Predicting Determinants of Telemedicine Adoption in Healthcare: An Artificial Neural Network Approach

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Abstract— **With the proliferation of technologies and internet, deployment of telemedicine applications in healthcare are continuing to grow at an explosive rate around the globe. However, challenges confronting the healthcare industry, particularly telemedicine service providers are the poor acceptance and use of telemedicine by the users in the healthcare system. The study aimed to develop a model that explores the determinants influencing user acceptance of telemedicine in healthcare using Multilayer Perceptron (MLP) Backpropagation (BP) method-based Artificial Neural Network (ANN) model. The dataset used for this study were built on the primary data gathered from 384 users (patients) by employing a questionnaire being a set of information on predicting factors of telemedicine adoption from Dhaka division of Bangladesh. The findings show that effort expectancy, performance expectancy, social influence, facilitating condition, task-technology fit, and e-health literacy are significant predictors of telemedicine adoption. The outcome of the research would be useful for evolving technology driven healthcare services.**

Keywords— Healthcare, Telemedicine Adoption, Artificial Neural network, Multilayer Perceptron, Confirmatory Factor Analysis.

I. INTRODUCTION

Users' adoption and continuing usage of a technology determine its long-term viability and sustainability. Despite the potential of telemedicine, there is a growing concern that although the numbers of telemedicine service providers and platforms are increasing, actual telemedicine activities by the users remain low, especially in developing countries [1][2]. Apparently, the eventual success of telemedicine depends on whether users' use telemedicine as a channel for their healthcare. Recently, understanding users' decisions to adopt telemedicine has gained the attention of both the research, healthcare industry as well as commercial community. Like most information system adoption studies, it is often difficult to predict the adoption behaviors of telemedicine user's, due to the complexity and uncertainty involved in the decision makings.

However, Artificial Neural Network (ANN) often referred as Neural Network offers a modeling method that enables the mapping of highly complex functional relationships. ANN is an intelligent model (smart system) that resembles human-like thinking through learning and training and has the ability to obtain knowledge, store it by synaptic weights, and recall it for decision making in similar environments, situations, or events. The ANN model consists of three types layers: an input layer, hidden layer(s), and an output layer, as shown in Fig. 1. Besides, the key elements comprising an ANN include neurons, activation function, and weights. The input layer is the introduction of data to the network where the features or independent variables are connected to it, the hidden layer is data processing, and the output layer is the results from data processing where the dependent variable or the final outcome resides. The neural network modeling has been successfully applied in predicting mobile commerce adoption [3], acceptance of cloud-based virtual learning environment [4], smartwatch adoption in healthcare [5], adoption of cryptocurrency [6] and many other domains. According to Vallée et al. [7], artificial neural networks are effective in enabling the interpretation of complex phenomena, discovering new patterns and predicting outcomes. The superiority of using this approach is that the neural network model can learn complex linear and non-linear relations between predictors and the adoption decision [8]. Moreover, compared to traditional regression approaches, neural networks are more stable and have higher prediction accuracy [9]. Therefore, the study has been conducted to develop a model that explores the determinants influencing user acceptance of telemedicine in healthcare using Multilayer Perceptron (MLP) Backpropagation (BP) method-based Artificial Neural Network (ANN) model.

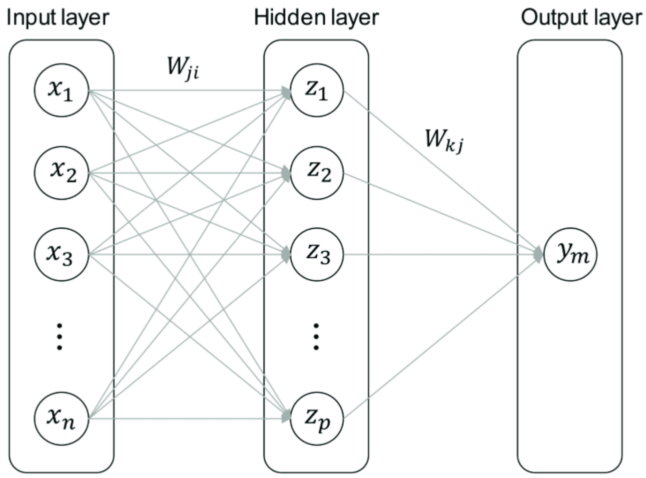

Fig. 1. Artificial Neural Network (ANN) Model Structure

II. METHODOLOGY

This section extensively discusses the various methods and materials employed in the research. Although, neural network is the main form of analysis in this research, Confirmatory Factor Analysis (CFA) has been utilized to determine the feature (item) reliability, factor reliability, and convergent and discriminant validity.

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A. Variables and Measures

Initially, the researcher conducted a comprehensive literature review in order to contextualize the theoretical underpinning, conceptualization of the factors, and to develop the survey questionnaire for collecting the data. A total of 31 features (items) that would possibly influence the intension to adopt telemedicine were outlined and were grouped into seven factors considering the theoretical underpinnings to predict telemedicine adoption. Then, by soliciting the experience of an expert panel consisting of three educationalists, and/or researchers the features of the corresponding factors that are considered to have an effect on the intention to adopt telemedicine were reviewed. All the factors and measuring features of the factors were adapted from literature on technology adoption, particularly telemedicine (e-health/m-heath) adoption. A total of 27 items/features were used to measure the influencing factors and 4 items were used to measure outcome variable i.e., telemedicine adoption. The items in the study were measured on a five-point Likert scale that ranges from 1 (Strongly Disagree) to 5 (Strongly Agree).

B. Data Collection

The study's data collection method was a drop-and-collect survey, and paper-based questionnaire was distributed in person. After a fast screening question about whether the respondent utilized telemedicine services in the previous 12 months, interviewers proceeded to the survey and the process was carried out till the defined 384 sample size was collected. The sample size achieved the minimum requirement of 1 independent variable to 10 sample (1:10) as recommendation by Hair et al. [10].

III. DATA ANALYSIS

Within the first stage of data analysis, CFA has been carried out since the feature to latent variables (factors) have been extracted from theoretical considerations. Confirmatory Factor Analysis is a statistical process that involves examining the reliability of the individual feature (item reliability), factor reliability, and convergent and discriminant validity. The association between the factors and its respective features assessed by the outer loading is statistically known as item (feature) reliability. Convergent validity measures whether items can effectively reflect their corresponding factors, while discriminant validity measures whether two factors are statistically different from each other. As first step of evaluation procedure, item loadings were examined. In the study, a loading criterion of greater than 0.60 was considered as significant [11]. The analysis of the item reliability shows that out of 31 items, six items (eHL2, eHL4, eHL7, FC3, TT4, SI4) fail to meet the recommended cut-off point of 0.6 on their corresponding factor. Items with less than a 0.6 loading value were eliminated. Table 1 shows each item's loadings.

The reliability of the factors was examined using Cronbach's Alpha (α) coefficients. As indicated in Table I, the empirical results revealed that the Cronbach's alpha values for all variables vary from 0.71 to 0.87, which exceeds the minimum standard value of 0.7. The statistic used to determine the factor's convergent validity is the average variance extracted (AVE) for all items on each factor. The AVE threshold is 0.50, indicating that the factor explains at least 50% of the variability of its items, indicating good convergent validity [12]. With AVE values ranging between 0.57 and 0.79 (Table 1), the study confirmed convergent validity.

The Fornell–Larcker criterion was used to evaluate the discriminant validity. The square root of each factor's AVE score
was required to be higher than its highest correlation with other factors in the model to determine the discriminant validity of the Fornell–Larcker technique. As seen in the Table 2, the square root of each construct's AVE (in bold) has the highest value when compared to the correlations of other constructs. So, the items as well as factors are deemed as reliable and valid as they satisfied the criteria mentioned earlier. Therefore, the results of the analysis confirmed the features and factors theoretically defined in the research.

A. Multilayer Perceptron (MLP) Neural Network Model

Within the second data analysis stage, the Multilayer Perceptron (MLP) feed-forward-backward-propagation (FFBP) algorithm was employed. To perform so, the neural network module for IBM's Statistical Package for the Social Sciences (SPSS) was used. The MLP-FFBP method is the most popular and widely employed ANN technique [8]. In the FFBP algorithm, the input layer's neurons receive data, which sends the output layer's neurons in a forward direction through the hidden layer's neurons. Consequently, the generated errors are transmitted back to the input layer's neurons through the training process. There is no hard and fast rule for determining the ideal number of hidden layer; one hidden layer is typically utilized in the technology adoption model [13]. Fig. 2 represents the ANN model for this study. The input layer contains neurons which represent the factors performance expectancy, effort expectancy, facilitating conditions, social influence, task technology fit, and e-health literacy in the dataset. The output layer comprises the dependent variable, namely the user's adoption of telemedicine. The layers in between are referred to as 'hidden' layers. As shown in the Fig. 2, neural network model of the present study consists of six predictors, four hidden nodes, and one output variable. The

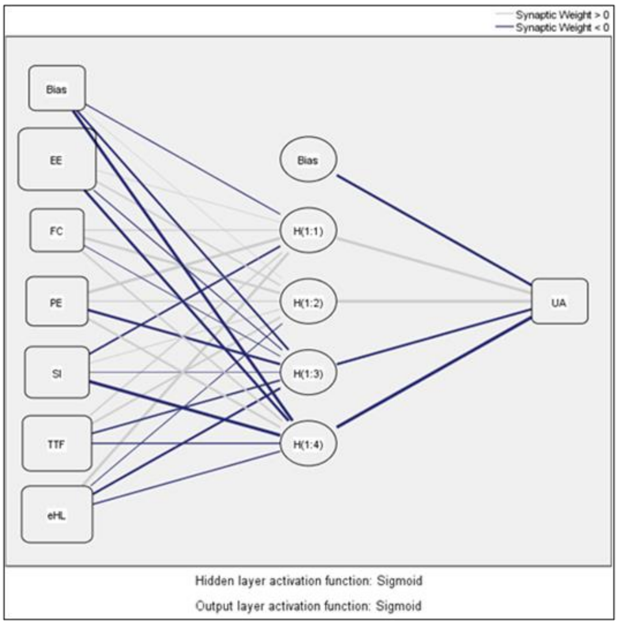

Fig. 2. ANN Model of the Study

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hidden layers are set to one, and there is no heuristic method for determining the hidden nodes in a neural network. The research follows the approach by Alam et al. [14] and Wang and Elhag [15] by examining 1–10 hidden nodes.

Over-fitting is a major issue in the modeling approach. To avoid over-fitting, a ten-fold cross-validation technique was performed to measure the trained network's prediction accuracy, wherein 90% of the data used for training and the remaining 10% of the hold-out data used for testing purpose [16]. To measure of the model's predictive accuracy, the widely used accuracy measure Sum of Square Error (SSE), and Root Mean Square of Error (RMSE) of both training and testing data sets for all neural networks, and the average and standard deviation for both dataset were computed (Table 3) as suggested by several scholars [9], [17]. The RMSE represents the error in training and testing. The closer the RMSE value to zero (0), the better the predicting capacity of the ANN model [18]. This is assuming that the ANN models should be considered as having a higher level of precision when recognizing the correlations because the mean RMSE values are relatively modest with minimal standard deviations in both the testing and training phases. Hence, the study demonstrates high prediction accuracy since the neural model's average RMSE is relatively small and similar.

B. *Sensitivity Analysis*

Furthermore, using sensitivity analysis, each input predictor's relative importance was calculated by dividing each predictor's relative importance with the highest importance predictor (Table 4) and expressed as percentage (%). The results show that EE is the most significant predictor of telemedicine adoption, afterward e-HL (99%), PE (93%), TTF (88%), SI (80%), and FC (73%).

Finally, a Goodness-of-fit index was computed using equation 1, that is relevant as well as comparable to the R^2 in Multiple Regression Analysis (MRA).

R^2 = 1-RMSE/s_2^y_________________________(1)

where s_2^y is the variance of the preferred output based on the average SSE in the testing process [19]. The neural network's R^2 value is 0.66, which implies, the model can explain 66% of the variance in user adoption.

TABLE I. RELIABILITY AND VALIDITY ANALYSIS

Factors	Items	Item Loading	Cronbach's Alpha (α)	Average Variance Extraction (AVE)
e-health literacy (eHL)	eHL1	0.73	0.81	0.63
	eHL3	0.77		
	eHL5	0.84		
	eHL6	0.83		
Effort Expectancy (EE)	EE1	0.75	0.74	0.57
	EE2	0.83		
	EE3	0.77		
	EE4	0.64		
Facilitating Conditions (FC)	FC1	0.88	0.71	0.63
	FC2	0.74		
	FC4	0.74		
Performance Expectancy (PE)	PE1	0.79	0.79	0.61
	PE2	0.84		
	PE3	0.79		
	PE4	0.71		
Social Influence (SI)	SI1	0.86	0.84	0.76
	SI2	0.89		
	SI3	0.86		
Task Technology Fit (TTF)	TTF1	0.87	0.87	0.79
	TTF2	0.9		
	TTF3	0.9		
User Adoption (UA)	UA1	0.8	0.79	0.61
	UA2	0.8		
	UA3	0.83		
	UA4	0.69		

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TABLE 2. DISCRIMINANT VALIDITY BASED ON FORNELL-LARCKER CRITERION

	EE	FC	PE	SI	TTF	UA	e-HL
EE	**0.75**						
FC	0.55	**0.79**					
PE	0.63	0.37	**0.78**				
SI	0.6	0.38	0.58	**0.87**			
TTF	0.47	0.54	0.3	0.39	**0.89**		
UA	0.64	0.59	0.58	0.58	0.51	**0.78**	
e-HL	0.54	0.64	0.42	0.5	0.43	0.61	**0.8**

TABLE 3. RMSE VALUES FOR TRAINING AND TESTING PROCESSES IN A TEN-FOLD ANN

Input neuron: EE, PE, FC, SI, TTF, eHL; Output neuron: UA				
	Training (90%)		**Testing (10%)**	
ANN	SSE	RMSE	SSE	RMSE
ANN 1	3.722	0.204	0.437	0.202
ANN 2	3.625	0.201	0.480	0.217
ANN 3	3.293	0.191	0.366	0.189
ANN 4	3.326	0.194	0.298	0.161
ANN 5	3.463	0.200	0.511	0.198
ANN 6	3.459	0.195	0.344	0.191
ANN 7	3.530	0.199	0.253	0.150
ANN 8	3.494	0.198	0.560	0.231
ANN 9	3.299	0.194	0.459	0.195
ANN 10	3.707	0.203	0.359	0.190
Average	3.492	**0.198**	0.407	**0.192**
SD	0.150	**0.004**	0.098	**0.022**

Note: SSE=Sum of Square Error, RMSE=Root Mean Square of Error

TABLE 4. NORMALIZED VARIABLE RELATIVE IMPORTANCE

Artificial Neural Networks (ANN)	Predictors					
	EE	FC	PE	SI	TTF	eHL
ANN 1	0.142	0.173	0.170	0.191	0.166	0.159
ANN 2	0.170	0.243	0.208	0.136	0.060	0.182
ANN 3	0.177	0.130	0.142	0.161	0.165	0.227
ANN 4	0.212	0.127	0.178	0.145	0.165	0.175
ANN 5	0.203	0.148	0.150	0.172	0.212	0.115
ANN 6	0.176	0.098	0.165	0.159	0.181	0.221
ANN 7	0.218	0.082	0.190	0.141	0.158	0.211
ANN 8	0.163	0.094	0.243	0.145	0.151	0.203
ANN 9	0.190	0.116	0.128	0.181	0.186	0.199
ANN 10	0.227	0.150	0.171	0.077	0.215	0.159
Average importance	0.188	0.136	0.174	0.151	0.166	0.185
Normalized importance (%)	100%	73%	93%	80%	88%	99%
Ranking	1	6	3	5	4	2

IV. DISCUSSION

Based on the findings obtained from the model, effort expectancy is the most influencing predictor of telemedicine adoption. The study's findings reaffirm that there is a substantial positive relationship between effort expectancy and telemedicine service adoption. Users may be deterred from using technology such as telemedicine if they found the technology (telemedicine platform) is complex and difficult to use.

The normalized relative importance ranking result shows that e-health literacy is the second strongest determinant of telemedicine adoption. The finding of this factor is sensible, as education and familiarity with the Internet and technology assist the review of information on any technology.

The result shows that performance expectancy is the third potential determinant of telemedicine adoption. The findings showed that users would have more inclination towards telemedicine if it is useful. Therefore, the telemedicine system (platform) should be properly developed in terms of users' needs to reflect the perceived usefulness of these services.

The result shows that task-technology fit factor is the fourth strongest predictor of telemedicine adoption. The results affirmed that the TTF factor directly impacts users' behavior intentions to adopt telemedicine services. Thus, users who feel that technology is well-suited to the task have a higher intention of adopting telemedicine services in healthcare.

The normalized relative importance ranking result shows that social influence is the fifth strongest determinant of telemedicine adoption. Thus, societal context is an influential factor on one’s intention to use the technology-enabled service and could bring more patient footfalls to the Telemedicine.

The result shows that the facilitating conditions is also important predictor of telemedicine adoption. Facilitating conditions include ICT infrastructure, Internet connectivity, accessibility, technical support, and any other services to assist the users in adopting and using telemedicine services. As a result, extending the use of telemedicine services necessitates enhancing the favorable environment, such as technology and human resources.

V. CONCLUSION

Telemedicine is already an emerging area in world-wide health services, following the Covid-19 pandemic, social distance restrictions, home working practices, and the acceleration of digitalization in healthcare services. It can provide patients with more regular and efficient care than traditional models of healthcare. Based on the research findings, it can be concluded that performance expectancy, effort expectancy, facilitating conditions, social influence, task technology fit, and e-health literacy have significant positive impact towards using telemedicine. A timely assessment of the problems encountered in the implementation of telemedicine services will help evolve the services. A more effective telemedicine system should be established by promoting such health services.

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