA; writing—original draft preparation, AOU, PU, and YA; writing—review and editing, AOU, PU, and YA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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