

Research Article

An Integrated SEM-Neural Network Approach for Predicting Determinants of Adoption of Wearable Healthcare Devices

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The advancement in wireless sensor and information technology has offered enormous healthcare opportunities for wearable healthcare devices and has changed the way of health monitoring. Despite the importance of this technology, limited studies have paid attention for predicting individuals' influential factors for adoption of wearable healthcare devices. The proposed research aimed at determining the key factors which impact an individual's intention for adopting wearable healthcare devices. The extended technology acceptance model with several external variables was incorporated to propose the research model. A multi-analytical approach, structural equation modelling-neural network, was considered for testing the proposed model. The results obtained from the structural equation modelling showed that the initial trust is considered as the most determinant and influencing factor in the decision of wearable health device adoption followed by health interest, consumer innovativeness, and so on. Moreover, the results obtained from the structural equation modelling applied as an input to the neural network indicated that the perceived ease of use is one of the predictors that are significant for adoption of wearable health devices by consumers. The proposed study explains the wearable health device implementation along with test adoption model, and their outcome will help providers in the manufacturing unit for increasing actual users' continuous adoption intention and potential users' intention to use wearable devices.

1. Introduction

By the advancement of wireless sensor and information technologies, wearable healthcare devices have emerged as a new technology through which people can easily monitor their physiological conditions. A wearable healthcare device can be defined as “a device that is autonomous, that is noninvasive, and that performs a specific medical function such as monitoring or support over a prolonged period of time” [1]. Consumers by adopting an appropriate wearable device, for instance, “Jawbone UP” and “Fitbit Flex,” can monitor and track daily health physiological conditions such as heart rate, perspiration, event notifications, sleep pattern, body temperature, and calories burned [2]. The collected data from wearable devices can be used by consumers to manage their health conditions via smartphones or other mobile applications. Furthermore, the physical data monitored by a wearable device can be transmitted to hospitals for

healthcare facilities. This means that remote monitoring of physical data and health status is feasible. Remote assessment of patients' health status might also remarkably decline medical expenses by reducing the number of unnecessary patient visits to medical facilities [3, 4].

The wearable health devices not only are considered as hardware but also discover users' important features by using mobile application and web software. These wearable devices are considered as a type of hardware which understands the effective features through the Internet and mobile application which are cooperated by the data gathered with the devices. A recent survey by Lee and Lee [4] found that, for decreasing the medical cost, the wearable healthcare device is considered as the best solution. The research carried out by Roman et al. [5] uncovered that wearable healthcare devices contributed to saving \$305 billion medical cost in the United States alone. Therefore, adoption of wearable healthcare devices is critical for individuals to save their medical cost.

Despite the functionality and significant anticipated benefits of wearable healthcare devices, there is a dearth of research investigating the individual's intention for the adoption of wearable healthcare devices because they are still within the early phase of commercialization [6]. This is in accordance with the research by Barnes et al. [7], which revealed that a considerable number of people were interested in using wearable healthcare devices; however, few of them adopted wearable healthcare devices. Therefore, identifying the key factors that influence individuals' intention for the adoption of wearable healthcare devices is significant, as it will assist wearable device providers to create the suitable marketing plan, leading to higher adoption rate of wearable healthcare devices.

To fill the gaps in the existing literature, this study has proposed a new research model for the forecasting of individuals' behavior intention and analyzing the key factors that influence the decision to the adoption of wearable healthcare devices. The originality of the model approached in this research revolves around the fact that, besides well-known predictors of new technology adoption, such as perceived usefulness and perceived ease of use, it also includes factors such as health interest, perceived expensiveness, consumer innovativeness, and compatibility, which were examined in few studies. Hence, this study aimed at identifying most key drivers that influence adoption of wearable healthcare devices and their particular relative significance. One of the primary shortcomings of conventional statistical techniques which are applied for the forecasting of individuals' behavior is that they generally test only linear relations among factors. In order to tackle this issue, neural network (NN) was applied for the relative importance of key factors, which can extract complex nonlinear relationships. The primary motivation for this research is the need to propose a model that addresses the shortcomings in previous studies in terms of predicting individuals' influential factors for adopting the wearable healthcare devices. Special attention is given to accomplish a more accurate forecasting method in comparison with the usual regression methods. In addition, to understand an appropriate research technique and gain benefits through the use of an integrated method, the SEM-NN model was applied.

The structure of the paper is arranged as follows: the literature review of prior studies on adoption of wearable technology is given in Section 2. In Section 3, the hypothesis and model developments are presented. The applied methodology is explained in Section 4, while in Section 5 neural network analysis and results are illustrated. Discussion and conclusion are given in Section 6, and finally, limitation and future research are described in Section 7.

2. Literature Review

2.1. Technology Acceptance Model. The analysis of individuals' behavior and determinant's drivers which influence their decision for new technology adoption, like health information technology adoption, is usually carried out using associated well-determined theories for adoption of technology, for instance, unified theory of acceptance and use of technology (UTAUT), theory of planned behavior (TPB), task-technology

fit (TTF), diffusion of innovation (DOI), and Technology Acceptance Model (TAM) [8]. In the information systems literature, to explore the determinants for acceptance of technology, TAM had been applied [9] as a powerful model to investigate the determinants of user acceptance [10]. Several studies in the information systems discipline have confirmed the explanatory power of TAM in the acceptance and adoption studies [11–14]. Moreover, to better clarify and forecast individuals' behavior, many studies have recommended that TAM should be extended by including other constructs [15, 16].

TAM consists of two main components: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is described as “the degree to which a person believes that using a particular system would enhance his or her job performance” [17]. PEOU is described as “the degree to which a person believes that using a particular system would be free of effort” [9]. TAM suggests links of the mentioned central constructs with other constructs, which are “behavioral intention to use the technology” (BI). BI is described as “the degree to which a person has to formulate conscious plans to perform or not to perform some specified future behavior” [18].

2.2. Related Studies on Wearable Technology Adoption. In the minds of users, smart watches and wearable technologies are considered as a new technology; therefore, the consumer's acceptance needs to be examined [19]. In spite of extensive theories for technology adoption, a limited number of studies have been performed to analyze the users' intention for wearable device adoption specifically in healthcare [2]. In this section, the summary of the previous studies on wearable technology has been presented. In the study conducted by Dehghani [19], the motivational factors including (enabling technologies, health-ology, and complementary goods) have been explored on continuous usage intention of smartwatches among actual users. Chae [20] extended the TAM acceptance model to examine consumer acceptance for smart clothing. The result of the study showed that PU is considered as the most influential factor, which influences consumers' attitude to smart clothing acceptance. Furthermore, the study by Lee and Lee [4] showed that health interest and personal innovativeness are statically significant factors for individuals' intention for wearable fitness tracker adoption. According to Yang et al. [6], that perceived value is a very important influential factor which influences user acceptance of wearable devices. Table 1 highlights the previous studies that contributed to wearable technology adoption.

3. Hypotheses and Model Development

The behavior intention is widely deemed as the best predictor of behavior in previous studies [8, 9]. Because wearable health technology is still in the very early phase of adoption, this study decided to examine behavioral intention as a dependent variable for wearable technology adoption, not actual use.

3.1. Perceived Usefulness. Perceived usefulness is considered among the core variables in the TAM model, and it is continually initiated to have an important impact on the

TABLE 1: Related studies on wearable technology adoption.

| References | Technology | Theory | Method | Variables |
|------------|------------------|---|-------------------|--|
| [19] | Smartwatch | N/A | Qualitative study | “Perceived usefulness, perceived ease of use, enabling technologies, functionality, complementary goods, continuous usage intention” |
| [21] | Wearable device | UTAUT | Survey | “Performance expectancy, hedonic motivation, privacy concern, facilitating conditions, hedonic, trust, effort expectancy” |
| [6] | Wearable device | Extended TAM | Survey | “Hedonic motivation, social influence, risk, functionality, perceived ease of use, visual attractiveness, perceived ease of use, brand name, perceived usefulness” |
| [22] | Wearable device | Reference group theory, TAM, and health belief mode | Survey | “Health belief, perceived convenience, health belief, perceived usefulness, perceived credibility, consumer innovativeness, perceived interpretability” |
| [2] | Wearable device | Privacy calculus theory | Survey | “Perceived privacy risk (information sensitivity, perceived prestige, legislative protection, personal innovativeness legislative), perceived benefit (perceived informativeness, functional congruence), adoption intention, actual adoption” |
| [23] | Smart glasses | Extended TAM | Survey | “Complexity, self-efficacy, usefulness, health concern, ease of use, risk, intention, external influence” |
| [24] | Smart glasses | Extended TAM | Survey | “Hedonic motivation, perceived ease of use, perceived usefulness” |
| [25] | Fitness wearable | N/A | Focus group | “Perceived effort, utilitarian benefits, gender, physiological traits, social influence, hedonic” |
| [26] | Wearable device | Extended UTAUT | Survey | “Facilitating conditions, social influence, trust, performance expectancy” |
| [27] | Smart glasses | TAM | Survey | “Technology risk, perceived usefulness, privacy, hedonic motivation, image, perceived ease of use, norms” |

acceptance of new technology. In the context of wearable technology adoption, Weng [28] defined PU that “user believes that using wearable devices would be beneficial to his or her health.” In comparison to other constructs in the TAM model, PU and PEOU are considered as antecedents and the most influential factors for new technology adoption. In several areas of the research, PU has found as the predictor of new technology acceptance; similarly, the studies on wearable technology adoption have explored that PU among the examined forecasters of intention to use wearable technology [6, 19, 22]. Similarly, to UTAUT and TAM2, PU has a direct influence on behavior intention (BI). The study expected that the consumer’s perceived usefulness of the health wearable technology will be influenced by perceived usefulness of the existing current applications of the wearable technology. Therefore, this study hypothesized that

H1: Individuals’ perceived usefulness affects their intention in the wearable healthcare device context.

3.2. Perceived Ease of Use. Perceived ease of use was considered also among the core constructs in the TAM model. Davis [9] who proposed the TAM model suggested that individual’s motivation on technology will be influenced by PU and PEOU. The role of PEOU as a contributing factor for use and adoption has been studied widely by TAM researchers. The results from these studies have found that there is an overall agreement among researchers that PEOU has an either indirect or direct and positive effect on individuals’ behavioral intention to use new technology in several contexts [12]. In line with the previous studies, this result also was approved in the context of wearable technology [24, 29]. Therefore, in the case of wearable health devices, PEOU is described as how the

product design is easy for use and how users expect that the wearable technologies will be easy to learn and an interaction technique. Therefore, this study hypothesized that

H2: Individuals’ perceived ease of use affects their intention in the wearable healthcare device context.

3.3. Initial Trust. In general, trust has been characterized by its stages of development. Jarvenpaa et al. [30] distinguished among mature and initial stages of trust. Wearable health devices are still in their early stage of development and adoption, and several consumers are not totally familiar with the product characteristics and whole aspects of it; therefore, they have initial trust (IT) on the product. But, after a while, mature trust will be developed once customers were consistently satisfied with the products and services. The proposed study focused on studying individuals’ initial trust in wearable health device. Liébana-Cabanillas et al. [8] revealed that trust is “a critical factor in stimulating purchases over the Internet, especially at this early stage of commercial development.” Although trust, not the only construct, is considered to predict the user’s behavior intention, many scholars found that there is a significant and positive relationship between trust and the user’s behavior intention [21, 31, 32]. Previous studies in various contexts widely supported the idea that trust has a positive influence on BI and is considered as the strongest predictor of BI [32, 33]. To extend these studies into wearable health devices, the following hypothesis can be proposed:

H3: Individuals’ initial trust affects their intention in the wearable healthcare device context.

3.4. Consumer Innovativeness. Rogers [34] defined innovativeness as “the degree to which an individual is

relatively earlier in adopting new ideas than the average member of his social system.” Steenkamp et al. [35] viewed consumer innovativeness (CI) as individuals’ willingness and tendency to be attracted by new products or technology. Previous studies have validated important influence of CI on BI. The DOI theory which proposed by Rogers [36] revealed that users with high innovativeness are able to handle uncertainty and higher intention for new technology adoption. Other studies have confirmed that CI affects the BI for new product, service, or technology usage [2, 4, 22, 35, 37]. Since the wearable health device technology is quite new, the existing users are early adopters, so CI may be of high importance on intention to adopt. Thus, in the proposed study, we hypothesize that

H4: Individuals’ consumer innovativeness affects their intention in the wearable healthcare device context.

3.5. Compatibility. The compatibility is defined by Adopter [38] as “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters.” Moreover, Lu et al. [39] revealed that “compatibility captures the consistency between an innovation and the potential adopters’ existing values, current needs, and present lifestyle.” Several studies described the compatibility variable as “technical compatibility” by assessing the existing hardware and software for how the technology is compatible. As stated by Rogers [40], compatibility is considered as an essential factor for innovation adoption and has significant influences on users’ behavioral intention for technology adoption. Further studies also have proven the significant influence of compatibility on BI in several contexts such as knowledge sharing [41], mobile payment [39], e-learning acceptance [42], and mobile commerce [43]. Therefore, this study described compatibility as the degree to which wearable health device’s compliance with the functionality of other products (for instance, smartphones, tablet, and PCs), users’ lifestyles, and business demands. Hence, the following hypothesis was proposed:

H5: Compatibility affects an individual’s intention in the wearable healthcare device context.

3.6. Health Interest. Health interest (HI) as defined by [4] is referred to “the degree to which the person is interested in improving or maintaining his/her health.” Additionally, HI is a sign of the quality of people’ life for health actions and concerns [44]. Several previous studies on wearable technology devices have supported that HI has a direct and positive influence on users BI [4, 45]. Hence, consumers with high HI are more interested to use and adopt the wearable health device. Also, they are more interested to purchase products. Therefore, the following hypothesis was proposed:

H6: Health interest affects an individual’s intention in the wearable healthcare device context.

The proposed study has developed the research model, as shown in Figure 1, for examining the factors which influence

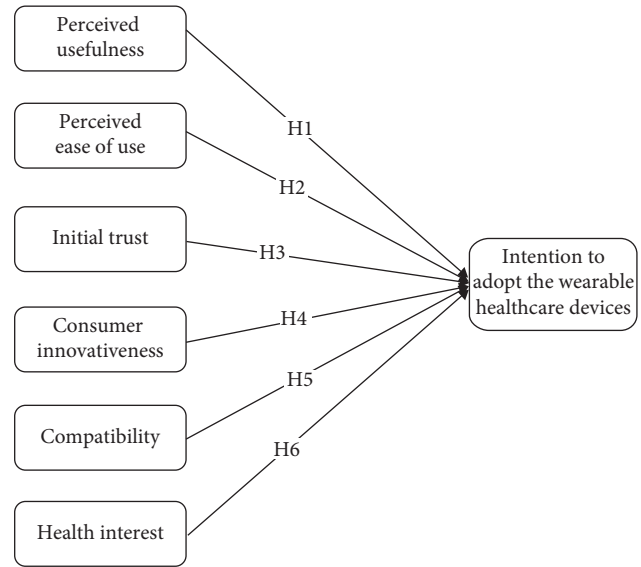


FIGURE 1: Research model.

an individual’s intention for wearable healthcare device adoption.

4. Methodology

4.1. Structural Equation Modelling-Neural Network Approaches. In this study, a two-step multianalytical approach, including a neural network (NN) analysis and structural equation modelling (SEM), was employed. For testing the research hypotheses and identifying the antecedents/predictors of wearable health device adoption, the SEM is normally used. However, several studies have applied the integrated SEM-NN approach in a different context for adoption such as m-commerce [46], social CRM adoption [47], e-learning [48], brand extension [49], ERP system [50], and IOS adoption [51]. Therefore, in the initial stage of the analysis, the SEM was applied to verify factors that have significant influence on wearable health technology adoption. Thereafter, in the second stage, we used the NN analysis for more accurate prediction of substantial factors for wearable healthcare adoption. As the SEM approach just used statistical modelling for the liner model, sometimes it over simplifies the complexity of the technology adoption model when users make the decision for technology adoption [52]. In order to tackle this concern, the NN analytical approach was employed to test the linear as well as the nonlinear relationship among adoption factors and wearable health technology adoption decision. The NN additionally makes it possible to achieve more precise predictions in comparison to the typical regression techniques [53]. Additionally, utilizing the two-stage SEM-ANN approach that is predictive analytical approach provides a further holistic comprehension and gives significant methodological contribution through the analytical viewpoint. This is because the noncompensatory neural network analysis is able to enhance the weak points regarding the linear and compensatory SEM analysis [50]. Thus, to understand a sensible research technique and gain a benefit

through the use of an integrated technique, the two-staged SEM-NN method was suggested by previous researchers [49, 54, 55]. Hence, the proposed study primarily used the SEM to test the model and associated hypotheses. Based on the results of the SEM analysis, significant/supported variables will be used as input to the NN analysis. This is one of the new studies on wearable health device adoption which integrated SEM and NN.

4.2. Sample and Procedure. A survey questionnaire was used in this research to test the hypotheses. The proposed study used purposive sampling technique. The data were obtained from the users who have experience and awareness of the wearable devices such as smart watches, heart monitoring devices, calories burn monitoring devices, and sleep trackers and have the experience of using wearable devices. In total, 178 participants, including university students, researchers, and office workers, in Malaysia were involved in the survey. The characteristics of the respondents who joined the survey are shown in Table 2.

4.3. Measurement of Variables. As the focus of this study is consumers of wearable health device, the unit of analysis is individual. The questionnaire item was adopted from the previous literature [2, 3, 6, 20, 51] and supposed to be suitable in this study. Twenty-eight items were used to measure the seven variables. All the items were measured by a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

4.4. Assessment of Measurement Model. For testing the measurement model of the constructs, whether they have adequate validity and reliability, two-step analysis was applied. Cronbach's α , composite reliability (CR), and average variance extracted (AVE) are used for constructs' reliability and validity. As revealed in Table 3, Cronbach's α for constructs was ranged from 0.75 to 0.85, which is above the acceptable value of 0.7 and exceeds the recommended score. CR scores for each construct were above the threshold of 0.70 [55], and AVE of all constructs surpassed the suggested value of 0.5. The square root of AVE was applied for calculating the discriminant validity [56]. The results showed that square root of AVE is higher than the correlations between this construct and the other constructs, which approved the discriminant validity of the constructs. The discriminant validity for measurement items are presented in Table 4.

Based on the above evaluation results, the measurement model for construction of reliability and validity has been accepted and met the recommended values.

4.5. Assessment of Structural Model. After confirmation of the reliability and validity to the measurement model, in the second step, evaluation of the structural model should be performed. As stated by Hair et al. [57], the coefficient of determination R^2 was employed for the predictive power of the structural model. Total predicted R^2 for the dependent variable is 0.64, which represents the substantial coefficient

TABLE 2: Characteristics of the respondents.

| Demographic factors | Frequency | % |
|--------------------------------|-----------|-------|
| <i>Gender</i> | | |
| Male | 73 | 41.02 |
| Female | 105 | 58.98 |
| <i>Age</i> | | |
| 25 or lower | 59 | 33.14 |
| 26–40 | 108 | 60.68 |
| 41 or older | 11 | 6.18 |
| <i>Education</i> | | |
| Under college | 8 | 4.49 |
| College or university | 138 | 77.53 |
| Advanced degree | 32 | 17.98 |
| <i>Occupation</i> | | |
| College or university students | 128 | 71.91 |
| Researchers | 36 | 20.22 |
| Office workers | 14 | 7.87 |

TABLE 3: Reliability and validity test.

| | Cronbach's alpha | Composite reliability | Average variance extracted (AVE) |
|------|---------------------|--------------------------|-------------------------------------|
| BI | 0.80 | 0.86 | 0.56 |
| C | 0.84 | 0.89 | 0.67 |
| CI | 0.79 | 0.86 | 0.61 |
| HI | 0.85 | 0.9 | 0.69 |
| PEOU | 0.78 | 0.86 | 0.6 |
| IT | 0.75 | 0.84 | 0.57 |
| PU | 0.76 | 0.85 | 0.59 |

TABLE 4: Discriminant validity for measurement items.

| | BI | C | CI | HI | PEOU | PE_ | PU |
|------|-------|-------|-------|-------|-------|-------|-------|
| BI | 0.745 | | | | | | |
| C | 0.597 | 0.82 | | | | | |
| CI | 0.7 | 0.598 | 0.783 | | | | |
| HI | 0.636 | 0.689 | 0.601 | 0.829 | | | |
| PEOU | 0.678 | 0.567 | 0.714 | 0.604 | 0.776 | | |
| PE_ | 0.646 | 0.607 | 0.608 | 0.585 | 0.615 | 0.758 | |
| PU | 0.651 | 0.558 | 0.684 | 0.512 | 0.648 | 0.532 | 0.766 |

TABLE 5: Structural model results.

| | <i>T</i> statistics | <i>p</i> values | Results |
|----------------------------------|---------------------|-----------------|-------------|
| H1: PU \rightarrow BI | 1.91 | 0.06 | Supported |
| H2: PEOU \rightarrow BI | 1.87 | 0.06 | Supported |
| H3: IT \rightarrow BI | 2.65 | 0.01 | Supported |
| H4: CI \rightarrow BI | 2.44 | 0.02 | Supported |
| H5: C \rightarrow BI | 0.48 | 0.63 | Unsupported |
| H6: HI \rightarrow BI | 2.49 | 0.01 | Supported |

of determination by Hair et al. [55]. The obtained result from the structural model assessment for the hypotheses is shown in Table 5. Of the six proposed hypotheses by this research, five hypotheses were supported and one hypothesis (H5) was not significantly influenced, and it was rejected. Hence, the result of this study shows that personal norm ($p = 0.63$,

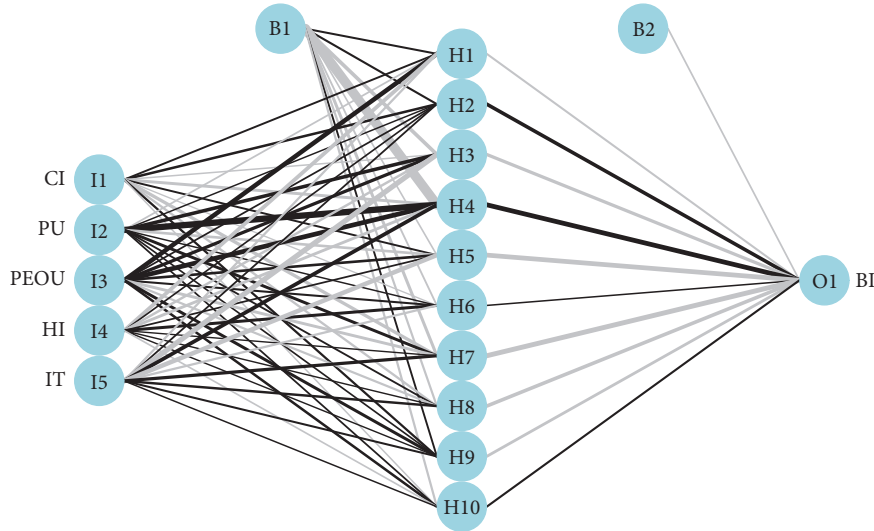


FIGURE 2: The proposed artificial neural network architect for 10 neurons. CI = consumer innovativeness; PU = perceived usefulness; PEOU = perceived ease of use; HI = health interest; IT = initial trust; BI = behavioral intention.

$t = 0.48$) does not have the significant influence on intention to wearable health device adoption.

5. Neural Network Analysis for Wearable Health Device Adoption

According to the results gained from the structural model assessment, five significant/supported constructs from the SEM analysis were applied to progress in the NN analysis. In this study, SPSS 21 was applied for modelling NN. As depicted in Figure 2, the applied NN analysis compromises three layers: the input layer, hidden layer, and output layer [58]. The input layer in the NN analysis compromised the five significant factors resulted from the SEM. The dependent variable which is the intention to adopt the wearable health device is considered as an output layer for the NN analysis. While there is not any specific role for identifying the hidden nodes in the NN analysis, to detect the hidden nodes (H1–H10 in Figure 2), the researchers [52, 59] have recommended examining the NN model by modifying the number of hidden nodes from 1 to 10.

The proposed study has applied the 10 hidden nodes to create the relative significance of the predictors. Hence, 70% of the data have been used as the train network model, and the remaining 30% of the data have been employed to test the forecasting accuracy of the trained network. Five factors, namely, perceived usefulness, consumer innovativeness, initial trust, perceived ease of use, and health interest, were examined. The root mean square error (RMSE) was applied to detect the accuracy of the proposed model. To measure the accuracy of the model, the RMSE of both testing and training data sets for all ten NNs were calculated and the results are presented in Table 6. The results of the sensitivity analysis of the input factors in the NN model are presented in Table 7. The attained results of the sensitivity analysis revealed that perceived usefulness

was the most significant factor for wearable health device adoption, followed by health interest, perceived ease of use, initial trust, and consumer's innovativeness.

6. Discussion and Conclusion

The goal of this research was to predict and prioritize factors influencing the wearable health device adoption by consumers. Within the model that proposed the casual relationship of consumer innovativeness, perceived usefulness, perceived ease of use, health interest, and initial trust, an individual's intention for wearable health technology device adoption in Malaysia was examined. The obtained results from the SEM showed that initial trust is the most influential factors for individuals to adopt the wearable health device. The result of this study is consistent with the previous result [21]. Many users trust the wearable technology, and they are more interested to adopt and use the products. The health interest was considered as the second significant factor which influences consumer's behavior intention for the adoption of the wearable health device. Consumer's interest and intention for new wearable health device will increase if the developer provide appropriate information about the devices and through right channels present the products to the people. This result is in line with the previous study by Zhang and Li [60]. The consumer innovativeness is considered the third significant factor based on the SEM analysis. The finding is aligned with the previous study on healthcare wearable technology context which discovered that consumers' innovativeness may possibly increase their intention toward the adoption of health technology device [22].

From a theoretical point of view, several studies investigated the wearable health technology adoption, and far less attention has been paid on the individual's decision-making behavioral intention to adopt wearable health device with a strong underpinning theoretical model. Since the theoretical development in this context is still at an early

TABLE 6: Results of neural network model.

| | Training | Testing |
|-------|----------|----------|
| ANN1 | 0.106922 | 0.106347 |
| ANN2 | 0.109983 | 0.109486 |
| ANN3 | 0.104876 | 0.120891 |
| ANN4 | 0.109657 | 0.110251 |
| ANN5 | 0.106044 | 0.108652 |
| ANN6 | 0.10587 | 0.111759 |
| ANN7 | 0.10857 | 0.11046 |
| ANN8 | 0.108333 | 0.110974 |
| ANN9 | 0.108955 | 0.115119 |
| ANN10 | 0.131162 | 0.108923 |

TABLE 7: Normalized variable importance.

| | Importance | Normalized importance (%) |
|------|------------|---------------------------|
| CI | 0.083 | 30.4 |
| PU | 0.273 | 100.0 |
| PEOU | 0.221 | 81.1 |
| HI | 0.267 | 97.7 |
| IT | 0.157 | 57.5 |

stage, proposing an adoption model for wearable health device is the most significant contribution of this research. This study is the initiative toward the use of the integrated -NN model to observe the predictors of the wearable health device adoption factors at the individual level. As mentioned above, the research on wearable devices adoption is rarely focusing on Malaysian consumers. Thus, this study is an innovative idea for this matter.

From a practical perception, this study provides numerous practical suggestions for providers, developers, and practitioners. For consumers who have adopted a wearable health device or have planned to adopt it, the proposed model can be applied as a guideline to support their decision-making process. Moreover, the proposed study presents opportunities for companies to change the attributes of the new product in order to decrease conflicting feedbacks and to boost the rate of adoption.

7. Limitations and Future Studies

The proposed research considered only the individuals' perception and intention, thus avoiding the researchers to study the barriers and hindering factors that influence the adoption of wearable health device. In addition, this study could not include other antecedents for health wearable device adoption in terms of an individual's viewpoint, such as TPB, DOI, and UTAUT predictors. Thus, in the future, researchers can study influential predictors for wearable health devices by employing another adoption theory. Additionally, our target sample was restricted to a Malaysian sample, which has not considered the technological and cultural alterations between diverse countries. So, it would be essential to test the results in other countries. Hence, another way to encompass this research will be conducted as a comparative study on the adoption of healthcare wearable devices among diverse countries.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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