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Socio-Technological factors affecting user's adoption of eHealth functionalities: A case study of China and Ukraine eHealth systems

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ABSTRACT Recent studies have shown the rapid adoption of digital health software applications worldwide. However, researchers are yet to fully understand users' rationale of eHealth systems. Therefore, the objective of this study is to analyze user attitudes to eHealth applications in China and eHealth system in Ukraine, and then provide insights and suggestions to the development of an eHealth application (eZdorovya) for health information services in general. The study includes a survey conducted by Chinese and Ukrainian users, after which thorough data analyses were conducted. Based on the Technology Acceptance Model (TAM), this research framework explores the influence of socio-technical factors affecting user's adoption of eHealth functionalities. Serial Multiple Mediator Model 6 (SMMM6) and a deep neural network-based approach were used to analyze the eHealth software users' rationale with the sample size of survey 236 end-users from China and 124 end-users from Ukraine. The key findings from the data analysis are: (1) if the software application is covering an important service function and is interesting to use, Chinese users will continue using it, (2) given an eHealth software with important or interesting function, it is inconclusive whether Ukrainian users will switch to use the application. (3) Deep neural network shows highly accurate prediction results and was given applied suggestions for Chinese and Ukrainian providers in the case of improving eHealth systems based on a raw prediction.

INDEX TERMS Chinese and Ukrainian eHealth systems, mediators, deep neural networks

I. INTRODUCTION

Advances in information and communication technology have provided new opportunities for enhancing existing health care infrastructure to reach wider segments of national populations, and have made eHealth systems very attractive for the purposes of public health management to improve the collection and distribution of data and information. Many studies have suggested that development and promotion of eHealth and the use of electronic processes in health encourages the efficient use of health-related resources including reducing costs, increasing the speed of delivery, saving time, preventing the overuse of or dangerous interactions in medications, reducing travel and removing the need for a physical space to treat every patient [19, 23].

However, there are no studies performed to identify residents' perception of eHealth impacts and attitudes toward eHealth, just a few have assessed relationships between eHealth development and community satisfaction.

This research summarizes the Chinese e-health case experiences (organization, business models, operations, competences and other unforeseen functionalities while comparing it with Ukraine eHealth system. Provide suggestions to Ukrainian e-health organizations based on China's experience. Other factors were also considered. Ukrainian terminology for "Good doctor", protection of personal data, combating corruption, open data (source and code), developing the eHealth together with business, minimizing the burden for taxpayers and finally looking at the benefits of European integration.

The contribution of this paper can be summarized as follows:

1. This empirical research is focused on analyzing how several factors/variables can influence or otherwise inert the respondent's willingness to continue to use services. It shows how the weighty functions positively influence the satisfaction and continue using of eHealth in both China and Ukraine.
2. The study also shows the different attitude that mediates the relationship between interest or importance on continue using of the eHealth system.
3. Satisfaction will mediate the relationship between interest or importance on continue using.
4. The relationship between the key functionality of advanced eHealth providers and the desire to use it in the future is explored through the nonparametric algorithm with a high degree of accuracy (over 80%).

The expected outcome of this research is the provision of a unique Public-Private Collaboration model that made the process of transformation effective, transparent and fast. The introduction of open source and open code as the part of technological implementation demonstrated the highest level of transparency and allowed a wide community to contribute to the National eHealth project. It also showcases the facts that international partners provided the project with all the essential financial and human resources and finally, the implementation of eHealth as the prominent part of the whole healthcare reform and one of the key anti-corruption initiatives that the majority of Ukrainian put as high priority. Therefore, based on the Technology Acceptance Model (TAM), this research further explores

- The influence of socio-technical factors affecting user's adoption of eHealth functionalities. The introduction and application of Serial Multiple Mediator Model 6 (SMMM6) and a Deep Neural Network-based approach used to analyze the eHealth software users' rationale with the sample size of the survey 236 end-users from China and 124 end-users from Ukraine.
- The key findings from the data analysis will be centered on are: (1) what will happen if the software application covering an important service function and if it was interesting to use, will Chinese users still continue using it? (2). If given an eHealth software with important or interesting function, will it be inconclusive whether Ukrainian users will switch to use the application? (4). what will be the result in applying the Deep Neural Network (DNN)? Will it show highly accurate prediction results for Chinese and Ukrainian providers in the case of improving eHealth systems based on a raw prediction?

The remainder of this paper is organized as follows. In Section II, the related works are presented. Section III presents the Technology Acceptance Model (TAM) as the conceptual framework for predicting acceptance of innovation and technology**.** The gathered data was statistically analyzed in Section IV to test the hypothesis Section V presents the proposed techniques. In Section V, performs the Mediation Modeling to test the hypothesis using PROCESS v3.2.01 for SPSS 25. Section VI shows the results of the DNN) analysis. Section VII discusses the results and make a comparison between eHealth China and Ukraine. Section VIII explains the limitation of this research. Section VIII concludes the holistic comprehension of machine learning methods in particular while using the MLP-DNN (multi-layer perceptron – DNN) model.

II. LITERATURE REVIEW

eHealth is the application of information and communications technologies encompasses a variety of digital applications, processes, and platforms including: electronic health record systems, TeleHealth (remote medical consultation), smartphone apps, remote monitoring devices, and biosensors, computer algorithms and analytical tools to inform decision making. [32] The use of technology and Internet connectivity provides new methods for utilizing and improving public and private health services.

Since 2014, China has acquired the fundamental conditions for the implementation of e-health, including the good governance, uniform medical diagnostic standard, hardware and software equipment and information networks, digital medical treatment equipment, manufacturing capacity, the initial EHR and electronic medical records experience. [25] The goals for eHealth in China are to remove the inequities, inefficiencies, poor quality, shortage of health resources, and improper distribution of health resources. They match the goals of e-health, which are efficiency, quality of care, evidence-based, empowerment of consumers and patients, education of physicians, widening the scope of healthcare, ethics, and equity [33]. By 2020, tertiary hospitals will also generally be able to provide online healthcare services, making it easier for patients to see their doctors [20, 21].

Ukraine's economy is among the largest in Eastern Europe with significant potential for growth: anticipated 3% GDP growth in 2019-2020. In 2017, 17 million people joined the eHealth in less than 6 months, which is every third Ukrainian. Ukrainian eHealth was developed by the state-owned enterprise eZdorovya [34] in cooperation with the government, business, IT and civil society. It enables to create a national highly secure eHealth system fast, effectively and transparently. Ukraine could save 0.2% GDP thanks to eHealth. Ukraine could have an increase in efficiency at about 0.28 (have to increase of 2% in overall system efficiency). [28, 29, 30]. Since the beginning of 2018, doctors and patients are signing the declarations to be able to work in the eHealth system. Until the end of 2019 medical events are going to be included in the eHealth system so all the data on this issue will be available online. In addition, the data in the eHealth central component database will be supplemented by the description of the patient's complaint, diagnosis, and electronic prescription. Also, later they are going to introduce a fee for service and DRG-based payment for the entire scope of medical services in the country. [22, 24, 27]

Most of the previous studies [26, 31] have demonstrated increasing of the digital healthcare market in China with limited understanding of the relationships between the user's behavior of the main Chinese eHealth systems as well as the Ukrainian's one. The lack of such research limits the current literature on understanding user's behavior toward the impacts of eHealth in both countries that are important for delivering effective and efficient healthcare services. Therefore, the assessment of e-Health is becoming more valuable. The empirical study is needed in analyzing the booming eHealth industry in China and implementation of this experience on Ukrainian nascent eHealth industry. This research does not compare eHealth systems of the selected countries neither their business models, rather it is based on specific functionalities/characteristics of each system. These include: to investigate the functions of Chinese systems that the customers cared for the most while using the ehealthcare, to evaluate the Apps that performed best in providing services, to figure out the possibility to use the Chinese experience of the eHealth based on the survey and provide suggestions to the Ukrainian system.

III. MATERIALS AND METHODS

A. THEORETICAL FRAMEWORK AND HYPOTHESIS

The Technology Acceptance Model (TAM) was derived from the Theory of Reasoned Action [40], which explains the user behavior of information technology and has been continuously used as the conceptual framework for predicting acceptance of innovation and technology**.** The TAM specifies the causal relationship between system design features, perceives usefulness, perceived ease of use, attitude toward using and actual usage behavior. Overall, the TAM provides an informative representation of the mechanisms by which design choices influence user acceptance and should therefore be helpful in applied contexts for forecasting and evaluating user acceptance of information technology (IT).

For China and Ukraine were used Attitude as "Perceived usefulness", Satisfaction as "Perceived ease of use", Interest and Importance as "Behavioral intention", Continue using as "the Actual system use" and other variables for "External variables" that are shown in Spearman's Correlations (Table 1.1 and 1.2).

According to the results in China indicate that PEU (X17) Satisfaction of App (r=0.782, p=0.000 at 0.01 level 2-tailed), PU (X8.4) Attitude (r=0.561, p=0.000 at 0.01 level 2-tailed) all positively influence ASU Continue Using. The results in Table 3.1 indicate that BI (X14) Interest and (X11.2) Importance are significant factors influencing Continue Using at p=0.000 at the 0,01 level 2-tailed (r=0.291 and r=0.395 respectively). All EV (Attitude: X8.1; X8.2; X8.3; X8.5; X16.1; X16.2; Importance: X11.1; X11.3; X11.4; X11.5) showed significant positive correlation at the 0.01 level (2-tailed).

According to the results in Ukraine indicate that PEU (Y8) Satisfaction with ease (r=0.255, p=0.004 at 0.01 level 2-tailed), PU (Y11.5) Attitude (r=0.303, p=0.001 at 0.01 level 2-tailed) all positively influence ASU Continue Using. The results in Table 3.2 indicate that BI (Y18) Interest and (Y15.1) Importance are significant factors influencing Continue Using at p=0.000 at the 0,01 level 2-tailed (r=0.568 and r=0.349 respectively). Such EV as (Satisfaction: Y10; Interest: Y17; Y19; Y20) showed significantly positive correlation at the 0.01 level (2-tailed), others such as the following (Satisfaction: Y9; Importance: Y15.2; Y15.3; Y15.4) showed significant positive correlation at the 0.05 level (2-tailed).

This study developed a more adequate research framework by integrating the Technology Acceptance Model (TAM). The study draws upon the Technology Acceptance Model as the theoretical basis; it also uses the empirical findings as a pragmatic explanation of key factors affecting willingness to Continue using or switching into App and Continue using eHealth systems. A structured questionnaire was used based on TAM to collect data from respondents in China and Ukraine. The Serial Multiple Mediator Model 6 (SMMM6) was used to estimate direct and indirect effects of the pathways analysis for China and for Ukraine as following: Path 1 "Importance-Continue Using", Path 2 "Interest-Continue Using", Path 3 "Importance - Interest to switch to App&Continue Using", Path 4 "Interest - Interest to switch to App&Continue Using". The DNN was used for prediction results of willingness to Continue Using and Switch into App and Continue Using with the high degree of accuracy trained with all variables for each matrix and comparing it with SMMM6.

Taking into consideration mentioned above, our current research is focused on analyzing how several factors/variables can influence or otherwise inert the respondent's willingness to continue to use services.

Our empirical study will be focused on testing the following Hypothesis:

5. The weighty functions will positively influence satisfaction and consumers will continue using eHealth.
6. Attitude will mediate the relationship between interest or importance on continue using.
7. Satisfaction will mediate the relationship between interest or importance on continue using.

8. The relationship between the key functionality of advanced eHealth providers and the desire to use it in the future can be explored through the nonparametric algorithm with a high degree of accuracy (over 80%).

B. SURVEY

This research uses the survey method to collect data. The online questionnaire was created based on TAM using items adapted from Davis [40] and two Applications: wj.qq.com that developed via the Chinese social network (WeChat) for gathering data from the native and non-native residents of China and Google Forms developed by Google for gathering data from residents of Ukraine via social network Facebook and messenger Viber. The main criteria were: 1) to stay in the country for more than 3 years; 2) have an experience using eHealth systems (for example Haodf, Guahao, eZdorovya, etc.).; 3) be no less than 18 years old and no more than 60 years old.

Our sample size and the preliminary survey was based on the following main criteria: (1) access to certain medical and other groups with native and non-natives of China and (2) access to Ukrainians via Facebook and Viber groups that have been using eHealth system in Ukraine. Due to time-consuming cost-benefit analysis, we worked with 236 quality samples in China and 124 quality samples in Ukraine. The lack of enough sampling will be mentioned in limitations and future discussions.

Altogether, there are 40 items for China and 32 items for Ukraine. All items were measured using a 5-point Likert scale (range from strongly disagree -1to strongly agree -5), except the demographic profiles in both countries. Multiple choices in eHealth providers and ranking (Preference; Importance) in China and four items related to satisfaction in Ukraine were measured using a 10-point Stapel scale (1- very dissatisfied, 10- very satisfied).

IV. MATERIALS AND METHODS

DATA ANALYSIS

The gathered data were statistically analyzed to test the hypothesis. Spearman's correlation coefficient was used because of categorical questionnaire survey data to measure relationships between the e-Health constructs.

According to the respondent's demographics Beijing – 19.9%, Hunan – 14.4%, Hebei – 9.7% are the provinces with the main percentage of both native and non-native respondents in China. The respondents actively started using eHealth in China almost 3 years ago (2019 – 24.6%; 2018 – 28.8%; 2017 – 22.0%). The most preferred are www.alihealth.cn 24.1% and www.haodf.com 21.1%, however, respondents prefer using both websites – 9.3% respectively.

The most respondents were from the residents of: Kyiv – 66.1% Rivne – 16.1% and Ivano-Frankivsk regions, 4.0% respectively. The respondents actively started using eHealth

TABLE I
SPEARMAN;S CORRELATIONS (CONTINUE USING IN CHINA, X18)

X8.1	X8.2	X8.3	X8.4	X8.5	X11.1	X11.2
,490**	,466**	,426**	,561**	,542**	,359**	,395**
X11.3	X11.4	X11.5	X14	X16.1	X16.2	X17
,338**	,325**	,287**	,291**	,413**	,329**	,782**

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

TABLE II
SPEARMAN;S CORRELATIONS (SWITCH TO APP AND CONTINUE USING IN UKRAINE, Y16)

Y8	Y9	Y10	Y11.5	Y15.1	Y15.2
,255**	,209*	,238**	,303**	,349**	,228*
Y15.2	Y15.3	Y17	Y18	Y19	Y19
,228*	,204*	,503**	,568**	,413**	,413**

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

in Ukraine 1.5-3 months ago (24.2%), however 3.5-5 months ago and 7.5-9 months ago, there were two active periods of started using the system, for 15.3% each.

The correlation matrix is shown in Table 1.1 and Table 1.2. The main variables have shown a significant correlation.

V. MEDIATION ANALYSIS

Mediation modeling was performed to test the hypothesis using PROCESS v3.2.01 for SPSS 25 for Windows, written by Andrew F. Hayes [9, 13] based on conceptual Serial Multiple Mediator Model 6 and tested Hypothesis 1, 2, 3.

Model 1 "Importance China", Model 2 "Interest China", Model 3 "Importance Ukraine" and Model 4 "Interest Ukraine" were estimated with such dependent variables (Y) as "Continue Using in China" and "Interest to switch & Continue using App in Ukraine" respectively and Independent variables (X) as "Importance" and "Interest" for all models. Mediators were implemented as "Attitude" and "Satisfaction". [8, 18]

In accordance with the mediation analysis that is most often guided by the procedures outlined by Baron and Kenny [1], the potential mediation effect of Importance and Interest on Continue Using or Interest to switch into App and Continue Using. A necessary component of mediation is a statistically and practically significant indirect effect. The direct and indirect effects were tested using the macros created by A.F. Hayes [11, 12] through the Serial Multiple Mediator Model that is shown in statistical diagram form with two mediators (Attitude and Satisfaction).

The total, direct and indirect effects were calculated (Table 6) according to the tested hypothesis and independent-dependent variables relationship [7, 10].

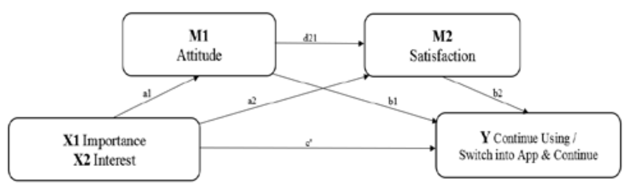

FIGURE 1. Paths analysis.

Path 1: Importance-Continue Using (China).
The path analysis demonstrated a direct effect of Importance (X11.2) on Continue Using (X18), with indirect effects of Attitude (X8.4) and Satisfaction (X17) on Continue Using (X18).

TABLE III
DIRECT AND INDIRECT EFFECTS OF IMPORTANCE ON CONTINUE USING (CHINA)

Direct Effect of Importance on Continue Using					
Effect	SE	t	P	LLCI	ULCI
,0738	,0397	1,8593	,0642	-,0044	,1521
Indirect Effect of Importance on Continue Using					
Effect	Boot SE	Boot LLCI		Boot ULCI	
Ind 1 X11.2→X8.4→ X18 =,0580	,0220	,0164		,1026	
Ind 2 X11.2→X17→ X18= ,0926	,0412	,0160		,1755	
Ind 3 X11.2→X8.4→ X17→X18,1381 = ,1381	,0301	,0832		,2023	
Total Indirect Effect of Importance on Continue Using					
,2887	,0528	,1865		,3960	

Path 2: Interest-Continue Using (China)
The path analysis demonstrated a direct effect of Interest (X14) on Continue Using (X18), with indirect effects of Attitude (X8.4) and Satisfaction (X17) on Continue Using (X18).

TABLE IV
DIRECT AND INDIRECT EFFECTS OF INTEREST ON CONTINUE USING (CHINA)

Direct Effect of Importance on Continue Using					
Effect	SE	t	P	LLCI	ULCI
,0530	,0339	1,5608	,1199	-,0139	,1198
Indirect Effect of Importance on Continue Using					
Effect	Boot SE	Boot LLCI		Boot ULCI	
Ind 1 X14→X8.4→ X18=,0296	,0135	,0072		,0597	
Ind 2 X14→X17→ X18=,1026	,0329	,0407		,1700	
Ind 3 X14→X8.4→ X17→X18=,0638	,0233	,0198		,1119	
Total Indirect Effect of Importance on Continue Using					
,1961	,0476	,1074		,2938	

Path 3: Importance-Interest to switch into App &Continue Using (Ukraine)
The path analysis demonstrated a direct effect of Importance (Y15.1) on Interest to switch into App &Continue Using (Y16), with indirect effects of Attitude (Y11.5) and Satisfaction (Y8) on Interest to switch into App &Continue Using (Y16).

TABLE V
DIRECT AND INDIRECT EFFECTS OF IMPORTANCE ON SWITCH INTO APP AND CONTINUE USING (UKRAINE)

Direct Effect of Importance on Continue Using					
Effect	SE	t	P	LLCI	ULCI
,2550	,0770	3,3105	,0012	,1025	,4075
Indirect Effect of Importance on Continue Using					
Effect	Boot SE	Boot LLCI		Boot ULCI	
Ind 1 Y15.1→Y11.5→ Y16=,0370	,0324	-,0224		,1074	
Ind 2 Y15.1→Y8→ Y16= -,0150	,0240	-,0658		,0326	
Ind 3 Y15.1→Y11.5→ Y8→Y16,0229	,0151	,0017		,0601	
Total Indirect Effect of Importance on Continue Using					
,0449	,0377	-,0219		,1271	

Path 4: Interest- Interest to switch into App &Continue Using (Ukraine)
The path analysis demonstrated a direct effect of Interest (Y18) on Interest to switch into App & Continue Using (Y16), with indirect effects of Attitude (Y11.5) and Satisfaction (Y8) on Interest to switch into App & Continue Using (Y16).

TABLE VI
DIRECT AND INDIRECT EFFECTS OF INTEREST ON SWITCH INTO APP AND CONTINUE USING (CHINA)

Direct Effect of Importance on Continue Using					
Effect	SE	t	P	LLCI	ULCI
,4321	,0607	7,1241	,0000	,3120	,5522
Indirect Effect of Importance on Continue Using					
Effect	Boot SE	Boot LLCI		Boot ULCI	
Ind 1 Y18→Y11.5→ Y16= ,0178	,0171	-,0078		,0593	
Ind 2 Y18→Y8→Y16= -,0235	,0207	-,0687		,0159	
Ind 3 Y18→Y11.5→Y 8→Y16=,0124	,0092	-,0003		,0347	
Total Indirect Effect of Importance on Continue Using					
,0067	,0283	-,0460		,0687	

TABLE VII
DIRECT AND INDIRECT EFFECTS OF X ON Y

	CHINA		UKRAINE	
	Y : Continue Using; X1 : Importance (X11.2)	Y : Continue Using; X2 : Interest (X14)	Y :Interest &Continue Using; X1 : Importance (Y15.1)	Y :Interest &Continue Using X2 : Interest (Y18)
Indirect effect 1 (a1b1)	,0580	,0296	,0370	,0178
Indirect effect 2 (a2b2)	,0926	,1026	-,0150	-,0235

Indirect effect 3 (a1d21b2)	,1381	,0638	,0229	,0124
Direct effect (c')	,0738	,0530	,2550	,4321
Total	,3626	,2491	,2999	,4388

VI. DEEP NEURON NETWORK ANALYSIS

In the current study, we would like to show the results of the DNN analysis as an alternative to the parametric mediation analysis, since non-parametric machine learning allows for prediction without the requirement of a normal distribution of quantities. DNN covers a large number of observations of independent variables allows predictions based on data that are not normally distributed and do not have a significant correlation relationship.

DNN has achieved breakthroughs in modeling nonlinearity in wide applications, such as image recognition, machine translation, and speech recognition [35, 36].

DNN research has made tremendous progress in the last several years. The empirical success of deep learning has thus far eluded interpretation through existing lenses of computational complexity, numerical optimization [5] and classical statistical learning theory [37]: neural networks are highly non-convex models with extreme capacity that train fast and generalize well.

In fact, not only do large networks demonstrate good test performance, In fact, smaller networks may cause underfitting while larger networks may cause overfitting, so a suitable framework needs to bring forward. However, the use of DNN is sometimes restrictive due to large size and intensive computations. To address these issues, many different techniques have been suggested including vector quantization, weight pruning, and hashing trick.

There exists in the literature a limited number of works that make use of DNN to predict users behavior. In the current study MLP-DNN (multi-layer perceptron – D) was used that showed high results in prediction users behavior.

Figure 2 shows the overall research procedure using the MLP-DNN method of our study. Our network is made up of four hidden layers with eight neurons for each.

Based on ideas of deep learning [2, 3, 4, 6, 14, 38, 16, 17. 41] we used the proposed methodology.

Throughout different examples, we found that statistical pre-processing plus a decomposition of the series into easy-to-observe features improves its overall performance (computational efficiency and accuracy). The proposed methodology (see Fig. 2) is described as follows: statistical pre-processing; deep perceptron; deep neural net.

We were using multi-layer backpropagation or time delay networks using the sets of inputs and outputs.

The quantity of hidden layers depends on data complexity. As always, the amount of neurons per hidden layer is a degree of freedom that depends on the available data. The 3- and 5- layers were tested but the optimal results were shown on 4- hidden layers. For the main analysis, we searched for values for 5 outputs (categories). Different categories were used on the input (for example if we have 5 answer choices - 5 neurons [0,1,0,0,0]; 2 choices- 2 neurons; in case of gender: F - 0,1; M - 1,0; Age: 0,5; 0,2; 0,1). On the output, the dependent variables were converted into categories (5 neurons/categories). For additional analysis (practical applications), we used float mode (what should be improved). Thus, we had 1 “y” output (5- “1”; 1 - “0”) or (5- 1; 4- 0,8; 3- 0,6; 2- 0,4; 1- 0,2). ReLu was used as an activation function in our experience. Learning rate = 0, 0001.

The main steps of network training and results:

The first step was to obtain the experimental dataset and collecting data in a table. The next step was converting the data into module Pandas data frame (two columns one with independent and another with dependent variables in the category format). The last step was creating the one cycle with the number of iterations, due to the limited amount of a data set. The processes carried out inside the cycle of iterations include the following: 1) mixing data; 2) dividing the data frame into train and validation of data; 3) creating a network and teaching on fitting data a certain number of epochs (200, 500, 600, 2000, etc.,); 4) at each episode, the accuracy on validation of data (P from p) was measured and recorded; 5) each next iteration in this list is added

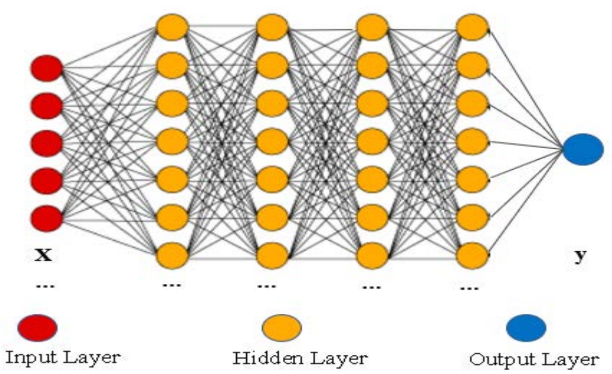

FIGURE 2. **Deep Neural Network (MLP-DNN).**

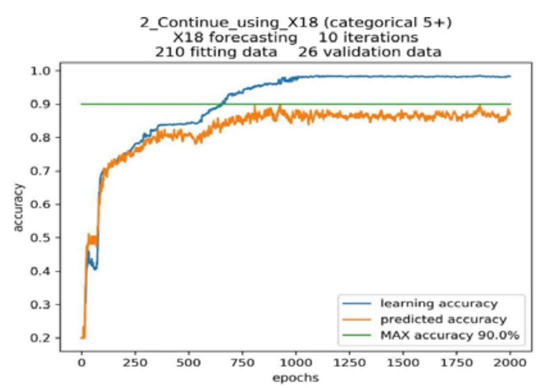

FIGURE 3. **DNN results for X18 (Continue Using in China)**

(+%...); 6) the average value of the number in the list is determined.

Analyzing the willingness to continue using the Chinese eHealth on 2000 epochs with 10 iterations that can be seen in Figure 3, analysis was taken with 210 fitting data and 26 validation data and the result shows prediction accuracy with the MAX value reaching 90.0%. Adding additional variables (X10.3; X10.5; X10.6; X13.3) to others (in the previous experiment) that showed a significant correlation at the 0.01 level 2-tailed (including Satisfaction, Attitude, Interest, Importance) we can see increasing in max accuracy results in 2.12%. It is advisable for Chinese eHealth providers to use not only the main variables with a significant correlation but others as well for making a decision in improving the interest of consumers while continue using the system to achieve a higher MAX accuracy result.

Analyzing the interest to switch to eZdorovya App and continue using in Ukraine can be seen in Figure 4. For analysis were taking 104 fitting data and 20 validation data for 10 iterations. The results on 2000 epochs were shown prediction accuracy with the MAX value reached 84.0%. All variables that showed the significant correlation at 0.01 and 0.05 levels as well as insignificant correlation at no less than 0.117 was used for the forecasting and can be offered to Ukrainian eHealth provider (eZdorovya) as the key to making a decision in improving the interest of consumers to continue using the system with a high MAX accuracy for a small dataset.

Besides, simulated certain values of independent variables, we can develop a model for predicting human behavior by changing different meanings. This allows us to make recommendations for eHealth providers improving the effectiveness and efficiency of the use of eHealth systems, both in China and in Ukraine.

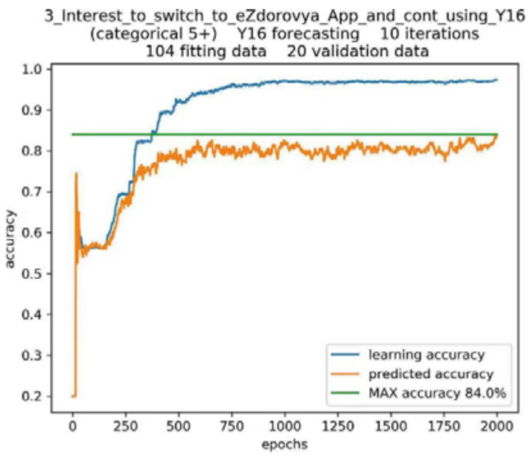

FIGURE 4. **DNN results for Y16 (Continue Using in Ukraine)**

TABLE VIII
RAW PREDICTION OF THE INFLUENCE OF THE MAIN INDEPENDENT VARIABLES ON CONTINUE USING

Scale	China			
	Attitude (X8.4) Haodf	Importance (X11.2) AliHealth	Interest (X14) Guahao	Satisfaction (X17) AliHealth
1	0.5216	0.5724	0.8556	0.5858
2	0.5512	0.5821	0.8864	0.5660
3	0.5642	0.5755	0.8708	0.5755
4	0.5726	0.5794	0.8733	0.6422
5	0.5783	0.5872	0.8811	0.7413
Scale	Ukraine			
	Attitude (Y11.5)	Importance (Y15.1)	Interest (Y18)	Satisfaction (Y8)
	eZdorovya			
1	0.6831	0.6451	0.8497	0.5743
2	0.5702	0.6405	0.8627	0.6729
3	0.6454	0.6454	0.8411	0.6389
4	0.7427	0.6077	0.8981	0.6516
5*	0.6175	0.7345	0.9362	0.6525

* in Y8 (Ukraine) the 10-score scale with the following: "6" - 0.64545125; "7" - 0.64196354; "8" - 0.72490317; "9" - 0.75007397; "10" - 0.6837713

To show the results in the practical application of the neural network, we created 2400 possible examples were created for increasing or decreasing the indices of independent variables both in China and in Ukraine. To understand the impact on the Continued using the system of each individually important independent variable that we analyzed in mediation analysis, we used the same values for all other independent variables on a scale of 1-5 or 1-10. The neural network divided the values from 0 to 1. We received the results of the raw prediction and the normal prediction (raw prediction * 5). A description and detailed analysis of a large dataset that we received after analysis obtained is a basis for further research. Table 7 includes the main independent variables, and the graphs show the impact of each variable on the desire to continue to use the eHealth system. For this analysis, we chose the users of Beijing as a focus group according to the largest number of responses received on the questionnaire.

According to China's results, there was a difference between gender and age. In X8.4 (Attitude), women in the age group 26-30 years old have a higher prevalence of raw prediction than males at the same age group, however it observed on the contrary at the age of 36-40. In this case, the difference in meanings shows between male and female varies by no more than 0.08 divisions in X8.4. However, the independent variables X11.2 (Importance), X14 (Interest) and X17 (Satisfaction), show a tendency in higher raw prediction rates for men than for women with an average difference of 0.04 values, including the higher results among the 26-30 than the 36-40 year-olds surveyed. Due to the insufficient number of data in Ukraine, there were no differences in gender and age.

In this experiment, according to the graphs presented in Figure 5, the effect of each major independent variable was backed up by additional independent variables with an average grade of each of 3 points on a scale of 1-5. The graph, X8.4 (Attitude to a self-selected doctor or hospital) shows a gradual and smooth increase of the function. Thus, according to the average result of the survey (with the rate of 3.54 out of 5), we can suggest the Haodf provider to invest in the development of this functionality that gives positive results on the users desire to continue using the application (Δ = 0.0084 increasing from "3" to "4" or Δ = 0.0141 between "3" and "5" respectively).

According to the graph, X11.2 (Importance of pharmaceutical applications), shows a skewness that depends on the different user's relationship to this functionality: for example, in case of investing enough money in the promotion or improving the interface. The interest of consumers to continue using the Alihealth application can significantly increase when the average results of the survey show 3.88 out of 5. It also indicates insufficient expectations when investing a small amount of capital. According to the graph X14 (Interest in clinics outside China), we cannot recommend Guahao to invest in the development of this function. Therefore, it is not appropriate to consider making a significant investment that at this stage cannot significantly increase the interest of this function in the population of Beijing (the average value according to the survey was received 3.467).

In graph X17, (satisfaction with the application) with the investment of even insignificant capital will be observed a tendency to increase interest in continuing using of the application, while still 3.477 is the average value for this variable (Δ = 0.0667 increasing from "3" to "4" or Δ = 0.1658 between "3" and "5" respectively).

The use of eHealth system is at the early stage in Ukraine, so it is necessary to distribute investments rationally. The focus group was chosen in Kyiv, according to the largest number of applicants there. For example, in Figure 6.1 in Y11.5. (Attitude to eZdorovya system quality services) there is the existing anti-rating at the beginning and in Y8 (Satisfaction of the system) there is a peak in the beginning through the existing protest category of users. In our opinion, it is necessary to make not a significant investment, because of the tendency that declines in interest in both variables at a significant investment. However, in Figure 6.2, the Satisfaction (Y8) shows the rapidly increasing from "7" to "9" (1-10 scale) with the highest result at "9" that indicates that investments will positively influence on continuing use the system in the given interval, but without reaching the maximum index "10". In the case of Y15.1 (importance of e-prescriptions) and Y18 (interest in the insurance), only significant investment in the functionality, interface or advertising can increase the interest in continuing the use of the system with the transition to the application.

The significant investments in increasing of willingness to Continue using through Importance of e-prescriptions can achieve significant results (Δ = 0.1268 increasing from "4" to "5"). Among the selected features, users are most valued by the interest in the possibility of connecting the insurance system investing in which can show the following results Δ = 0.0569 increasing from "3" to "4" or Δ = 0.0951 between "3" and "5" respectively.

The more in the network of neurons and the more we train in more epochs, the more possibilities to overhang the network (overfitting). In this study, overfitting is clearly observed in Ukraine firstly because of not enough amount of data, as well as many epochs and neurons.

According to the raw prediction Figure 6.1 and Figure 6.2, it shows that, China has a positive affinity for increasing the interest in an individually selected doctor or institution through the app. It is also a positive indicator for a possible recommendation in adding the mobile version of eZdorovya with the functionality of choosing an appropriate doctor or medical institution in Ukraine.

Therefore, in comparing Chinese and Ukrainian functionalities, we can argue that according to Figure 7, the

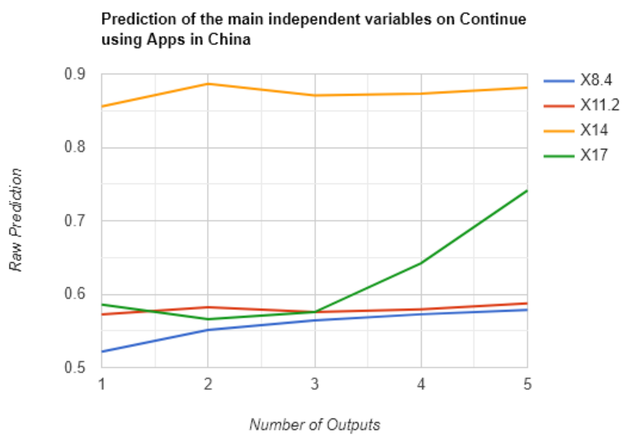

FIGURE 5. Raw prediction of the main independent variables on Continue Using Apps of the eHealth providers in China
A.X8.4 Attitude; B.X11.2 Importance; C.X14 Interest; D.X17Satisfaction

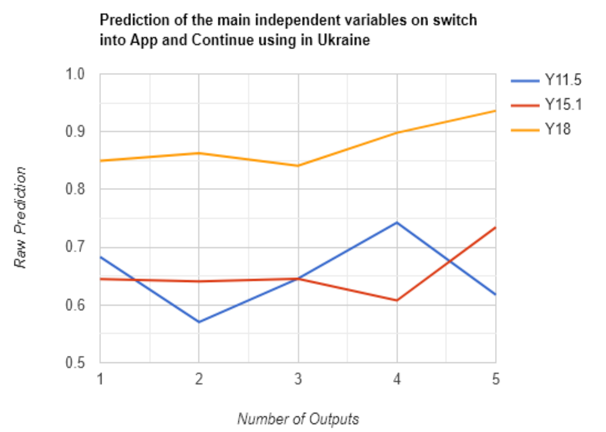

FIGURE 6.1 Raw prediction of the main independent variables of the eHealth provider in Ukraine (1-5 scale)
Y11.5 Attitude; Y15.1 Importance; Y18 Interest

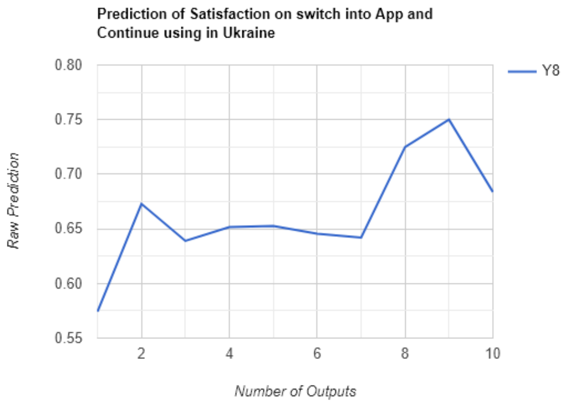

FIGURE 6.2 Raw prediction of the main independent variable of the eHealth provider in Ukraine (1-10 scale)
Y8.Satisfaction

Interest in using pharmaceutical applications is significant both for China (X11.2 ICN) and for Ukraine (Y15.1 IUA). It is noted that in both countries the most significant interest is in the Satisfaction of the use of systems AliHealth (X17 SCN) and eZdorovya (Y8 SUA) respectively. We noted that users believe that in China AliHealth App prevails over both categories of functional and China's experience of investing in the development of these characteristics is necessary. We can recommend to Ukraine to pay attention to the peculiarities of development, including the marketing strategy of each of these functions/characteristics in AliHealth Apps.

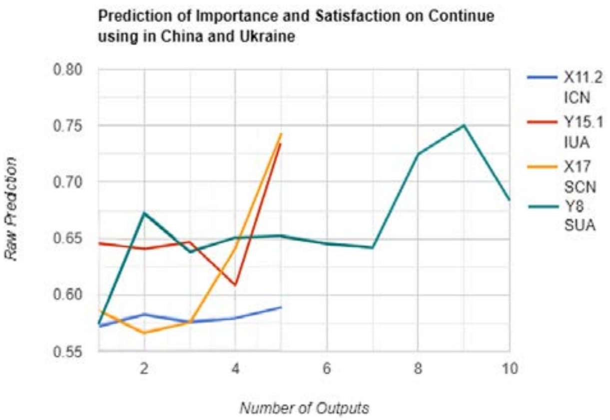

FIGURE 7. Raw prediction of the main significant independent variables of the eHealth providers in China and Ukraine
X11.2 ICN (Importance China), Y15.1 IUA (Importance Ukraine), X17 SCN (Satisfaction China), Y8 SUA (Satisfaction Ukraine)

VII. DISCUSSION

Most of the answers (variables) were distributed normally except X8.1, X10.6, X11.1, X11.3, X11.4, X11.5, X13.5, X16.1, X13.1 in China; Y16, Y19, Y20, Y12 in Ukraine that has a clear skewness. Most of answers the have a positive correlation that was expected and key variables (China: X11.2, X14, X18, X8.4, X17; Ukraine: Y15.1, Y18, Y16, Y11.5, Y8) showed a significant correlation at 0,05 level and X14 (China) at 0,01 level. Few significant correlations were in China in X10.1, X10.3, X13.5, X14. There was no significant correlation in Ukraine only in Y21 except between Y19 and Y15.1 at 0,01 level, which means that in most cases there is a significant relationship between the characteristics of eHealth and desire to Continue Using (**Hypothesis #1 accepted**).

Using conceptual Serial Multiple Mediator Model 6 and PROCESS extension in SPSS by A.F. Hayes, it received the set of indirect, direct and total linear regression models that explain the relationship between importance/interest and willingness to continue using/switch into App & continue using. All regression model summaries show good feet of experimental data ($P<0,05$) in China. According to the conceptual model mentioned above, in China the direct effect independent variable Importance on dependent Continue Using = 0.0738, total indirect effect =0.2888 and independent variable Interest on dependent Continue Using = 0.0530, total indirect effect =0.1961 which means that there is a significant role of mediators on Continue Using the App. Thus, our **Hypothesis #2 and #3 are accepted for China** and mediators Attitude (X8.4) and Satisfaction (X17) have an important role in the comprehension of the relationship between X and Y (Importance/Interest and Continue Using respectively).

Performing the same path analysis in Ukraine, we have investigated the relationship between Importance/Interest and Switch to App & Continue using through mediators, Attitude and Satisfaction is not significant. According to conceptual model, direct effect independent variable Importance on dependent Switch to App &Continue using = 0.2550, total indirect effect = 0.0449 is with a significant difference. The similar shows with the direct effect of the independent variable Interest on dependent Switch to App &Continue using = 0.4321, total indirect effect = 0.0067 is with an extremely significant difference. It means that in Ukraine, the direct effects of both paths are much higher than total indirect effects, both Mediators are useless to describe the relationship between X, and Y and **Hypothesis #2 and #3 are rejected for Ukraine**.

Since the set of linear regression equations and mediation function approach does not allow to get a full understanding of the association between dependent and independent variables (because of their not normal distribution among several variables and in some cases insignificant correlations), there is a need of using the machine learning methods to identify connections between independent and dependent variables. The non-parametric method of machine learning (DNN) based on training data allows us to learn the dependence between a complete set of independent variables. Their influence on the prediction of the dependent variable has been used in this study. After the training of the neural network, it was possible to achieve maximum value of foresight accuracy (learning accuracy –

about 99%) that allowed the neural network to predict a different set of data to verify the quality of the prediction. According to the results of prediction using the neural network, a degree of accuracy about 83% is seen that allows us to conclude that on the basis of our training data, the neural network can have a high degree of accuracy to predict behavior and attitude of people to eHealth systems and continue to use it on the basis of the entire spectrum of independent variables. Experiments with the possibility of practical recommendations for independent variables Attitude, Interest, Importance and Satisfaction showed significant gender-related and age-related interdependencies in China with predominance in higher raw prediction results among males at the age of 26-30 and did not show any dependence due to insufficient data in Ukraine that is the reason for further research. As for practical recommendations for China, the possibility of a gradual increase in the interest to continue using applications with rational investment in the functional, interface or media promotion X8.4 (Attitude), X11.2 (Importance), X17 (Satisfaction) can be utilize, considering that a significant investment in the X17 (Satisfaction) could increase the interest in continuing to use the application in the dependence of $\Delta = 0.1658$ increasing from "3" to "5". At the same time, investment in the X14 (Interest) is not recommended. According to Ukraine, it is suggested to invest in Y18 (Interest) and Y15.1 (Importance) with possible significant results ($\Delta = 0.0951$ increasing from “3” to “5” and $\Delta = 0.1268$ significantly increasing from “4” to “5” respectively). Based on the Chinese experience the recommendation in a mobile version of eZdorovya application with the functionality of choosing an appropriate doctor or medical institution in Ukraine has been provided. Thus, the **Hypothesis #4 is accepted**.

VIII. LIMITATIONS

Due to time-constraints in gathering the questionnaire survey, enough data was not collected. Compared to mediating analysis, the DNN analysis takes a lot of time to train the neural network, revise learning accuracy and raw prediction. The over-fitted was observed because of not enough data, many epochs, and neurons.

IX. CONCLUSION

Current study helped to get the more holistic comprehension of machine learning methods in particularly using the MLP-DNN (multi-layer perceptron – DNN) model that can be as a background for further research for predicting the willingness to continue using and eHealth user’s behavior. According to applied experiments suggestions in the rationality of investments have been given to Chinese eHealth providers particularly in the functional, interface or media promotion with increasing the Continue using of applications through X8.4 (Attitude), X11.2 (Importance) and significantly through X17 (Satisfaction). Suggestions were given for developing the Ukrainian eZdorovya system to invest in Y18 (Interest) and through significant investment in Y15.1 (Importance) the possible significant result in switching into an application and Continue using the system can be achieved. The other data showed interesting results in skewness on graphs that are the reason for further research. In the near future, the eHealth of other countries including that of Saud Arabia will be considered.

The current work was checked by PlagScan and received 8% as the similarity index.

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