**An Analysis of Key Factors for Continuous Use Intention of Health Wearable Devices: Desktop Literature Review**

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**Abstract**

Information Technology is more transparent and penetrating into the lives of people in the society. The study has noted that technology and innovation transformed into a form that can be wearable. There is a paucity of inquiry on the actual use behaviour, improvement expectancy and continuous use intention of latest healthcare computing. To fill this gap a critique of literature was done on an article whose research questions were three namely: First, do the inside and external activities associated with employing a healthcare wearable device impact the actual use behavior of the device? Secondly, does the actual use of healthcare wearable devices have an impact on the user’s health enhancement expectancy? And thirdly, does the user’s health improvement expectancy attained by employing healthcare wearable devices? The reviewed article was anchored on multiple models. Its data was analyzed by using both descriptive and inferential statistics. Structural equation modeling was also employed in performing confirmatory factory analysis. It was evident that there were a methodological, references, study settings and theoretical gap which require to be filled in this study. The findings of the study are expected to contribute to both theory and practice regarding the usage of healthcare wearable devices.

**Keywords**: Healthcare wearable devices, Continuous use intention, User

Experience, Model

1. **Introduction**

This article “An Analysis of Key Factors for Continuous Use intention of Healthcare Wearable Devices:”, studied by (Lee & Lee, 2020) has closely examined and analyzed the effects of both internal and external factors on actual use behaviour and health improvement expectancy and continuous use intention of the healthcare wearable devices.

This document critiques the research carried out by (Lee & Lee, 2020). The authors’ study examined and analyzed the relationship between the key factors and the continuous use intention of the healthcare computing devices. The first section of this paper discusses the literature review, healthcare industry and wearables, healthcare wearable devices and its applications and the research models. This goes ahead to discussing both research methodology and structural equation modelling. The second section of this article provides a critique of various scholars’ works with the objective of establishing the existing gaps n literature on the topic of interest. The critique s based on research theoretical models, research methodology, the findings/results of the study, summary and conclusions, references.

* 1. **Background to the Study**

With the rapid advance in mobile technology because of vast innovations, the use of mobile devices has skyrocketed. It is estimated that almost 70% of the world’s population use mobile devices (Ericsson, 2017). Markets and Markets (2017) speculate that the worldwide mobile healthcare market will grow from USD 63.4 billion in 2013 to 90.4 billion in 2022. According to Strategy Analytics (2019), the global smart watch shipments reached 12.3 million units in June, 2019 thus representing a 44% increase from 8.6 million units in June, 2018. Wearable devices are increasingly becoming very popular platforms for healthcare services, particularly given the increasing interest in health, well-being, disease prevention and fitness. Also because of the paradigm shift towards healthcare that is personalized and controlled by individuals (Lee, 2018). Furthermore, the shift within the medical paradigm, from disease treatment to prevention and health management has provided the users of wearable devices new experiences that are not available from traditional healthcare-related products and services (Lee, 2019).  
  
Today’s digital wearables however, converged products of smart sensors, Artificial Intelligence (AI), big data, the Internet of Things (IoT), robots, and radar technologies, can assist to manage and stop diseases. These devices are going to measure the center rate, body temperature ,blood pressure, and respiration of the elderly living in homes and facilities, and by detecting their risk indicators, like worsening disease conditions, falls, and other life-threatening phenomenons (O’Donovan *et al*., 2009; Pataranutaporn *et al*., 2019).  
  
As such, many companies have developed wearables and smartphone applications to provide an honest range of healthcare services, and this trend is predicted to accelerate (Braithwaite, 2018). Despite the rapid growth of the healthcare wearable devices market, the adoption of these devices and related technologies is diverse as different social segments and countries have varying degrees of socio-technical development (Yoon *et al*., 2020). Employing the technology acceptance model (TAM), TAM2, Unified Theory of Acceptance and Use of Technology (UTAUT), and UTAUT2 models, or the scrutiny of technology or market trends (Wang *et al*., 2009), there is little inquiry on user acceptance behavior and thus the particular use of such wearable devices.  
  
It is imperative to identify factors affecting the persistent use intention for healthcare wearable devices. New technologies can increase in value given that they are widely communication within the market which induces further product advancements. The diversification of obtainable products helps reduce user burden, especially from a financial standpoint. Additionally, the success of healthcare applications is set by continuous use intention, not by just technology acceptance or adoption rates in the industries. Therefore, it is imperative to seem at post-adoption attitudes, such as the use intention and its Association to user characteristics. The quest on the key factors influencing user acceptance behavior is required to sustain the use of and the interest in healthcare applications of wearable devices. There is a paucity of inquiry on the actual use behavior, health improvement expectancy, and continuous use intention of latest healthcare devices.  
  
To realize the research objectives, this study develops an inquiry model supported by the Knowledge, Attitudes, Practices, and Beliefs (KAPB) model, a frequently employed method within the event and delivery of health education schemes for preventive activities, the UTAUT2 model related to the acceptance of latest technologies, and Theory of Planned Behavior (TPB). This study therefore, attempts to answer the next three research questions: (1) Do the both inside and external activities associated with employing healthcare wearable devices impact the actual use behavior of the device? (2) Does the actual use of healthcare wearable devices have an impact on the user’s health enhancement expectancy? (3) Does the user’s health improvement expectancy (should there be any) attained by employing healthcare wearable devices? An inquiry model is proposed to answer these three research questions. The findings of the study are expected to contribute to both theory and practice regarding the usage of healthcare wearable devices for health improvement and disease prevention in the society.

**2.0 Literature Review**

Healthcare devices ought to support not only the growing need for remote medical services without spatial and temporal restrictions but also the increased need for medical services among senior citizens that suffer from reduced mobility and a shortage of access to professional medical services (Panner, 2019). There are numerous factors that facilitate the expansion of remote oriented healthcare market a bit such as the aging boomer generation, the foremost important age group within us, also because the increasing number of persons with chronic diseases likes cardiovascular and diabetes issues (Panner, 2019). Additionally, the expansion of remote medical services is projected to infer momentum as 5G technology, which became commercially accessible in 2019, which can expand network coverage (Lee, 2019). This COVID-19 pandemic has further highlighted the importance of remote oriented healthcare delivery (Chadha *et al*., 2020; Cohen *et al*., 2020).  
  
Wearable devices refer to Information technology (IT) driven devices which can be carried on the user’s body, such as the wrist, arm, or head (O’Donovan *et al*., 2009; Pataranutaporn *et al*., 2019). Advancements in wearable technologies and thus the growing need from consumers who anticipate taking care of their own health have profoundly influenced the healthcare industry including insurers, providers, and technology companies (Phaneuf, 2020). It is anticipated that the demand for products and services using digital health technology for the aged will still inflate with time. Such increased demand is additionally reflected within the accelerating availability of a spread of healthcare wearable devices and applications.

(Ding *et al*., 2021) on their article, “Wearable Sensing and Telehealth Technology with potential Applications in the Corona-virus Pandemic”. This article reviews enabling technology and systems with various application scenarios for handling COVID-19 crisis. The article featured wearable devices appropriate for monitoring the persons at risk and those in quarantine, unobtrusive sensing devices for detecting the disorders and for monitoring the patients with relatively mild symptoms, telehealth technologies for the remote monitoring and diagnosis of COVID-19 and related diseases.

(Wright & Keith, 2014) in their study, “Wearable Technology: If the Tech Fits, Wear it”.   
This study explores the various types of devices and major players, like smart watches, Smart Cloths/Smart Textile, Smart glasses, how medical community looks at goggle glasses, libraries explore wearable technologies.  
**2.1.1 Healthcare Industry and Wearables**

With the popularization of smartphone use, applications of wearable technology have exploded, converged with AI (AI), IoT, and smart sensing devices. Today, they are widely used not only within the healthcare industry but also in gaming, communications, industrial operations, and safety. As an example, in healthcare, IBM offers a sincere kind of mobile services through its Mobile Wireless Health Solutions. Wearable devices in healthcare include various forms including wearable fitness trackers, smart health watches, wearable ECG monitors, wearable sign monitors, and biosensors (Phaneuf, 2020). First and foremost, Wearable health devices are often accessories, sort of a wristwatch. The first function of accessories employed by most users for the well-being and fitness. Detailed functions include the facility to sync to smartphone applications; store and manage Information on key data points, notably the user’s psychological status; monitor sleep patterns; track calories burned and consumed; and record distance travelled.  
  
Secondly, wearable health devices are often within the type of clothing. Smart clothing, which uses computer chips to exchange electrical signals and data, or uses special materials to connect with a smartphone to use various functions, can measure changes in blood flow, biological rhythm, breathing, and thus the health of their users and accumulate data (Patel *et al*., 2012; Phaneuf, 2020; Yoon *et al*., 2020).  
  
Thirdly, wearable health devices are often attached to the body. Sensimed, a Swiss firm, puts a contact lens-type medical device on glaucoma patients to measure their pressure for 24/7. Changes within the pressure are the foremost important believe diagnosing glaucoma, and its progression is often caught up through uninterrupted monitoring of the pressure. These contact lenses use sensors and antennas inside the lens to measure the pressure of the user, transmit and record the data to a wise device in real-time, and store it on the doctor’s computer via Bluetooth (Patel *et al*., 2012; Phaneuf, 2020).   
  
Fourthly, there are biopsy wearables. The foremost sophisticated wearables are often transplanted within the user’s body or be consumed by users. Presently, technologies of this type include ingestible sensors on the patient’s medication to work out of the medication is being ingested in real-time and technology that allows a wireless sensor to be implanted on the skin to verify real-time changes in blood sugar levels for patients who need to be constantly monitored, like patients with diabetes. The growing demand for healthcare services because of the aging population is fueling the adoption and use of digital health within the care and treatment of elderly. The universal marketplace for healthcare wearable devices is predicted to grow at an annual rate of growth of 30%, from 2.5 billion dollars in 2015 to 12 billion dollars by 2020. In spite of the outburst of interest in health wearables, there is currently no specific agreement on the research, terminology, and thus the scope of applications to both well-being and fitness management.

**2.1.2 Healthcare Wearable Devices and Applications**

Pataranutaporn *et al*. (2019) recommended that “wearable technology has enabled on-body real-time sensing and computing of human physiological information.” Phaneuf (2020) reported that wearable technology, including electronic devices in healthcare, is meant to gather data on users’ personal health and exercise. Phaneuf (2020) lucidly defined a healthcare wearable technology as “…consumers can wear, like Fitbits and smart watches, and are designed to gather the information of users’ personal health and exercise.” Ravindra (2019) described it as “… that is noninvasive and autonomous, which performs a specific medical function, be it supports or monitors, over a prolonged period of some time.” These definitions of healthcare wearable device imply that a healthcare wearable device can help prevent disease and review the user’s health conditions. Furthermore, a healthcare wearable device are often attached to the body or combined into a neighborhood of the body to strengthen and supplement the healthcare capabilities of the physical body and be adjusted consistent with the user’s willingness.  
  
This study focused on users who use healthcare devices. As a result, during this study, a healthcare application or device is defined as a mobile-based healthcare application or device worth to provide information, measurement, and management of physical and exercise data also as other healthcare-related content required for private health management.

**2.1.3 Technology Acceptance Model (TAM)**

TAM has theoretical foundations on theory of reasoned action (TRA) from psychology (Fox & Connolly, 2018) to research user behavior regarding the acceptance of latest technologies; the study utilized the two concepts from TAM: perceived simple use and perceived usefulness. Specifically, the study assumed that when more users feel that a selected system is both easy to use and useful, it could positively impact attitudes towards its use, and thus the use intention of the system (Davis *et al*., 1992). Although TAM has been widely used and applied in studies of user intentions and behaviors regarding the acceptance of latest technology, it had been noted repeatedly that TAM cannot be worth to measure the actual use intentions. This criticism led to the event of TAM2 (Venkatesh & Davis, 2000).  
  
Venkatesh *et al*. (2003) proposed Unified Theory of Acceptance and Use of Technology (UTAUT) to build out the restrictions of TAM and TAM2 models. UTAUT could even be a model that merges multiple theoretical models which may be worth to investigate new technology acceptance, including TRA, TAM, the business motivation model, TPB, the Model of PC Utilization innovation diffusion theory, and social cognitive theory (Venkatesh *et al*. , 2003, 2012; Al-Tarawneh, 2019). As factors influencing user intention and behavior, UTAUT included effort expectancy, performance expectancy, social influence, and facilitation condition, also as voluntariness of use, age, gender, and knowledge as moderating variables. However, like TAM, UTAUT was also criticized for not having the facility to incorporate all the variables associated with technology use. Therefore, Venkatesh *et al*. (2012) developed UTAUT2, which infused the three factors of hedonic motivation, price value, and habit. The most noted difference between UTAUT and UTAUT2 is that UTAUT could even be a model developed for explaining acceptance intent and use within the organizational context, while UTAUT2 could even be a model for improving the predictability of technology and repair acceptance and use during a consumer-use context.   
  
Through empirical analysis, Venkatesh *et al*., (2012) found that UTAUT2 was a way better predictor than UTAUT of acceptance intention, increasing the explained variance from 56% to 74%, and of technology use from 40% to 52%. However, it is also necessary to spot use intentions by incorporating the perception, attitudes, and expected values of consumers regarding their acceptance of latest technologies. Supported the UTAUT model in healthcare system, Cimperman *et al*., (2016) found that health improvement expectancy, facilitation conditions, effort expectancy, and perceived security directly influence use intentions. However, during a study that scrutinized the influence of home-based remote healthcare services for the elderly on service use intention, computer anxiety had a negative effect on effort expectancy.  
  
In a study of the items affecting the acceptance of smart glasses, Rauschnabel *et al*., (2015) underscored the importance of the functional benefits and social compliance and suggested that folks with open and outgoing nature trend to be willing to embrace smart glasses. The features, compatibility, aesthetics, and brand of wearable devices were found to impact perceived benefits and value, which they were found to positively impact the utilization intention (Yang *et al*., 2016).

**2.1.4 Knowledge, Attitudes, Beliefs and Behavior Models and Theory of Planned**

**Behavior**

Many theories are developed to elucidate or speculate health-related behavior supported the perception that health is affected by social and behavioral factors. The leading models include the Health Belief Model (HBM) and thus the Knowledge, Attitudes, and Practices (KAP) Model (Humphis, 2000). However, it has become one of the foremost widely used social cognition models in health psychology (Rosenstock, 1974; Becker, 1977; Abraham & Sheeran, 2015). The HBM suggested by Becker *et al*. (1977) posits that motivations to initiate and maintain health-protecting behavior are influenced by perception variables, like personal vulnerability to disease, seriousness, and worries concerning the disease, benefits of taking action, and barriers to behavioral changes (Harris & Garcia-Godoy, 2004). The KAP model is based on HBM, which is the foremost generally used method for prevention activities designed for the general public. The KAP model is used to gauge the knowledge, attitudes, and practices of the general public regarding their health behavior, diseases, and health issues employing a structured survey (Humphis, 2000). Knowledge could also be a more profound concept than simply understanding, and it includes the acquisition, management, and use of knowledge and technology. Attitude is an acquired factor that has cognitive, emotional, sensory, and behavioral tendencies (Raina, 2013; Rav-Marathe *et al*., 2016). Practice is defined as applying knowledge and rules to finish during a final action (Badran, 1995).  
  
The KAP model are often effectively applied to research knowledge gaps, cultural beliefs, and behavior patterns among populations, and it facilitates the understanding of individual experiences, opinions, and behaviors (Johnston & Warkentin, 2010; working group on Monitoring & Evaluation, 2014). However, because of the criticism that the KAP model ignored the role of beliefs in individual actions, the KAPB model was proposed. KAPB, which began as a theory for learning and is now widely applied to the world of healthcare and emphasizes the importance of appropriate health information also as positive beliefs and attitudes permanently health practices (Frank, 2004; Johnston & Warkentin, 2010). The KAPB model emphasizes the role of practice for improvement, as effort is required to understand the issues with one’s current health behaviors before improving them. Therefore, the KAPB model is typically utilized in health-related fields to provide education for the maintenance and betterment of health, improve attitudes and beliefs, and motivate the intention to act.  
  
Theory of Planned Behavior (TPB) could also be a widely known theory that explains the connection between consumers’ attitudes and behaviors. TPB could also be an idea that expands on the previous TRA without its limitations (Ajzen, 1998; Fishbein & Ajzen, 2010). TRA posits that attitudes towards behaviors and subjective norms influence behavioral intentions, which then cause behaviors. TPB was developed to predict behaviors during which individuals have incomplete voluntary control. Concerning self-esteem and self-efficacy, TPB expands on the concept of perceived behavioral control (Ajzen, 2002). TPB, similarly to TAM includes the intention of action; intention refers to the extent to which executing specific actions are voluntary and thus the quantity of voluntary effort toward such action (Ajzen, 1998).  
  
For the requirements of this study, it is vital to note that there is an outsized volume of research that indicates that both TRA and TPB have utility in predicting health behaviors which the observed statistical relationships among their internal constructs, which are supported behavioral, normative, and control beliefs, have significance across an honest range of contexts (Armitage & Christian, 2003). Both models supported an individual’s attitudes and social norms, also because the person’s perceived control as accurate predictors of behavioral intentions, through an evaluation of the available information (Ajzen, 1998; Armitage & Christian, 2003). HBM also includes a self-efficacy component to elucidate health behavior. Perception, knowledge, and attitudes toward a health issue may influence health behaviors, as explained by HBM and KAPB models.  
  
As a consequence, this study was anchored on multiple theories discussed during this section as follows. The UTAUT2 model was used to explain new technology acceptance; the KAPB model was used to understand the behaviors associated with implementing of health prevention activities, and TPB was used to understand the connection between consumer attitudes and behaviors.

**3.0 Research Methodology**

This study used a literature critique for four articles on the topic under investigation to bring out the methodological gaps which calls for further research.   
**3.1.1 Data Collection**

To test the proposed research model with associated hypotheses, the researcher collected data from the general public and medical personnel through a survey questionnaire. As most of the measurement items within the questionnaire were from previous studies, the study took the double translation protocol (Harkness, 2011). The questionnaire was first developed in English then was translated into Korean by a bilingual academician within the service operations management arena. The Korean version of the questionnaire was then translated back to English by another bilingual faculty within the healthcare management area. Three bilingual faculties examined the 2 English versions and located no significant difference. The questionnaire was tested during a pilot survey involving thirty-five participating volunteers (15 medical personnel and 20 general public).  
After the pilot study, several measurement items of the constructs were modified because the survey participants found them ambiguous and difficult to answer. We distributed 500 questionnaires of the ultimate version to every group: general public and medical personnel. For the medical personnel group, we randomly selected doctors, nurses, medical technicians, and pharmacists at several general hospitals that accepted our request for data collection, also as staff at public health centers. For the overall public group, we also randomly selected volunteers among business people, visitors to health centers or hospitals, university employees, and college students. We factored n respondents’ behavior to attenuate respondent variance n each group. Subsequently, a complete 288 useable questionnaires were received (a response rate of 28.8 for the sample group); medical personnel-129 out of 500 questionnaires distributed (a response rate of 25.8%); general public—159 of 500 distributed (a response rate of 31.8%). The questionnaire provided measurement items for knowledge, attitude, belief, technological and social factors, actual use behavior, health improvement expectancy, and continuous use intention. The characteristics of respondents are summarized n a table. The categorized respondent types are medical personnel (44.79%) who are engaged within the healthcare field and general public (55.21%) representing non-healthcare related persons. within the sample, 100% of the respondents had experience using healthcare wearable devices/apps, 87.85% for quite one year. The three sorts of healthcare wearable devices/apps the respondents have used are smart watch (52.78%), Fitbit (28.47%), and smartphone with health apps (18.75%). the most purpose of using healthcare wearable devices/apps was listed within the following order: activity measure (37.15%), pulse (23.96%), stress index (23.96%), sleeping (11.81%), and vital sign (3.13%). to beat an uncertain crisis like COVID-19, respondents thought healthcare devices/apps can help strengthen the following: system (43.75 %), exercise (32.64 %), relieve stress (14.93%), and walk (8.68 %).  
  
The questionnaire utilized 5-Point Likert scales to live the constructs. Measurement items from previous studies were modified to suit this research. This study employed SPSS 23.0 and AMOS 23.0 softwares. Structural equation modeling (SEM) was chosen because it provides the tools necessary to check the hypotheses. Cronbach’s alpha values were used to measure the composite reliability of the survey questionnaire. It was realized that all the coefficients for the study constructs exceeded the minimum threshold value of .70 for exploratory constructs (Nunnally, 1978). Within the reliability test, Cronbach’s alpha for social factors was very good and loaded at (.839) and knowledge was rock bottom (.727). All the Cronbach’s alpha values were statistically significant at p-value < .05. The fitness indices of CFA for the entire sample, group1, and group2 supported the recommended threshold values; CFI, RMR SRMR, RMSEA, and χ2/df were satisfactory for the entire sample model, but not GFI. Group1 and group2 satisfied all the recommended values. As validity refers to the accuracy of measurement items, confirmatory correlational analysis (CFA) may be a way of testing how well measured variables represent the constructs for the study. The standardized factor loadings and t-values for measurement variables and results of CFA to check measurement models for the entire sample, Group1 (medical personnel), and Group2 (general public), using the AMOS software. The values of standardized regression weights for knowledge, attitude, belief, technological factors, social factors, actual use behaviors, health improvement expectancy, and continuous use intention were all greater than .5 indicating all variables proposed by the study were statistically significant at the .05 level. The convergent validity, which needs the typical variance extracted (AVE), should be greater than .5 (Fornell & Larcher, 1981). All measurement items met the edge value. Since the values of composite reliability (CR) of data, attitude, belief, technological factors, social factors, actual use behaviors, health improvement expectancy, and continuous use intention were all greater than .7, convergent validity was satisfied. The off-diagonal elements are the correlation between latent variables. For adequate discriminant validity, the root of the AVE of any latent variable should be greater than the correlation between a given latent variable and other latent variables (Barclay *et al*., 1995). As computed, statistics satisfied these requirements, lending evidence of discriminant validity.

**3.1.2 Structural Equation Modeling and Hypothesis Testing**

After examining the measurement model using partial method of method of least squares, the relations between the constructs were addressed. The hypotheses were tested by exploring the trail coefficients. As a result of the goodness of fit test, compared to the recommended values, during this model, the values of CFI (.918), RMSEA (.053), RMR (.067), SRMR (.072), and χ2/df (2.289) were good fit indices, but GFI (.830) was below the required threshold. The results present the importance of the test for the research model with hypotheses. For H1, H2, and H3, the standardized path coefficient between actual use behaviors and knowledge (H1), attitudes (H2), and beliefs (H3) were .436, .177, and .174, respectively.   
  
These three hypotheses were statistically significant at the .01 level and thus supported. The results of this study are almost like that of previous studies of the users with high internal knowledge, attitudes, and beliefs about the use of healthcare wearable devices/apps that more likely would cause their actual use (e.g., Cho, 2016; Chen & Lin, 2018). This means that the actual use of the healthcare wearable devices/apps is based on the users’ knowledge about healthcare, changing attitudes toward healthcare, and belief in using devices. For H4 and H5, the standardized path coefficients between actual use behavior and technological factors (H4) and social factors (H5) were .155 and .153, respectively, and statistically significant at the .05 level, supporting both hypotheses. These results are also almost like those of previous studies (e.g., Venkatesh *et al*., 2003; 2012; Chen & Lin 2018). As an example, f users can easily access certain technology systems, and then cause actual use behavior. The new healthcare wearable devices/ apps can invoke actual use behavior to form value through quick access to technology systems. For H6, the standardized path coefficient between actual use behavior and health improvement expectancy was .976, and statistically significant at the .001 level, supporting the hypothesis. For H7, the standardized path coefficient between health improvement expectancy and continuous use intention was .337, and statistically significant at the .001 level, also supporting H7. These results are almost like that shown by previous studies, the upper the expected performance for health improvement through the device the upper the intention to use continuously (e.g., Venkatesh *et al*., 2003; 2012; Bonzan *et al*., 2015; Cimperman *et al*., 2016). The patients had a positive health improvement experience with healthcare wearable devices/apps, they need a bent to share their experiences and recommend others to use devices/apps. It means that direct or indirect experiences or expected values impact on continuous use intention of wearable devices/apps.  
  
**4.0 Article Critique**

The study critiques various subsections which include background to the study, literature review, the study methodology, results, conclusion and references.

**4.1.1 Literature Review**

(Lee & Lee, 2020) have straightforwardly explained the theoretical models which they have used in their study. These models are Technology Acceptance Model (TAM), Knowledge, Attitudes, Beliefs and Behaviour Models (KABBM) and Theory of Planned Action (TPA). The KAPB model is typically utilized in health-related fields to provide education for the maintenance and betterment of health, improve attitudes and beliefs and motivate the intention to act. As a consequence, this study was anchored on multiple theories UTAUT2, KAPB and TPS as lucidly discussed in this section. The UTAUT2 model was used to explain new technology acceptance; the KAPB model was used to understand the behaviors associated with implementing of health prevention activities, and TPB was used to understand the connection between consumer attitudes and behaviors.

The study has shown how these theories are informing this study carried out by (Lee & Lee, 2020). The research tried to demonstrate the relationship which exists between these theories and the main variables of the study captured in the research questions. The study has also used empirical literature review to shed light on what other researchers have done in regards to the subject of the study. The literature used healthcare industry and wearables as well as healthcare wearable devices and applications which are fairly relevant and of better quality.

Robin and Keith (2014) in their article, “Wearable Technology: If the Tech Fits, Wear it”, despite their extensive exploration in the types of devices and their major players, it is not clear on the methodology which they used in conducting this study. In the same article done by Robin and Keith (2014), there is no mention of theory, framework, model or even architecture which supported this study, hence a theoretical gap which requires to be filled.

According to Albahri *et al.,* (2019) in their study entitled, “Based Multiple Heterogeneous Wearable Sensors: A Smart Real-Time Health Monitoring Structure for Hospitals Distributors”. Although this article has fairly explored the other main components of the study like data analysis, presentations and interpretations, it has not explained any model, framework or even a theory in which it was grounded on hence a theoretical gap which calls for attention from researchers to fill.

However, the literature could be more informing if it could have reviewed more materials in other areas like business, games and sports, education and transport sectors so that the audience is aware of the trends, patterns and derive more insights on the subject.

**5. Research Methodology**

The study methodology was reviewed n terms of research design, results and conclusion.

**5.1.1 Data Collection**

Sang and DonHee (2020) defines its target population which constituted the general public and medical personnel. Data was collected using survey questionnaires. The questionnaires were tested during a pilot study for composite reliability and construct validity. The questionnaire items were found to be ambiguous and complex to answer. The study used volunteers, university students and employees as well as business people to answer its research questions. This study used SPSS version 23 and IBM SPSS AMOS version 23 for analysis and presentation of the findings. In another study carried by Robin and Keith (2014), it was deduced that there was no mention of a research philosophy, research paradigm or research approach which the study was anchored on, and this is evident that there is a methodological gap which requires to be filled in this study.

According to (Albahri *et al.*, 2019) in their study entitled, “Based Multiple Heterogeneous Wearable Sensors: A Smart Real-Time Health Monitoring Structure for Hospitals Distributors”. This study used descriptive statistics method of means and standard deviation to analyze its data. The researchers have richly presented their findings using graphs, APA tables and pie charts. The study validation of the data was accomplished however, reliability of this study was not conducted hence its limitation. This study focused on hospitals selection for individual patients. This introduced a study setting gap which calls for attention so that other areas like sports, business, transport, games and education among others can also be studied.

**5.1.2 Results of the Study**

(Lee & Lee, 2020) used inferential statistics called structural equation modelling (SEM) because t could provide the tools needed to confirm the research hypothesis. The results were presented using APA tables. Reliability of the questionnaire was successfully tested using Cronbach’s alpha coefficient which was above .70 meaning that reliability was good. Convergent validity was achieved using average extracted variance (AEV) whose measure variable loadings were greater than .50 meaning that the variables proposed by the study were statistically significant. Confirmatory factor analysis which used standardized regression weights for the measured variables all loaded at .50 indicating that all the variables which were considered by the study were statistically significant. The entire path coefficient loaded above .30 hence converging to specific constructs of the study. This study used BM SPSS AMOS software for data analysis. (Lee & Lee, 2020) study has extensively used inferential statistics in data analysis, testing for both reliability and validity of the questionnaire, the study’s results could be considered as credible since they were statistically significant.

In spite of all these strengths, this study suffers from a number of limitations like not visualizing the results of the study using path analysis diagram which could have quickly demonstrated the relationship between the measured variables and the latent variables of the study. Although, the study used SPSS AMOS for data analysis to realizing structural equation modelling, that is not the only software that that could have been used for CFA and path analysis diagram, there are more other superior software like R, Python, Lisrel for students, Scala and Julia programming languages which are richly endowed with data analysis and visualization tools. Besides the use of path analysis, the study could have utilized the violin plots and even box plots which visually show the distribution of data. This study again has used a particular target population but it does not tell the audience how they sampled their target population. Nevertheless, this study has not mentioned anywhere under methodology on the research approach which they used and the research philosophies which informed their study. The study neither mentions the research paradigm nor do the philosophical stances and the research approach which supported the research. Additionally, the study has not explicitly stated the type of research design used. If this study could be redone in future and the aforementioned limitations considered critically, it could be really a very rich research.

**6.0 Summary and Conclusion**

This study combined KABP, TPB, and UTAUT2 models for an empirical analysis of things that influences the continual use intention of healthcare wearable devices or applications. An enquiry model, along with associated hypotheses, was proposed. The results of the study revealed that continuous use intention of healthcare wearable devices/apps should be prioritized for improving health conditions or preventing diseases. The study results confirmed the positive effects of knowledge (H1), attitudes (H2), and beliefs (H3) of internal factors on actual use behavior of healthcare wearables/ apps. These results shed new insights about how healthcare wearable device manufacturers can develop their products to increase user intention to use them.

The actual use behavior is influenced by internal factors. The study also found positive relationships between actual use behavior and technological factors (H4) and social factors (H5), as a neighborhood of external factors. Since the actual use behavior is influenced by social trends and convenience of using technology, t s vital to provide an honest user experience. These results indicate that both internal and external factors are important for increasing actual use behavior, supported the social and technical demands of consumers. Furthermore, the results of the study revealed positive relationships between actual use behavior and health improvement expectancy (H7). Humphis (2000) suggested that “improved population health depends on changing the behavior of people,” like who are healthy (e.g., people with regular exercise regime), who are ll (e.g., heavy smokers), and therefore the way health promotion s delivered (e.g., community health clubs). The study results confirmed that every one proposed hypotheses were supported for both groups (medical personnel and general public: H1, H2, H3, H4, H5, H6, and H7).

The results of the study have significant practical implications for the healthcare industry. The healthcare environment has witnessed a shift from treatment-centered services to prevention and management-centered services with the patient’s self-control and use of advanced healthcare devices (Lee, 2018; Lee & Lee 2020). Besides, public interest n health has grown significantly with the aging population, which has given rise to demands for customized healthcare services with self-management or heath control devices. Today, there s a various sort of smart healthcare wearable devices, tools, or apps available and new ones are being introduced to the market (e.g., AliveCor’s personal EKG, TEMPTRAQ to monitoring the temperature, Blinq wearable rings, Philips smart sleep, Wireless patient monitoring, etc.).

Health-related institutions and policymakers should make t easy and straightforward to use wearable devices. Manufacturers of wearable devices should lower the worth of their products n order that general public can buy and use them for his or her health benefits. Lindhult *et al*., (2018) suggested that product-oriented manufacturing companies got to understand consumer needs and pursue service innovation to make greater value for consumers. Therefore, the results of this study can provide practical guidelines for the producers of healthcare wearables/apps which will provide value for the greater good.

This study didn't comprehensively examine the influence of individual user’s characteristics, health status, and therefore the sustainable use intention of wearable devices. These limitations provide future research opportunities. It is also important to think about how new or additional health data are often generated and employed by wearables and applications. This is often a sensitive area that involves data security, privacy, and therefore the digitalization of healthcare data. There are many new future research opportunities in this area, like contact tracing for the COVID-19 infected patients using such wearable devices.

**6.0 References**

(Lee & Lee, 2020) article has greatly acknowledged the veterans of research in this discipline using APA referencing style. The reference materials used in this study are very current. However, the in-text citation has not followed the APA referencing rules as noted in a number of authors and the authorship year but not separated by a comma and in some instances where two authors are involved (Lee & Lee, 2020) have not used the ampersand symbol as required. This means that APA referencing style could have been accurately achieved by using any type of auto-citation referencing management software like citavi, Mendeley, RefWorks, PaperPile and Zotero among others.

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