Journal of Business Research 156 (2023) 113369

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Digitalization in omnichannel healthcare supply chain businesses: The role of smart wearable devices

Victor Chang [a,*], Le Minh Thao Doan [b,*], Qianwen Ariel Xu [a], Karl Hall [b], Yuanyuan Anna Wang [c,d], Muhammad Mustafa Kamal [e]

[a] Department of Operations and Information Management, Aston Business School, Aston University, Birmingham, UK
[b] School of Computing, Engineering and Digital Technologies, Teesside University, Middlesbrough, UK
[c] Department of Public Health and Preventive Medicine, FMNHS, Monash University, Australia
[d] Suzhou Industrial Park Monash Research Institute of Science and Technology, China
[e] School of Strategy & Leadership, Coventry University, Coventry, UK

ARTICLE INFO

Keywords:
Wearable devices
Healthcare
Ethical issues
Privacy
Security

ABSTRACT

The advancement in technology has fostered the prevalence of the Internet of Things (IoT), which enhances healthcare business quality, offers a seamless customer experience, and maximizes turnovers and profits. Consequently, omnichannel services have emerged by integrating online and offline channels and providing customers with more real-time information and services to increase their engagement. Healthcare wearable devices appear as a salient tool to connect healthcare providers and patients and thus become an essential part of the omnichannel environment. Along with this trend, the ethical concerns while using these devices have increasingly intensified and are significant barriers to market expansion. Nevertheless, there is a lack of studies discussing the role of wearables in omnichannel hospital supply chain management and examining the influence of those above concerns on healthcare wearables adoption. Therefore, this study explores these gaps through an integrated approach. Furthermore, we proposed a framework integrating the traditional statistical and machine learning-based approach to analyze a large amount of data; and thereby facilitate a data-driven analytic model to manage omnichannel healthcare supply chain businesses.

1. Introduction

The emergence of digitalization and the Internet of Things (IoT) has transformed healthcare businesses and their operations. The traditional healthcare business model has shifted toward a more comprehensive focus on how healthcare providers and patients co-construct wellness and health value, driving a new omnichannel communication platform that increases information access to patients and empowers their decision-making (Dahl et al., 2021; El-Masri et al., 2022). In fact, consumer-centric and information-rich healthcare have been proposed and strongly recommended by the Health Information Technology Framework (Thompson and Brailer, 2004). A new era of healthcare defined by a patient-centric culture is on the horizon. The omnichannel strategy could align patient journeys with care plans, improve patients' experiences, optimize the clinical process and eliminate former inefficiencies by using innovative technology and data-driven analytics. By doing so, patients better understand their health and the physicians' advice by integrating information from many sources. In many ways, advancing and integrating omnichannel resources have become fundamental valuable co-creation components in healthcare services delivery (Dahl et al., 2018).

Digital health involves engaging patients for clinical purposes, such as collecting, organizing, interpreting, and using clinical medical data and managing results (AMA report). The digitalization advantages have presented an unprecedented chance for patients to have a wider range and more mindful healthcare choices. Therefore, to improve healthcare quality and reduce costs, patients' greater access and engagement with digital information are crucial factors (Chérrez-Ojeda et al., 2018). The tools used in digital health include digital health information inquiring, electronic medical records, patient portals, mobile health, telemedicine, healthcare wearables, and other remote monitoring appliances. Particularly, COVID-19 has accelerated digital health and fitness application

* Corresponding authors.
E-mail addresses: v.chang1@aston.ac.uk, victorchang.research@gmail.com (V. Chang), L.Doan@tees.ac.uk (L.M.T. Doan), 220247906@aston.ac.uk (Q. Ariel Xu), K.Hall@tees.ac.uk (K. Hall), Anna.wang@monash.edu (Y. Anna Wang).

https://doi.org/10.1016/j.jbusres.2022.113369
Received 9 January 2022; Received in revised form 30 September 2022; Accepted 6 October 2022
Available online 19 December 2022

growth by integrating data science and intelligence technology into traditional healthcare.

Healthcare wearable devices, namely wearables, are emerging as a salient tool to track and manage individuals' health and provide more in-depth information about their behavior, guidance, and health information. It plays an essential role in omnichannel strategy in the new age's healthcare sector (Montgomery et al., 2018). Wearable technology also allows healthcare businesses to continuously improve their competitiveness and responsiveness and adapt their omnichannel operational approaches and technologies to real-time data (Ogbuke et al., 2022). Wearables range from daily fitness activity trackers such as Fitbit to more advanced medical technology managing and preventing disease. Indeed, the recent breakthrough in wearable technology is expected to fuel the transformation in the health paradigm towards virtual and voluntary follow-up and diagnosis of sicknesses at home. Patients also acknowledge that a key benefit of healthcare wearables is that it offers healthcare service providers the opportunity to monitor and communicate with them anytime and anywhere and helps patients engage more in health service interactions. Besides, driven by the scarcity of medical resources, many wearables such as VitalPatch have been officially permitted by the United States Food and Drug Administration to facilitate remote patients' care and monitoring in the health sector (FDA, 2020).

Despite promising results of wearables in an omnichannel strategy for the healthcare business, notable research gaps exist in the literature. First, like other emerging technology, ethical issues are long-lasting topics but usually neglected. Although wearable devices allow omnichannel healthcare supply chain businesses to communicate with patients seamlessly, such devices expose many risks associated with their sensors and omnipresent data collection and storage. Remarkably, the acquisition of Google's Fitbit raised a question of concerns to public users about data privacy (Bourreau et al., 2020). At the same time, the privacy of healthcare wearables has received more attention, while the other associated ethical issues were underestimated. These issues are the barriers to wearables in omnichannel supply chain collaboration. Hence, a literature search and investigation of ethical matters related to wearables was performed to comprehensively understand the ethical facets of using healthcare wearables in previous research (Bourreau et al., 2020). The study aims to create awareness of the current ethical implications of wearables users in the health sector, supporting omnichannel supply chain management.

Another barrier to healthcare wearables in the omnichannel strategy is patients' adoption, which has been emphasized as a lack of investigation and needs to be addressed for usage studies of future wearables (Sinha and Gupta, 2019). Significantly, the actual usage of wearables has not been completely elucidated (Chandrasekaran et al., 2020). Exploring and accessing this matter will drive healthcare wearables' growth and assure its prosperity in commercialization and popularity. Moreover, the increase in wearables adoption by patients will facilitate patient-hospital real-time interaction, which improves patient satisfaction, hospital resources allocation and supply chain collaboration. Some studies have investigated the driving forces of wearables' adoption in healthcare from the technological aspects (Farivar et al., 2020) or health-related aspects (Zhang et al., 2017). There is thus an opportunity to establish key determinants that describe patients' attitudes towards wearables, particularly as they relate to the healthcare decision-making process. Besides, other challenges, particularly ethical implications, remain a little-known area. Heretofore, only a little research explored ethical concerns such as privacy influence on wearables' adoption (Li et al., 2016), especially in the omnichannel environment where technology such as wearables is the key driver of success. Hence, this study addresses to fill this gap by examining the actual usage of wearables and their predictors in healthcare, such as demographics, privacy and security concerns, technological and health-related factors.

An integrated-methods approach is opted to understand the ethical concerns and factors involved in using wearables in healthcare. It gives an overview of contemporary ethical issues and aggregates qualitative and quantitative findings from privacy and security concerns and their impact on the usage of smart wearables. First, a qualitative review of the studies on healthcare wearables' ethical concerns is performed to create a frame for the subsequent steps in the analysis. Next, the quantitative Health Information National Trends Survey (HINTS, 2021) data are used to magnify understanding by examining the influence of ethical concerns and other predictors on the use of wearable devices in the omnichannel healthcare model. An integrated-method strategy supports the aim of this study to provide in-depth insights into the contemporary ethical issues in the literature while investigating the potential factors that affect the use of wearables in healthcare from the survey results. The research questions are (i) What are the ethical implications for using healthcare wearables in the omnichannel healthcare supply chain business, and which one is the most critical identified ethical concern in the extant literature? (ii) How do ethical concerns and other factors impact the use of wearables?

While research shows that patients have increasingly used healthcare wearables to interact with omnichannel environments to enhance ones' experiences (Chen et al., 2018), current research lacks investigation of the wearables' roles and their predictors and implications. Thereby, our contribution is fourfold. First, to the best of our knowledge, it is the first time healthcare wearables' roles in the omnichannel healthcare supply chain business are discussed. A framework to utilize wearables and IoT to enhance patients' experience and engagement is proposed. Second, this paper systematically reviews the ethical concern of wearable devices in the healthcare sector and summarize these ethical challenges. Next, wearables' actual usage in healthcare, a relatively unexplored topic, is investigated in this study using US national survey data. We apply a data-driven model, machine learning in big data analytics (BDA), to predict wearables adoption and demonstrate how this approach could enhance supply chain management. Finally, the impact of privacy and security concerns, which are the most discussed ethical concerns in literature and the current challenge in omnichannel strategy, are highlighted and examined.

Consequently, this study has notable practical implications for omnichannel healthcare supply chain businesses and the wearables industry by providing the contemporary ethical challenges of wearables in healthcare and raising awareness of the existing issues with recommendations. Determinants of actual wearables use are investigated and predicted by the proposed framework taking into consideration the potential influence of privacy and security concerns on consumers' uses, which point out as emerging future research areas in the omnichannel healthcare supply chain business. Based on this study's framework and suggestions, digitalization and big data analytics have a critical role in the omnichannel healthcare supply chain business, and wearables facilitate the healthcare transformation process and supply chain management.

This paper is organized as follows. It starts with an introduction to the topic, followed by the literature review presenting the relevant works of healthcare wearables, their influential factors, and the associated ethical challenges. Section 3 describes the methodology, while Section 4 presents our analysis and results. Finally, the findings are discussed, and the implications are provided in Section 5.

2. Literature review

2.1. Digitalization in healthcare

Digitalization has been defined as the sociotechnical phenomena and processes used by individuals, organizations, and society to adopt and use digital technologies (Frenzel et al., 2021). It has fundamentally transformed our society in the last decades. Although digitalization has been developed for decades, the current wave is very different because consumers and citizens expect more digital services and products, particularly real-time services, which have influenced almost all private and personal aspects. The growth of digital technologies means digitalization invades our social-cultural world (Royakkers et al., 2018). For example, plagiarism of healthcare wearables has become easier due to the ease of data access (Wibawa et al., 2021). Moreover, using healthcare wearables to find a date and shopping also produces a wide variety of personal and private data. Those big data will raise some ethical concerns (Karatas et al., 2022). For example, privacy issues and digital security are the most of the public and political focus up to date. In particular, the way of storage and management of big data generated by healthcare wearables has become a hot topic because highly sensitive data reflects the health of the general public. How those ethical concerns influence the adoption and use of healthcare wearables are still less studied.

Digitization can facilitate the omnichannel business from the improvement of omnichannel retail (Ishfaq et al., 2022). Omnichannel retail allows consumers to access the whole available shopping channels, such as mobile internet devices, computers, in-store, and television (Min, 2021). Consumers can playfully adopt healthcare wearable devices by comparing products in all different available retail channels and tracking order deliveries in time through digitalized product flows if they purchased a product from the online platform. At the same time, retailers can also effectively deal with fulfillment processes via analyzing big data collected from different fulfillment nodes (Gibson et al., 2018).

Digitization is not only a contemporary strategy to integrate with physical and online retail worlds but also results in social norms of supply chain management (Ishfaq et al., 2022). Retail enterprises can co-innovate with digital platforms to create value. For example, Swedish company, Rapunzel, lowered its risks and costs by leveraging Amazon's platform to reach consumers around the world (Mostaghel et al., 2022). Online consumer reviews are a dominant factor in influencing consumers' adoption of digital business, and it is also crucial to impact retail firms' external interactions with their consumers. For example, digitization makes healthcare wearables collect a massive amount of data, containing health-related information and sensitive personal data possible, and spread it via social networks to create social norms in time. This may cause concerns about confidentiality and data privacy, as well as other ethical concerns due to data leaks from those social media. On the other hand, exposed social norms may boost omnichannel business from positive social norms.

2.2. Big data, machine learning and digitalization in healthcare data analytics

The fourth industrial revolution, or Industry 4.0, has transformed healthcare to extraordinary levels on the basis of digitization, AI and other disruptive technologies. For instance, AI has helped healthcare customers to enhance operational practice through user knowledge and to achieve better care and improve the patient journey (Leone et al., 2021). However, it also leads to an exploding data generation (Guha and Kumar, 2018). In fact, the amount of data collected from healthcare is growing exponentially, and information insights have become the key drivers of healthcare system success (Kraus et al., 2021). The more information is obtained, the more optimally and effectively the decision can be made. Also, based on the predictive model, the trends and patterns can be uncovered. However, at the same time, tons of data from every aspect of our lives are collected, stored, and managed. The volume of data now becomes large and unmanageable, especially for traditional applications. More precious information and trending insights can be gained quickly and cost-efficiently with advanced AI technology and machine learning (ML) (Huang and Rust, 2021).

Particularly in the healthcare system, a massive number of data in various forms such as clinical data, genomic data, patient's medical history, and other personal medical data need to be managed and processed. Therefore, medical data are complex and predicting models for diagnosis and prognosis are very significant for patients' treatment. There is a need to propose efficient methods and tools to analyze big medical data, especially the growing precision and personalized medicine for illness treatment. Numerous research projects have been conducted to evaluate AI and ML's clinical decision-making and support (Buchlak et al., 2020). Numerous AI and ML applications, such as image-guided medical aid, computer-aided diagnosis, multimodal image fusion, and so on, are available to clinicians and support them in making clinical decisions through past data. Numerous research projects have ML also resolved to reduce healthcare costs and improve patient-clinician communication (Shailaja et al., 2018). AI can automate healthcare administrative systems and optimize the current process, including managing patients' records and appointments. Healthcare management can also utilize techniques to forecast inpatients' waiting times and places in the relevant department to manage hospital resources effectively (Ordu et al., 2021). Besides, the healthcare provider can use the prognostic model to estimate hospital room admissions. Thus, ML deployment could benefit patients by reducing price, enhancing accurate diagnosis rate, or diffusing experience.

2.3. Omnichannel in the healthcare business

With the increasing growth in digitization and IoT applications, consumers can communicate and interact with firms across different channels such as mobile, online, and offline. It has shifted toward an omnichannel environment, emphasizing a unified consumer experience rather than simply promoting transactions. Omnichannel business rs to a strategy that operates in diverse physical and online channels with a synergistic integration to offer customers a seamless and uninterrupted shopping journey (Lynch & Barnes, 2020). It also indicates the implementation of different channels to interact with customers precisely due to a unified operation, where customers can interact with the business seamlessly. In other words, an omnichannel environment is an integrated strategy where customers can seek information and purchase through various channels simultaneously (Min, 2021). Past research has shown that this perfect integration across channels could promote customer experiences and business performance (Mirzabeiki & Saghiri, 2020; Bijmolt et al., 2021).

In the healthcare context, omnichannel strategy can be defined as integrating and coordinating a healthcare service provider's actions across different healthcare delivery and communication channels and patient touchpoints that offer patients a seamless journey (Varadarajan et al., 2021). The omnichannel approach can assist in restructuring healthcare providers' current workflow involving onsite patient appointments, back-office tasks, triage nurses, and patient medical records management. Optimizing the patient administration process is an excellent example of an efficient and interactive workflow in the healthcare omnichannel environment (Reuveni, 2017). A patient can make an appointment, get billing, and confirm insurance eligibility either by pre-check-in via online portals or self-service kiosks. By integrating different online and physical channels, the patient has more choice and flexibility in booking; hence, the patient's experience and satisfaction when using healthcare services are improved. Besides, this flexible and self-service-oriented procedure will gradually replace and reduce the necessity for clinic receptionist support, thereby cutting patients' waiting times and costs.

Healthcare businesses are beginning to understand the critical role of omnichannel. Nevertheless, getting there and effectively implementing the services is unexpectedly tricky. Azoev et al. (2019) found that the precise incorporation of digital channels into an omnichannel environment might delete clients' boundaries, drive business growth, and allow businesses to apply their digital skillset to avail their traditional channels. Engaging patients via various digital and interpersonal touchpoints will benefit healthcare providers and patients. Improved access and integration to health information also initiate higher involvement and conscious reflection about their health choices (Dahl et al., 2019), leading to enhanced health-related outcomes and patient experiences

(Dahl et al., 2018). Although there are several benefits of an omnichannel strategy providing healthcare businesses, such as promoting innovation, driving growth, and improving long-term performance, some challenges prevent this strategy from achieving its full potential. Consequently, ascertaining how to embrace an omnichannel strategy while respecting the privacy of customers is a significant challenge for healthcare businesses.

2.4. Healthcare wearables and the influential factors

Wearables refer to smart electronic devices worn on a user's body, such as the arm (e.g., fitness trackers), head (e.g., smart helmets), or wrist (e.g., smartwatches), to measure, analyze, and transmit information (Tavakoli et al., 2020; El-Masri, Al-Yafi, & Kamal, 2022). They are widely used in healthcare to measure vital signs, such as heart rate, body temperature, and blood pressure, or to monitor physical activities. Typical wearables will obtain health information from users through a sensor, then send data to mobile or computer applications and clouds to store and analyze data via Bluetooth. By integrating intelligent technology, wearables can be used to access real-time information and recommendation, detect and analyze movement or disease based on human physiological and pathological information (Guk et al., 2019). Wearables are a part of the IoT that facilitates the healthcare system and provides technical support to keep track of patients' health, implement clinical tests, and assist medication judgment. Wearables present an opportunity to create a more seamless healthcare experience and involve long-term condition patient management. Consequently, many medical conditions are treatments would benefit from adopting wearable devices.

The intelligent technology in wearables is continuously investigated and improved to facilitate the emergence of connected healthcare. The increasing usage of wearables in our daily lives and healthcare systems will generate enormous and different data sources, eventually increasing the need for improved digital health records and a data-driven medical knowledge base. Along with this growing trend, there are more worries about ethical issues such as data privacy and security when using these devices (Azodo et al., 2020; Martinez-Martin et al., 2021; Thakare et al., 2022).

2.4.1. Ethical concerns of using healthcare wearables

More research about ethical concerns has been studied about wearables in healthcare. As stated above, the popularity of wearables leads to more concern about the dark side of these devices about hidden harmful impacts. As the advantages of healthcare wearables have been taken more concentration while their ethical concerns were neglected, a systematic review of ethical risks of using wearables was presented in this part to introduce what ethical issues were discussed in the prior studies. This qualitative analysis identifies and synthesizes literature conclusions to explore a research question and make results more accessible to practitioners and researchers. In particular, the literature search and investigation are implemented to determine the associated ethical implication of wearables and their current state in the health sector. Our study follows the PRISMA methodological framework for literature search and investigation (Page et al., 2021). Many criteria for exclusion and inclusion are applied to determine articles as follows (e.g., see Appendix C).

Heretofore, many different ethical issues have been discussed in the literature, such as privacy (Segura Anaya et al., 2018), security (Cilliers, 2020), informed consent (Allhoff and Henschke, 2018; Martinez-Martin et al., 2021), and trust (Bourreau et al., 2020). Such issues have become extremely challenging in the omnichannel healthcare supply chain business, where the development of IoT and wearable devices are the key concepts driving on-demand and remote healthcare services (Shah and Chircu, 2018, Hermes et al., 2020). Previous work has raised concerns about data collected through wearables, especially inaccurate data and false reports due to sharing devices with another person or security issues in data transmission (Sharon, 2016). Besides, the personalized medicine and treatment offered by wearables may significantly rely on AI modeling of the patient and types of disease, which may have false-alarm and false negative cases. Moreover, the aging population and poor access to technology are other ethical challenges in adopting healthcare wearables (Howard, 2021). As there are several associated ethical issues, this section describes the two most prevalent concerns – privacy and security, which are also one of the main driving forces of using wearables and will be investigated further in the following quantitative study in this paper.

First, the main challenge for wearables adoption is the privacy of sharing information model. Wearables can collect a massive amount of data, containing health-related information and sensitive personal data, spreading to others using social networks, threatening confidentiality and data privacy (Segura Anaya et al., 2018). *Second*, another privacy issue is that the wearables company does not disclose the information they collected about users and allows users to choose which information to record and access (Cilliers, 2020). For example, once wearables have been integrated into users' daily lives, their personal information, such as preference and geographical location, is recorded and analyzed by others. *Third*, collecting and storing unnecessary data become a crucial privacy concern, mainly when users are unclear about purposes and which parties can access the stored data. According to a study about the emergency department (ED), although wearables could be a solution to reduce crowding, clinician privacy concerns are the top challenges in adopting this technology in ED (Castner and Suffoletto, 2018).

In theory, keeping the collected data private should be encrypted and made physically secure. Hence, the second ethical concern while using these devices is related to data security. In many cases, stored data on the local device lack proper encryption, such as no user authentication and compulsory password safeguard (Jurcut et al., 2020). Besides, to allow the flexibility and support of wearables, many different mobile sources could connect to the devices, enhancing the threat of tampering and leakage. Additionally, the data transmission is usually by short-range technology like near-field communication (NFC) or Bluetooth, making it more vulnerable to cybersecurity risks of external attacks (Babun et al., 2021). Security is also a prominent concern for healthcare facilities, which need reliability at all operation levels. However, many security matters of wearables have been reported. According to the literature, the devices had several vulnerabilities, including an insecure firmware and cloud interface, insufficient authorization, and lack of transport encryption, which could most likely lead to unauthorized viewing, copying, transferring, and even stealing of personal data (Slepchuk et al., 2022).

Therefore, as the concerns about ethical matters while using wearables are gaining more public attention, it is important to identify their relevant ethical implications, especially for the healthcare sector. Based on the above discussions, this study proposes the first hypothesis:

H1: Individual concerns about data privacy and security will be negatively related to the use of healthcare wearables.

2.4.2. Other determinants of healthcare wearables

The increasing desire from consumers to monitor their health has dramatically affected wearables growth in the healthcare sector. Besides privacy and security concerns, many determinants influenced the spread of healthcare wearables, including demographics, technology self-efficacy, health-related variables, and physical activities. Demographics such as age, gender, and education have been observed to affect consumers' adoption. However, prior studies regularly underestimate these variables and treat them as control variables, not in the main framework. Nonetheless, wearables literature has shown that higher educated, younger, and wealthier people are more likely to adopt healthcare wearable devices (Chandrasekaran et al., 2020). Besides, males tend to use these intelligent devices more than females based on observations (Wiesner et al., 2018). Jiang et al. (2017) and Ha and Park

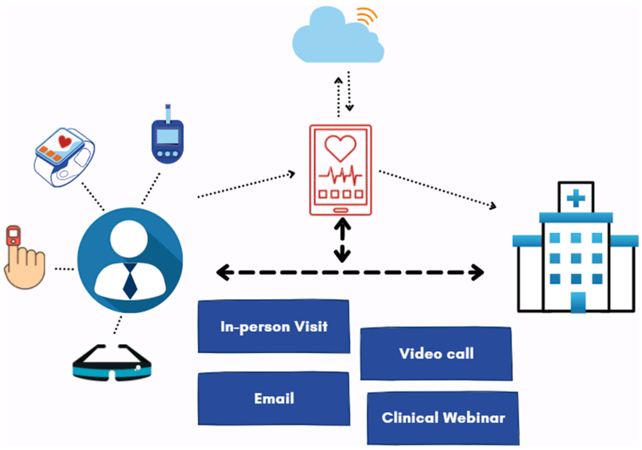

Fig. 1. Healthcare Wearables in the Healthcare Omnichannel Environment.

(2020) also tested the impact of marital status on the intention to use mobile health applications on cancer survivors and older Korean adults, respectively. The marital status showed significance in the work of Jiang et al. (2017) while insignificant in the work of Ha and Park (2020). Mitchell et al. (2019) examined whether the use of technology to manage health among older people varies by race/ethnicity and concluded differences between whites, older blacks and Hispanics. As a result, following the prior literature, this study explores their demographic effects on using wearable devices and makes the following hypotheses:

H2: The age of an individual will be negatively related to its use of healthcare wearables.
H3: The gender of an individual will be correlated to the use of healthcare wearables.
H4: The education level of an individual will be positively related to its use of healthcare wearables.
H5: The income level of an individual will be positively associated with its use of healthcare wearables.
H6: The marital status of an individual will impact its use of healthcare wearables.
H7: The race/ethnicity of an individual will impact its use of healthcare wearables.

There is a growing concern from the public about personal healthcare management. Remarkably, the emergence of wearables in healthcare allows medical providers to track patients' health outside the hospital, which is extremely helpful for care plans and chronic illness management. Moreover, one of the crucial functions of healthcare wearables products is checking and monitoring health status (Zhang et al., 2017). Consequently, it appears as a prominent means to control chronic conditions and monitor physical activities. Hence, more and more consumers are using wearables for positive health improvement. Furthermore, physical activities are strongly associated with healthcare wearables because doing exercises could improve both individuals' health (Xie et al., 2020). Consequently, physical activities and health-related variables such as general health conditions and the presence of chronic disease are essential constructs to predict the use of wearables. Therefore, we propose the eighth hypothesis as follows:

H8: The importance a person places on health management will be positively related to its use of healthcare wearables.

The younger age group is more susceptible to technological advances and tends to adopt these devices. Technology self-efficacy, an individual's belief in doing a technological task as their intention, has been studied to determine the levels of technology adoption from consumers. Apparently, this concept should be unquestionably important in predicting wearables use. However, Lee and Lee (2018) revealed that this construct did not impact wearable health tracker choice. In contrast, according to qualitative research by Abouzahra and Ghasemaghaei (2020), self-efficacy toward technology was found as an influencer on the choice and confidence levels to adopt wearables. Accordingly, this construct will be examined in this study as its empirical findings are still conflicting. As a result, we propose the following ninth hypothesis as follows:

H9: User experience with other technology products will be positively correlated with the use of healthcare wearables.

Despite the enormous benefits that users derive from the IoT, there are challenges that come with it that need attention, particularly data privacy and security. On the one hand, these two issues pose a huge dilemma for many businesses, organizations as well as public organizations (Tawalbeh et al., 2020; Deep et al., 2022). On the other hand, because of the privacy and security issues previously encountered in the use of IoT products, concerns about this issue are greatly increased before using other emerging technology products, thus hindering the acceptance of these innovative products (Merhi et al., 2019). While using wearable devices, users usually contribute their health and private data to a centralized cloud database managed by wearable organizations. As discussed in the above section, wearables users are consequently exposed to privacy and cybersecurity risks, such as unauthorized access and external attacks. In fact, data protection and security remained the obstacles limiting the use of wearable devices (Deloitte, 2015). Besides, Marakhimov and Joo (2017) unearthed that privacy profoundly affects healthcare wearables adoption. Consumers are increasingly worried about privacy and security issues while using these devices. According to Li et al. (2016), consumers will decide to adopt wearables if the benefits outweigh the losses from privacy and security. Therefore, they will judge the benefits and risks of wearables to decide whether they should continue using the devices. This study also explores the effect of privacy and security concerns on using wearable devices and makes the following hypothesis:Fig. 1.

H10: User experience with other technology products will be positively associated with people's data privacy and security concerns.

In order to continue the popularity of wearables, it is crucial to understand and explore the above determinants of these devices' adoption. Hence, we investigate the antecedents impacting the actual usage of healthcare wearables by the following research question:

What are the critical determinants associated with healthcare wearables use?

3. Methodology

This study uses an integrated-methods methodology comprising qualitative and quantitative data to enrich the explored topic from multi-perspective viewpoints and draw a more comprehensive context. Therefore, the ethical issues and other predictors affecting the use of wearables in healthcare are provided for an in-depth understanding. The research methodology is shown in Fig. 2.

First of all, this study searches and investigates the literature in the healthcare domain and about the use of wearables and related concerns and the application of AI in the healthcare domain. Through the literature search and investigation, we identify the most discussed concerns and construct the model by defining the concerns as independent variables and the use of healthcare wearables as the dependent variable. The results of the literature review are presented in Section 2, and the proposed model is presented in Fig. 3. Some of them are latent variables. The dataset employed comes from Health Information National Trends Survey (HINTS) by the National Cancer Institute. In the next step, based

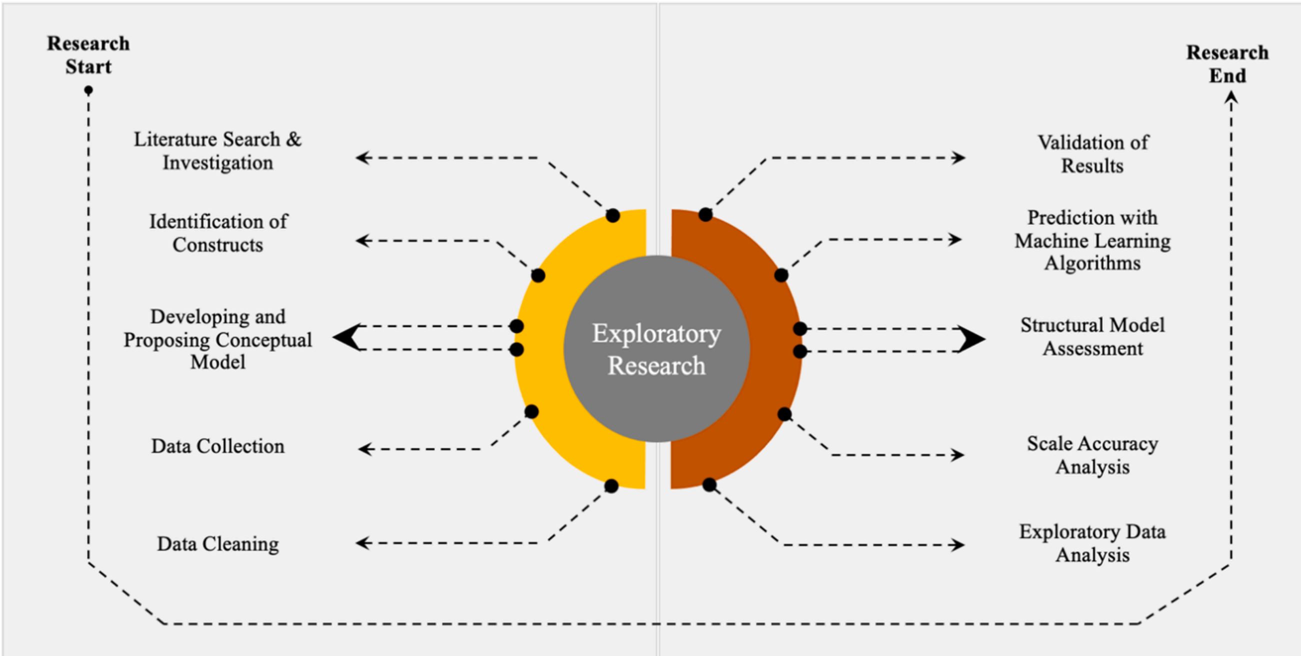

Fig. 2. Research Methodology.

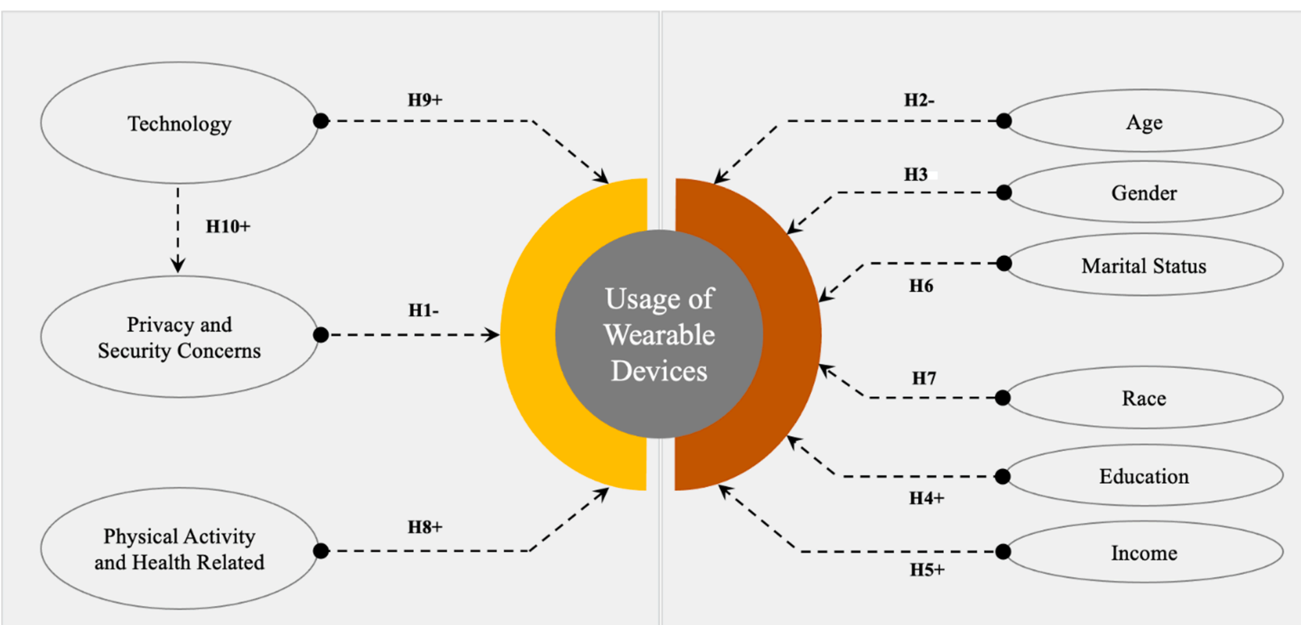

Fig. 3. The Proposed Conceptual Model.

on the concerns identified in the process of literature search and investigation, the questions in the HINTS that measure these concerns are selected, and the corresponding attributes and data are collected. The attributes are employed as constructs to reflect latent or independent variables. The complete proposed model is shown in Fig. 3. In addition, we clean the data by checking duplicated, missing, error, or inapplicable values. In the next step, the exploratory data analysis is conducted to study the demographic characteristics of respondents, the construct distribution and the correlation of the constructs. The PLS-SEM with SmartPLS 3.0 is used to analyze the impact of the concerns and demographics on the use of healthcare wearables. In the fifth step, the scale accuracy analysis is performed to evaluate the reliability and validity of the measurement model. We evaluate the reliability using Cronbach's alpha, composite reliability (CR), and AVE, and the validity using the Fornell-Larcker criterion and heterotrait–monotrait (HTMT) ratio. After that, the structural model assessment is conducted to explore the relationship between the use of healthcare wearables and its antecedents and identify the significant antecedents. Finally, machine learning algorithms are performed to predict healthcare wearables users. The results of feature importance are used to validate the result of the structural model assessment.

Table 1
Demographic Characteristics of Respondents.

Respondent characteristics	Using healthcare wearables in the past 12 months (n = 2,687)			
	Total %	**Yes %**	**No %**	**P value[a]**
Total sample, n(%)	100	25.87	74.13	N/A
Gender				< 0.001
Male	46.63	10.46	36.17	
Female	53.37	15.41	37.93	
Marital status				< 0.001
Married	48.98	14.40	34.57	
Other	51.02	11.46	39.56	
Age group				< 0.001
18–34	17.4	6.48	11.02	
35–49	23.45	7.37	16.08	
50–64	32.27	7.82	24.45	
65–74	18.53	3.2	15.33	
75+	8.26	1.00	7.26	
Race				< 0.001
Hispanic	18.61	4.32	14.29	
Non-Hispanic Asian	4.95	1.30	3.65	
Non-Hispanic Black American	13.17	2.83	10.35	
Non-Hispanic White	59.77	16.41	43.36	
Non-Hispanic Others	3.50	1.00	2.49	
Education				< 0.001
Less than high school	5.32	0.48	4.84	
High school graduate	17.68	3.24	14.44	
Some college	31.11	7.89	23.22	
College graduate and more	45.89	14.25	31.63	
Annual household income (US $)				< 0.001
<20,000	15.26	1.94	13.32	
20,000 to < 35,000	13.17	2.38	10.79	
35,000 to < 50,000	13.40	2.87	10.53	
50,000 to < 75,000	19.24	4.95	14.29	
More than 75,000	39.93	13.73	25.20	

a. Wald chi-square test.

3.1. *Quantitative study*

3.1.1. *Dataset description*

This study applies Health Information National Trends Survey – Cycle 3 and 4 (HINTS) data by the National Cancer Institute. The survey has nationally representative data for US citizens samples and aims to access the public's knowledge, perception, health-related information, and behaviors (HINTS, 2021). The HINTS survey data was widely used for many studies examining the use of technology in healthcare (Sherman et al., 2020; Xie et al., 2020). This survey used a sampling frame provided by Marketing Systems Group (MSG) of addresses in the US and conducted a stratified sampling method to address different density concentrations of population areas to avoid bias. Data collection comprised two periods:

- *The first* period was from January 2019 to April 2019, with a respondent rate of 30.3 %, and
- *The second* period was from February 2020 to June 2020, with a respondent rate of 37 %.

Questionnaires were mailed to participants based on the residential addresses in the MSG database, then a reminder message and two extra posts for non-respondents. A monetary reward of $2 was offered for every completed questionnaire to encourage participation. HINST Cycle 3 and 4 included 5,438 and 3,865 respondents, respectively. Therefore, there are a total of 9,303 respondents in our dataset, including 2,066 cases online and 7,237 cases by paper.

3.1.2. *Data analysis strategy*

The data includes several variables provided in SPSS, SAS, and Stata. For this study analysis, only relevant data could be extracted and converted to comma-delimited (CSV) format to further process in Python. Subsequently, data were cleaned by checking duplicated, missing, error, or inapplicable values. No respondent ID duplicates were observed in the dataset. Besides, the inappropriate and missing answers, coded for values < 0, were removed. 915 respondents answered in error, 10 unreadable responses, 2,941 missing values, 3,166 inapplicable answers were in the dataset. Consequently, 3,196 samples remained in the dataset after cleaning data.

Table 1 presents the characteristics of the participants. The independent constructs are demographic, privacy, security concerns, and health-related and technological factors. At the same time, wearables usage is the target construct indicating whether respondents have used electronic wearables to track their activities or health in the last 12 months. The antecedents' measurement items are described in Appendix A. All the analyses are conducted in a Python environment and SmartPLS 3 with the support of the Statsmode library for statistical computation and Sklearn for machine learning. The analysis is comprised of three steps:

- First, data analysis is conducted to obtain insights into the data. This step also applies the Wald chi-square test to compare patterns between demographic constructs and healthcare wearables usage.
- Then, Partial Least Squares Structural Equation Modeling (PLS-SEM), particularly SmartPLS 3.0 (Ringle et al., 2015), is employed for data analysis.
- Subsequently, machine learning algorithms, namely Logistic Regression, Gradient Boosting, and Neural Networks, are applied to

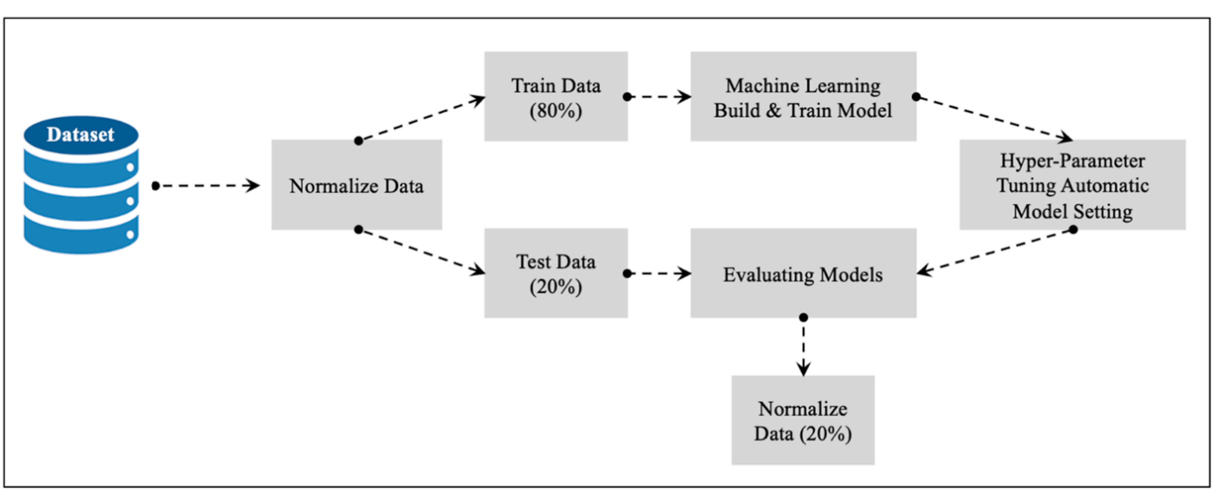

Fig. 4. Machine Learning Implementation Process.

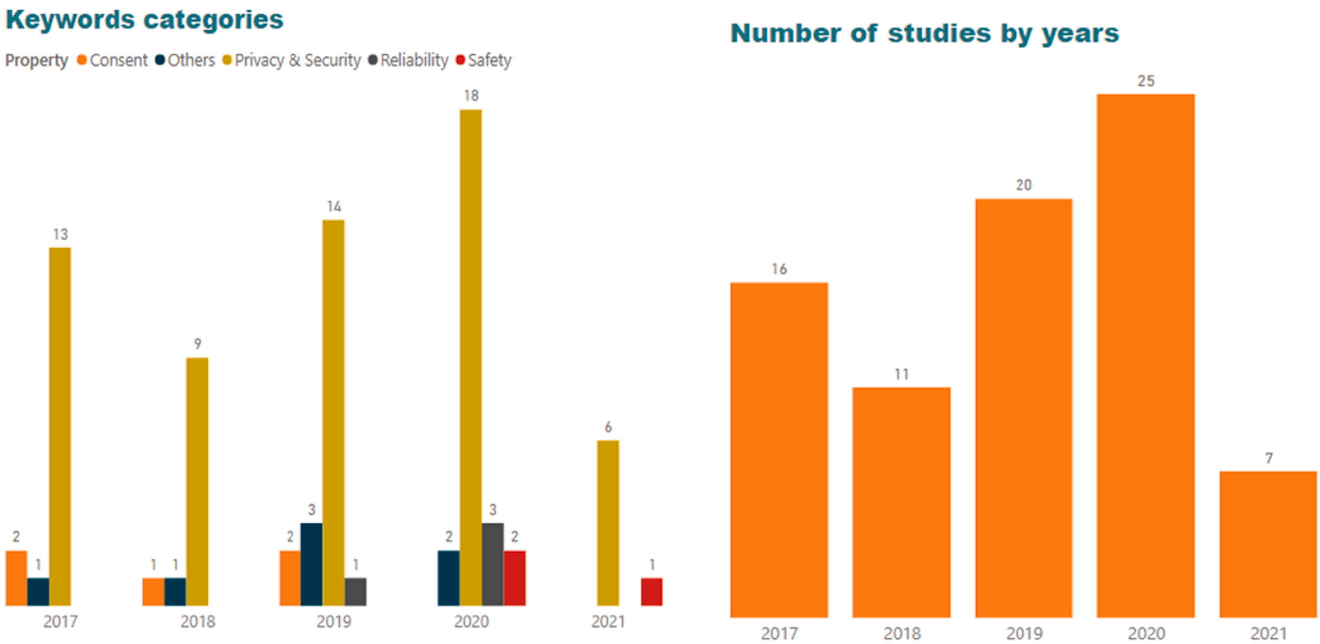

Fig. 5. (a) Records' Distribution through Keywords Categories Summary (b) by Years.

Fig. 6. Text Analysis Results – Word.

predict the use of wearables based on the proposed predictors from the survey.

The detail of the machine learning algorithm can be found in Appendix B. The machine learning implementation process is described in Fig. 4.

4. Analysis and findings

4.1. Results of the qualitative analysis

The search indicated 368 initially relevant articles, as depicted in Fig. C1 (Appendix C). Then, five duplicated documents were moved, and 363 records remained abstract screening with the aid of the NLP toolkit. Next, the review eliminated articles, not original research, unrelated to healthcare wearables, not having the main argument on ethical issues or from complete technical perspectives. Hence, we dropped 284 articles due to their ineligibility for the review scope. After reviewing the title and abstract, only 79 records met the inclusion criteria. These documents were then labeled with the primary categories: *consent*, *reliability*, *privacy* and *security*, *safety*, and *others*.

Fig. 5 illustrates the number of chosen articles and keywords ethical categories reported by year based on the articles generated. A growing drift in the number of research in wearables' ethics for the healthcare

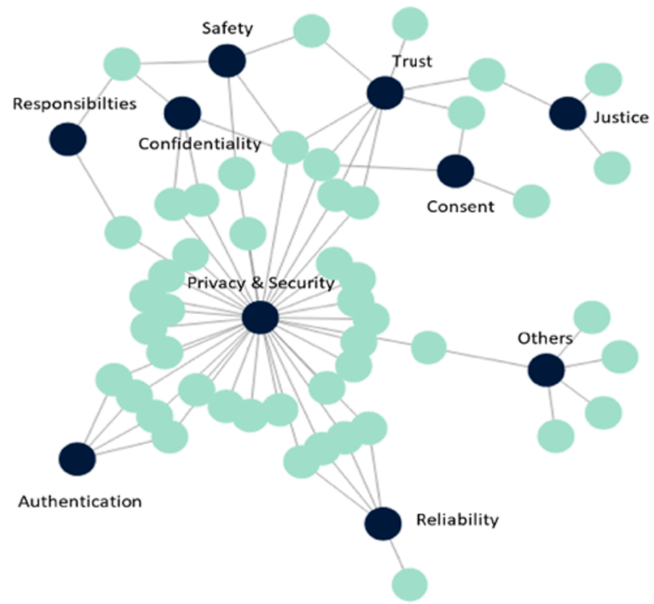

Fig. 7. Network Diagram of Key Concepts of Review Studies.

domain is observed except for 2018. A similar trend is seen in the number of privacy and security studies. In comparison, most research examines privacy and security matters, and other issues such as consent, reliability, and safety issues were followed. The ethical concept frequency of the selected studies is presented in the word cloud, in which font sizes indicate the frequency number of the corresponding concept. Furthermore, the text analysis by a word cloud chart is depicted in Fig. 6. As can be seen in the chart, privacy, security, and consent are the top three ethical concerns while using healthcare wearable devices. In addition, reliability, safety, confidentiality, and authenticity are other ethical matters discussed in the prior research. Besides, data management and governance are also gained attention in related literature. A network chart in Fig. 7 shows how the concepts in selected records are interrelated. The visual signifies that the central ethical issue in prior literature is privacy and security connected to other topics such as authentication, confidentiality, trust, and reliability. Further, an overview of top ethical concerns is discussed herein.

- Privacy concern was among the most frequently mentioned in our literature search for ethical issues in healthcare wearables. The literature mainly discussed data misuses, such as data anonymization and the individual information transfer outside devices' scope for this topic. Dave and Gupta (2020) emphasized the above issues for COVID-19 proximity tracking wearables cases. Besides, Monteith et al. (2021) presented that numerous wearables users may not violate their privacy. The reason is that the "surveillance capital" business model in many intelligent devices – where providers offer some free services but enable them to monitor the users' behaviors of those users – often without their explicit consent. Privacy policies, which generally comprise the ownership and purpose of using all data acquired, are usually available online. Consequently, massive personal information is collected from wearables, which can be consolidated, analyzed, and packaged to sell to other businesses to profit.
- Healthcare wearables can collect user health and private information, which may enhance tampering and leakage risks. Giansanti (2021) found that healthcare wearables were typically involved in a possibly susceptible to cyberattacks heterogeneous system where its components communicated through wireless. Hackers could then intentionally transmit unreliable data to the control system if the wireless connection is potentially unsafe. Therefore, approaches to assure data security from wearables and gain confidence from the public are needed.

4.2. Survey data results

Python 3.9 (Van Rossum and Drake, 2009) and its libraries were used to conduct all the analyses in this section, including Pandas and NumPy for loading, data preprocessing, Dataprep for exploring data, Matplotlib, Seaborn for data visualization, Statsmodels for statistical computation, and Sklearn for machine learning experiments. This study constructed the PLS-SEM model using the statistical software SmartPLS 3 (Ringle et al., 2015) to examine scale accuracy and access structural model. SmartPLS 3 was used because of its advancement in handling complicated relationships, capability to process both reflective scales and formative indexes, deal with single-item variables, and the latest statistical measures. The study findings are described below.

4.2.1. Exploratory data analysis

To investigate data, we used descriptive and crosstab tables. The final data included 2,687 US adult respondents aged 18 years or older, in which 53.37 % were female, 77.00 % had college or more, 59.77 % were non-Hispanic white. The Wald chi-square test results from Table 1 showed significant differences between users and non-users of wearables in healthcare across different demographic segments. Among the reported respondents, 25.87 % used healthcare wearables in the past 12 months, in which non-Hispanic white ones (16.41 %), female (15.41 %), married ones (14.40 %), graduated college and higher education ones (14.25 %), and ones had annual incomes higher than US$ 75,000 (13.73 %) were most likely adopting healthcare wearables. Fig. 8 shows the distribution of other independent variables in this study. As can be seen from the chart, more than half of the participants had chronic conditions, while more than two-thirds reported having good to very good general health. Moreover, nearly-two-thirds of them did not use tablets or mobile devices to support keeping track of health information, and only 13.44 % of them shared health information from the devices with their health providers.

The Spearman's Rank correlation matrix of features in this study is presented in Fig. 9. All features had correlation values <0.70, which signifies that multicollinearity was absent in this dataset and implied a more substantial regression calculation.

4.2.2. Scale accuracy analysis

We conducted the measurement model assessment following Hair et al. (2019)'s guidance for handling the PLS-SEM procedure to ensure every indicator was reliable and valid. First, Table 3 indicated no indicator loaded less than the minimum threshold value of 0.4. For the indicators with the loading factor from 0.4 to 0.7, we evaluated the average variance extracted (AVE) value to decide whether drop these indicators. As shown in Table 3, all constructs' AVE was higher than 0.5, which met the requirements for strengthening the content validity (Hair et al., 2017). Therefore, no indicators were required to drop in this case. Then, we accessed the scale reliability using Cronbach's alpha, composite reliability (CR), and AVE. Our results showed that all the above measures were acceptable values of 0.6, 0.7, 0.5 for Cronbach's alpha, CR, and AVE, respectively (Ursachi, Horodnic, and Zait, 2015; Hair et al., 2017). Therefore, the assessment results indicated that the convergent validity and reliability requirements were met, which meant our framework indicators could demonstrate consistency and explain variables.

Next, the Fornell-Larcker criterion and heterotrait–monotrait (HTMT) ratio were examined to verify discriminant validity. HTMT ratio was found as a novel method to overcome the previous traditional approach limitation (Henseler et al., 2015). According to Table 4, the AVE value's square root was higher for every variable than all the correlations between each pair of variables, indicating that discriminant validity requirements were satisfied. Moreover, as the rule of thumb, all

Fig. 8. Constructs' Distributions – Researched for this Study. Note: WearableDevTrackHealth, SharedHealthDeviceInfo, ConcernedPrivacy, Exercise, Chronic: 1 = No; 2 = Yes; For other measurements, please see Appendix A for further details.

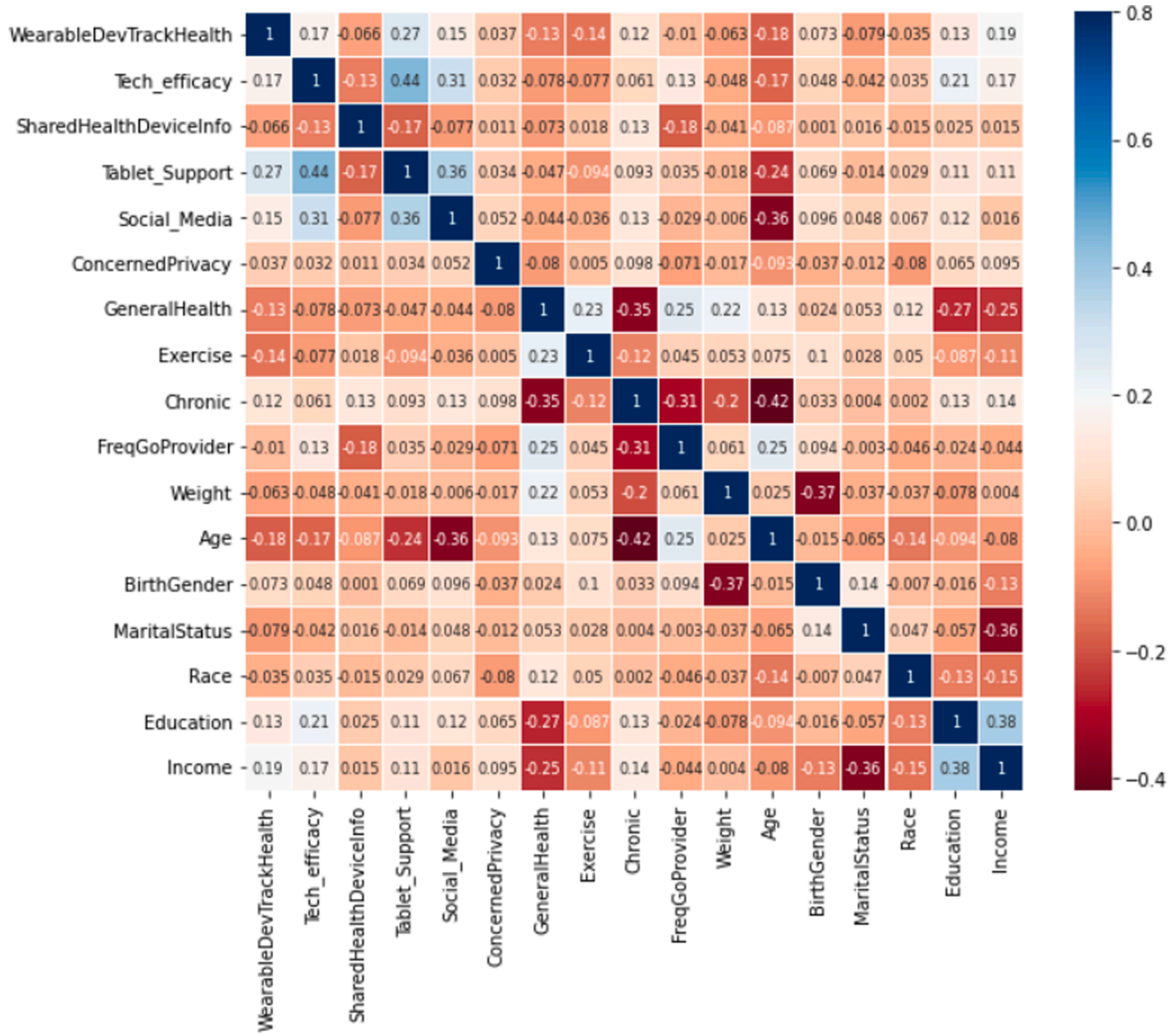

Fig. 9. Correlation Matrix.

Table 2
Total variance explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.580	18.428	18.428	2.580	18.428	18.428
2	1.763	12.593	31.021			
3	1.553	11.092	42.113			
4	1.140	8.143	50.256			
5	0.990	7.072	57.328			
6	0.918	6.557	63.885			
7	0.832	5.942	69.827			
8	0.792	5.660	75.487			
9	0.725	5.181	80.669			
10	0.651	4.648	85.317			
11	0.609	4.353	89.669			
12	0.512	3.655	93.325			
13	0.482	3.441	96.766			
14	0.453	3.234	100.000			

constructs' HTMT ratio value was required to be < 0.9 (Hair et al., 2017). From the analysis results in Table 4, all HTMT values satisfied this condition. Consequently, the results indicated rigid evidence of good discriminant validity for all constructs.

To avoid the common method bias (CMB) threatening the validity of our findings, we conducted Harman's single factor test to measure it (see Table 2). This method is realized using factor analysis and restricting the number of factors to 1. If the total variance for one factor is < 50 %, the results are not affected by the CMB (Roni and Djajadikerta, 2021). In our Harman's single factor test, the total variance for a single factor is

Table 3
Scale accuracy analysis.

Variables	Cronbach's Alpha	Composite Reliability	AVE	Factor Loadings
Age	1.00	1.00	1.00	1.00
Gender	1.00	1.00	1.00	1.00
Education	1.00	1.00	1.00	1.00
Health-related	0.61	0.75	0.53	0.41–0.85
Income	1.00	1.00	1.00	1.00
Marital Status	1.00	1.00	1.00	1.00
Privacy Security Concerns	1.00	1.00	1.00	1.00
Race	1.00	1.00	1.00	1.00
Technology-related	0.64	0.80	0.58	0.66–0.87
Usage of wearable device	1.00	1.00	1.00	1.00

18.428 %, indicating that our data and results are free from the CMB.

4.2.3. Structural model assessment

The structural model was accessed by bootstrapping 5,000 samples to compute the coefficient, 95 % confidence interval (CI), and the significance level with a threshold p-value of 0.05 to explore the antecedents of wearables use in healthcare (see Fig. 10). The quality of the structural model was investigated using the coefficient of determination (R^2) and predictive relevance (Q^2). The R^2 value of the dependent variable was 0.12, which signified the satisfied explanatory power of the model as the R^2 value was above the acceptable level of 0.1 (Mochales and Blanch, 2022; Galindo-Martín et al., 2021; Falk and Miller, 1992). In addition, the Q^2 values of all endogenous variables were higher than 0, indicating that the model has predictive relevance. Therefore, a satisfactory model for the proposed framework was concluded with these above findings.

Next, the outcomes were examined and displayed in Table 5. Except for Education, Privacy and Security Concerns, and Race, the framework's remaining relationships were significant, with p-values$<$0.05. Particularly, the Age ($p < 0.001$), BirthGender ($p < 0.001$), Health-related ($p = 0.003$), Income ($p < 0.000$), MaritalStatus ($p = 0.022$), and Technology-related ($p < 0.001$) values were significant with the confident level of 95 %, indicating they have a significant impact on the usage of wearable devices in the healthcare domain. Among them, the influences of Age ($\beta = 0.093$), Health-related ($\beta = 0.056$), and MaritalStatus ($\beta = 0.046$) were positive, while those of BirthGender ($\beta =$ -0.077), income ($\beta =$ -0.125) and Technology-related ($\beta =$ -0.207) were negative. Moreover, the Technology-related variable had a significant positive impact on Privacy and Security Concerns ($\beta = 0.043$, $p = 0.033 < 0.05$). However, the results also indicated that the influences of Education, Privacy, and Security Concerns, and Race on the use of wearable devices in the healthcare domain are insignificant, with p-values greater than 0.05. The findings suggested that age, gender, health-related factor, marital status, and technology-related factors were profoundly correlated with an increased possibility of using healthcare wearables. Other variables did not have significant effects on the use of wearables.

4.2.4. Machine learning models

The training and test performance results generated by classification reports of the three machine learning models are displayed in Table 6. The neural network showed the best results for both training and testing regarding accuracy, precision, recall, and F1 score. The one exception is the gradient boosting algorithm matching its performance in training precision. Therefore, it can be concluded that neural networks outperform logistic regression and gradient boosting algorithms at predicting healthcare wearables users. Next, the top five important features from experiment 2 were visualized in Fig. 11 According to the chart, the features that hugely influenced wearables users' prediction were tablet support, exercise levels, age, income and weight. Consistent with the results in structural assessment, people who are more familiar with technology, especially those who have experienced using tablets, are the most critical contributor to predict wearables users (see Table 5).

5. Discussions

Through an integrated-methods approach, we explore the role of wearables in the omnichannel healthcare supply chain business and the associated ethical challenges in this study. The wearable device appears as an inevitable tool to effectively manage the health business supply chain and facilitate omnichannel strategy because this emerging technology provides a solution to improve interaction and the co-valued relationship between hospitals and patients. Then, we investigate the influence of ethical issues (i.e., privacy and security concerns) and other predictors such as technology self-efficacy, health-related factors, and demographics on the use of wearables. Finally, recommendations and future research directions are proposed to promote the use of wearable devices in the omnichannel strategy of healthcare supply chain businesses.

5.1. Theoretical implications

Our study contributes to the growing stream of research exploring the role of IoT, AI and big data analytics in healthcare business transformation (Kraus et al., 2021; Dahl et al., 2021). First, the healthcare wearables in the omnichannel healthcare environment are discussed and emphasized. Wearables are a part of the IoT that facilitates the omnichannel healthcare system by providing technical support to monitor patients' health and implementing clinical tests remotely. It supports the transfer and exchange of information through omnichannel systems and provides real-time data about the health conditions and activities of patients. With the advancement of AI and big data analytics, omnichannel healthcare supply chain businesses could understand patients' physical condition, need, and wants. Consistent with Dahl et al. (2021), the insights from wearable devices enable the healthcare business to enhance patients' experiences and satisfaction and meet their

Table 4
Discriminant validity assessment - fornell-larcker criterion.

	Age	GEN	EDU	HTH	Inc	MAR	PRI	Race	TECH	WEAR
Age	**1.00**	0.01	0.09	0.45	0.06	0.08	0.09	0.15	0.40	0.18
Gender (GEN)	−0.01	**1.00**	0.02	0.08	0.13	0.14	0.04	0.02	0.12	0.07
Education (EDU)	−0.09	−0.02	**1.00**	0.26	0.37	0.04	0.06	0.11	0.23	0.14
Health-related (HTH)	0.32	0.00	−0.26	**0.72**	0.29	0.05	0.15	0.09	0.19	0.15
Income (Inc)	−0.06	−0.13	0.37	−0.27	**1.00**	0.36	0.10	0.12	0.14	0.19
MaritalStatus (MAR)	−0.08	0.14	−0.04	0.05	−0.36	**1.00**	0.01	0.03	0.06	0.08
Privacy and Security Concerns (PRI)	−0.09	−0.04	0.06	−0.11	0.10	−0.01	**1.00**	0.07	0.06	0.04
Race	−0.15	−0.02	−0.11	0.06	−0.12	0.03	−0.07	**1.00**	0.08	0.02
Technology-related (TECH)	−0.31	0.09	0.18	−0.10	0.12	−0.01	0.04	0.06	**0.76**	0.32
Usage of a wearable device (WEAR)	0.18	−0.07	−0.14	0.15	−0.19	0.08	−0.04	0.02	−0.27	**1.00**

Note: The lower and upper of the diagonal are bivariate correlations and HTMT ratio, respectively; diagonal elements are the square root of AVE (highlighted in bold).

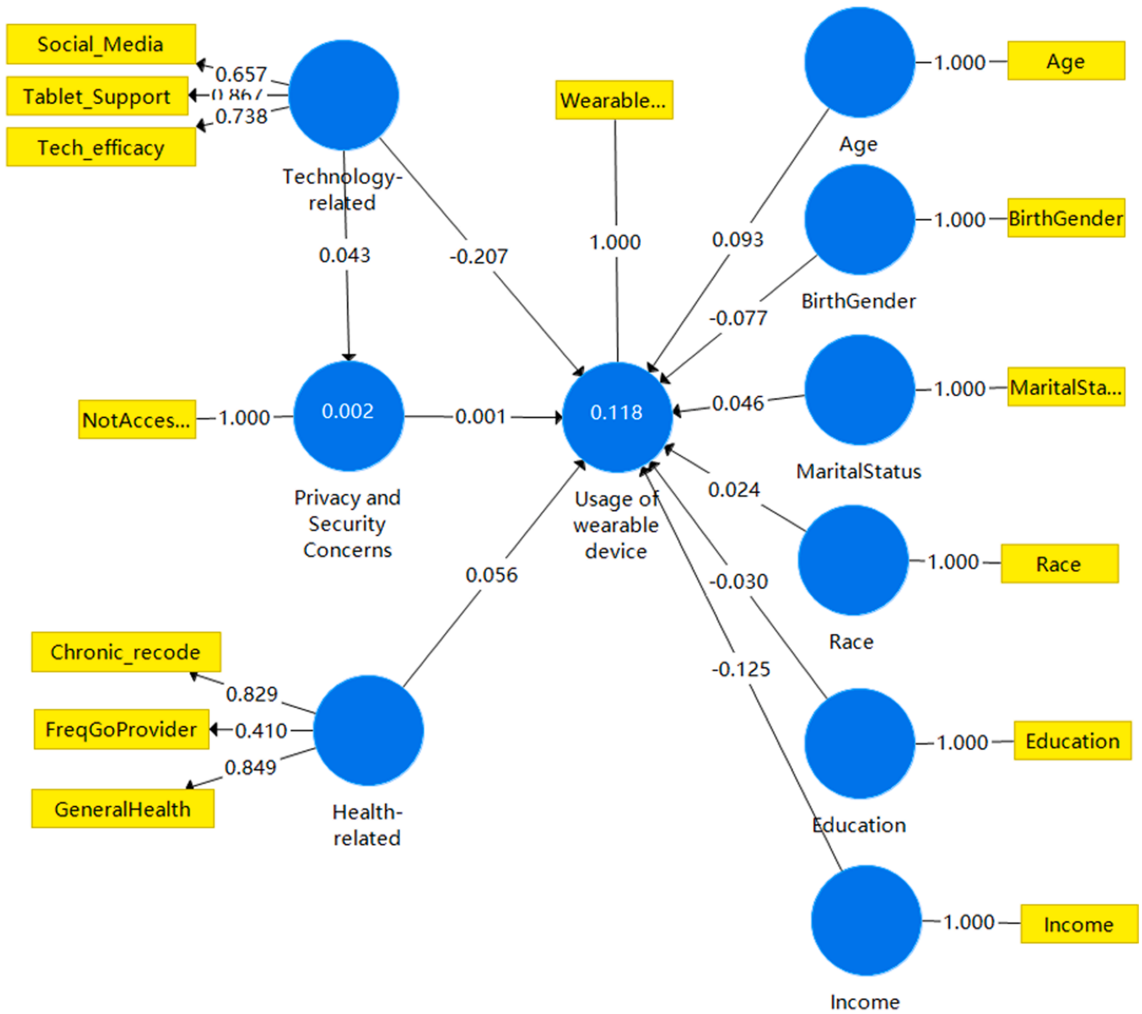

Fig. 10. PLS-SEM Framework.

expectations. Significantly, they present an opportunity to create a more seamless healthcare experience, which enhances patient interaction, communication, and engagement with healthcare providers (Hermes et al., 2020).

Table 5
Coefficients results.

Path	Coefficient (β)	P-values	Hypothesis testing
H1: Privacy and Security Concerns -> Usage of wearable device	0.001	0.974	Reject
H2: Age -> Usage of wearable device	0.093	< 0.001	Accept
H3: BirthGender -> Usage of wearable device	−0.077	< 0.001	Accept
H4: Education -> Usage of wearable device	−0.030	0.102	Reject
H5: Income -> Usage of wearable device	−0.125	< 0.001	Accept
H6: MaritalStatus -> Usage of wearable device	0.046	0.022	Accept
H7: Race -> Usage of wearable device	0.024	0.214	Reject
H8: Health-related -> Usage of wearable device	0.056	0.003	Accept
H9: Technology-related -> Usage of wearable device	−0.207	< 0.001	Accept
H10: Technology-related -> Privacy and Security Concerns	0.043	0.033	Accept

Through the literature search and investigation, the omnichannel healthcare and wearable technology literature have highlighted the ethical implications of using these devices is a relatively understudied area in the healthcare domain. Our findings indicate that privacy and security are the most concerning ethical matters. These concerns are also the contemporary challenge in adopting an omnichannel approach (Cui et al., 2021). After that, we investigate the effect of these concerns on the adoption of healthcare wearables through a quantitative study. Surprisingly, privacy and security concerns do not affect healthcare wearables adoption. This finding implies a strong implication about the current awareness level about the privacy and security of wearables. One reason is that consumers do not have enough understanding of the loss of privacy and potential security matters involved with many tech companies in the US. Fruchter and Liccardi (2018) discovered that privacy and security concerns were mentioned in only 2 % of online reviews of IPA products. Williams, Nurse, and Creese (2019) highlighted that although 84 % of US consumers were worried about their data, they rarely safeguard their information in action. Other potential reasons include consumers trusting the company or government, or being satisfied with their existing data policies, and not feeling targeted (Zeng et al., 2017; Liao et al., 2019).

In fact, many studies have found that privacy was not a consumers' primary objective; hence, they might lack the motivation to protect their personal data (Hughes-Roberts, 2015), including ignoring the permissions, accepting default settings without reading, skimming policies, and the growing trend of data exchange on social media. The proliferation of

Table 6
ML experiment training and test results.

	Logistic Regression		Gradient Boosting		Neural Network	
	Train	Test	Train	Test	Train	Test
Accuracy	0.80	0.79	0.81	0.78	0.82	0.80
Precision	0.77	0.75	0.80	0.76	0.80	0.78
Recall	0.80	0.79	0.81	0.78	0.82	0.80
F1	0.78	0.75	0.79	0.76	0.80	0.78

self-discloser on social media also intensifies the above issues and reduces the risk to consumers' privacy and security (Tsay-Vogel, Shanahan, and Signorielli, 2018). The threat to privacy and security and their safeguards should be escalated. More campaigns to raise awareness for consumers are needed. Besides, the government, the manufacturers, and the businesses should align to have a more trustworthy and transparent data protection framework. Rather than requiring compliance from the consumers, the empowering aspects of protection should be highlighted.

Finally, our findings are consolidated through the integrated-methods approach and present the most comprehensive examination of the antecedents of actual wearables usage in healthcare with the support of advanced machine learning models. Our findings conclude that a significant portion of US adults reported using healthcare wearables. The results also suggest that gender, exercise levels, age, marriage, income, general health, and technology use are crucial factors. In particular, younger, healthier, and wealthier females are more likely to use wearable devices. Additionally, technology-related factors have a positive impact on privacy and security concerns. Then, we propose a predictive model to predict the wearables' usage by machine learning algorithms. It helps the wearables industry identify its potential customers based on national survey data and advancements in data science and AI technology. Neural network models show the best performance in predicting wearables users. The important features analysis of the predictive model reveals that people who have experienced using tablets are the most critical contributor to predict wearables users.

Given the growing demand for wearables in recent years, it is crucial to understand its driving forces and barriers among the general population to keep this trend. Consequently, the ethical problems and the predictors of using healthcare wearables are reviewed and analyzed, contributing to the extant research in the healthcare and wearable technology domain. This research surpasses intentions to use and studies the actual usage of these devices. Our outcomes would benefit practitioners and researchers in overcoming the current challenge in wearables adoption and developing the ethical practice for a more transparent wearables market.

5.2. Managerial implications

Our study offers relevant implications for the management of wearables and healthcare organizations and policymakers. First, our findings suggest that digitalization or promoting digital skills will equip citizens to use wearables more effectively. Furthermore, gender, age, income, and health conditions are other essential features of our predictive wearables users model. The healthcare and wearable business might benefit from the above information to identify the target groups of customers to advance the current function and design and expand sales and engagement. The use of wearables will facilitate the omnichannel transformation of the healthcare sector, releasing hospital burdens, better-allocating resources, and effectively managing the supply chain.

Second, omnichannel healthcare supply chain businesses and the opportunities for data collection from wearables require a rethink of sales, marketing, management and operational strategies to enhance insights into the patient journey and adapt to Industry 4.0. The amount of available data from healthcare is increasing exponentially; hence, BDA has become an essential part of strategic decision-making (Sivarajah et al., 2017). Particularly, BDA and related techniques, such as AI and machine learning, can significantly improve supply chain management (Guha and Kumar, 2018). Our work demonstrates how management and business researchers could use big data analytics to support decision-making. In our case, the algorithmic classification model could enable profiling and prediction based on age, gender, ethnicity, health condition, and other information on a large scale (Dash et al., 2019).

A plethora of research has highlighted the importance of understanding contemporary ethical concerns, especially the practices and substantial development of omnichannel healthcare supply chain businesses and the wearables industry. Our literature review unveiled that privacy and security concerns are the most frequently studied fields, followed by reliability, consent, and safety. However, our quantitative survey analysis findings indicate that the influence of privacy and security issues on wearables' adoption is not significant in a real-world situation. Hence, practitioners and policymakers need to reinforce their endeavors to enhance the technology deliveries and ethical framework to maintain the popularity of healthcare wearables in the omnichannel environment. From the above findings, the following recommendations have been made:

- *First*, more policies and practices should be made to increase knowledge of ethical matters associated with healthcare wearable devices to related parties and clarify each individual's rights and obligations. Consumers should be aware of privacy, give prudence consent while sharing their data, and increase technical knowledge to safeguard their information, such as updating antivirus software. Besides, the wearable devices business should take on more responsibilities rather than only manufacturing devices. Healthcare supply chain businesses have to be aware of patient privacy and security risk, and work with the wearables sector should establish oversight and formulate practices to shield users' data privacy and safety. In order to maintain a sustainable omnichannel environment, healthcare businesses should focus on managing risk and protecting users from vulnerability, attack, and misused data.
- *Second*, the standardized procedures for regulating wearable devices should be escalated, particularly when integrating into the health sector. A more updated procedure and framework should approach contemporary ethical matters, including users' data privacy and

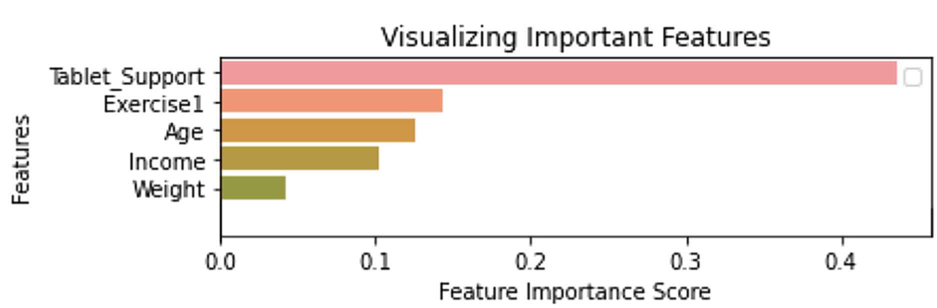

Fig. 11. Top Five Feature Importance Variables of Experiment 2.

security, to alleviate the current vague procedure. Besides, it is required to develop technical and statutory solutions for collecting, transferring, storing, and sharing data processes allowing authorized businesses to governance data and take responsibility for users. Industrial development should be closely linked with the standard code of practices. Hence, more research and additional investigations are needed to improve this aspect for safe, more careful, and practical wearable applications in healthcare.

- *Lastly*, a dynamic regulative framework solution might help facilitate the ethical improvement of wearable devices and not suppress their innovation, particularly in the health sector. Health providers and wearables businesses need to add more detailed guidelines for their products, which will benefit the consumers and both parties. Besides, this will assist consumers with more insight about wearables to mitigate the ethical risks and help prevent any potential future legal problems for providers. Another example is the General Data Protection Regulation (GDPR) framework regulating concise consent, avoiding data misuse, and strengthening data privacy. However, as digital data keeps growing, it is crucial to frequently research, improve, and update the GDPR and related frameworks to deal with any ethical issues promptly.

5.3. Limitations and future research

This study examines the current ethical issues and their influence and other factors on wearables' adoption among US adults. The framework can be applied to different contexts such as sports and fitness (Kim and Chiu, 2019) or to other countries to reproduce and expand the outcomes relied on in this study's conclusions. Ethical concerns about using wearables in the prior literature are also analyzed and emphasized in this investigation; however, further study and extension are expected to increase their privacy and security levels. Moreover, the review reveals associated ethical concerns in literature, including privacy and security concerns, data reliability, consent, and authenticity, while current quantitative design surveys examine privacy and security concerns. Future work can explore the influence of other ethical issues, such as data reliability and authenticity, on the use of wearables in healthcare. Besides, privacy and security concerns are accessed in the quantitative survey under a binary question (yes or no); in reality, people might have different degrees of those concerns, consequently impacting wearables adoption. Therefore, future work should conduct an empirical study to investigate different extents of the concerns.

The authors also offer some suggestions for future research in the field of healthcare operations. *Firstly*, future research could utilize IoT and BDA to give patients the option of networking their wearable devices with the healthcare system. Connected healthcare enables doctors to monitor a patient's basic physical condition and provide care even when the patient is not in the hospital, which maybe particularly convenient and cost-effective for patients with chronic conditions. Moreover, as ML algorithms have been studied in-depth, their predictive power has been significantly improved in various fields, including healthcare. On this basis, precision medicine has the potential to be achieved through the introduction of these intelligent technologies into the healthcare system. By analyzing the vast amount of medical data in the healthcare system that cannot be processed by the human brain, precision medicine may be able to provide effective advice to doctors. However, future research on this topic will need to pay attention to the ethical issues involved, such as patient privacy or the right to choose to use precision medicine technology.

CRediT authorship contribution statement

Victor Chang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Le Minh Thao Doan:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Qianwen Ariel Xu:** Writing – review & editing, Methodology, Formal analysis, Software, Investigation, Visualization. **Karl Hall:** Writing – review & editing, Investigation, Formal analysis, Software, Visualization. **Yuanyuan Anna Wang:** Writing – review & editing. **Muhammad Mustafa Kamal:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is partly supported by VC Research (VCR 0000168).

Appendix A:. Measurements Description

Group	Variables	Description
Technology-related constructs	- Technology self-efficacy	- Measured (from 0 to 4) if participants did electronic tools to perform four tasks: (1) make an appointment with the health provider, (2) search health information, (3) communicate with the provider by email or website, and (4) search medical test results.
	- Shared information	- Measured as binary values showing in the last 12 months, participants had shared their health data from mobile devices with any health providers.
	- Tablet Support	Measured (from 0 to 3) if participants used a mobile device like a tablet or smartphone to: (1) track progress on a health-related goal, (2) discuss with the health provider, and (3) make a treatment decision.
	- Social media	Measured (from 0 to 4) if respondents used the internet to (1) visit a social media site, (2) share health information on social media, (3) participate in an online forum for medical issues, and (4) watch health-related videos on YouTube.
Privacy and Security Concerns	- Concern about privacy and security	- Measured by binary values showing the concern about the privacy and security of participants' data for those do not access online record.
Physical activity and health-related constructs	- General Health Status	- A 5-Likert scale (reverse score: 1 is yes and 2 is no) measured from poor to excellent for participants to rate their health.
	- Physical activity	- Measured by binary values if respondents took moderate-intensity exercise more than 150 min per week.
	- Presence of any chronic conditions	- Measured by binary values if the respondents had any of these situations: heart condition, hypertension, chronic lung disease, or diabetes.

(*continued on next page*)

(*continued*)

Group	Variables	Description
	- Frequency of visiting providers	- The number of times in the last 12 months participants visited healthcare providers
	- Weight	- Measured respondents' weight in pounds

Appendix B:. Machine learning methodology

The Logistic Regression (LR) Classifier is a widely used algorithm for classification problems in machine learning because of its training efficiency and highly accurate results. It is an algorithm to classify the data as discrete outcomes. Also, in healthcare research, it is popularly applied and found to have good performances (Goodfellow, McDaniel, & Papernot, 2018). LR applies a logistic function, also known as a sigmoid function (σ), to predict values and maps values to the probability from 0 to 1 (Dreiseitl & Ohno-Machado, 2002) as the below formula:

$$\sigma(t) = \frac{1}{(1 + e^{-1})}$$

Gradient Boosting Classifier is an ensemble algorithm that combined many weak learning models to create a robust predictive one. In other words, it takes a sequential strategy to obtain predictions where each decision tree predicts the error of the previous one and eventually improves the gradient (error) (Ayyadevara, 2018). This technique is referred to as stochastic gradient boosting using an iterative method to develop a final model in a forward stage-wise fashion, progressively adding trees to the model. It is emerging and has become famous because of its effectiveness in complicated datasets classification (Goodfellow, McDaniel, & Papernot, 2018) (Figs. B1 and B2).

Multilayer Perceptrons are a class of Artificial Neural Network, and are groupings of interconnected artificial neurons, or nodes, that use computational algorithms for processing data. Each of these nodes have the capability of transmission to transmit and receive transmission from other nodes. These layers consist of the input layer, at least one hidden layer, and an output layer. These connections between nodes have hidden weight values representing the impact each node has upon the connecting layers. The weight values are finally fed into an activation function which controls the output. The rectifier linear unit (ReLU) is the primary activation function used in our model. This was chosen over sigmoid and hyperbolic tangent functions due to their limitations, namely sensitivity and saturation. The ReLU activation function can be defined as the below formula:

$$y = \max(0, x)$$

The machine learning implementation process is described in Fig. 5. As the data comprised different types and scales of features, we normalize all features using Robust Scaler to scale data based on the first and third quartile range to avoid outliers' potential impact. Next, the preprocessed data is split to train and test set with the ratio 80:20. Consequently, the models are built and trained using tenfold cross-validation. Grid Search tunes the hyper-parameters and automatically selects the optimal model. Finally, this study conducts two experiments and compares the results from the test set to select the best algorithm to predict the use of healthcare wearables. The confusion matrix and its derived metrics – accuracy, precision, recall, and F1 are used to evaluate the performance of models. As shown in Table B1, the confusion matrix includes four elements, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN). TP and TN are the numbers of wearables users, and non-users accurately predicted, respectively, while FP and FN are the incorrectly classified data. Accuracy is the ratio of accurate wearables users' identification and indicates the effectiveness of the model. Precision and recall scores measure the proportion of wearables users correctly predicted in respective out of all the actual users and all samples (users and non-users). Usually, there will be a trade-off between precision score and recall score, so the F1 score appears to balance these above two scores and is a widely applied performance evaluation metric.

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall}$$

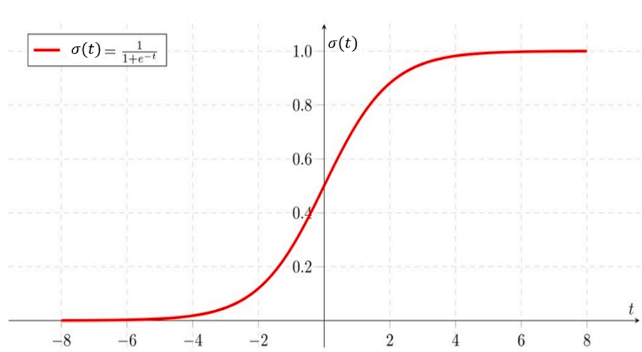

Fig. B1. Sigmoid Function.

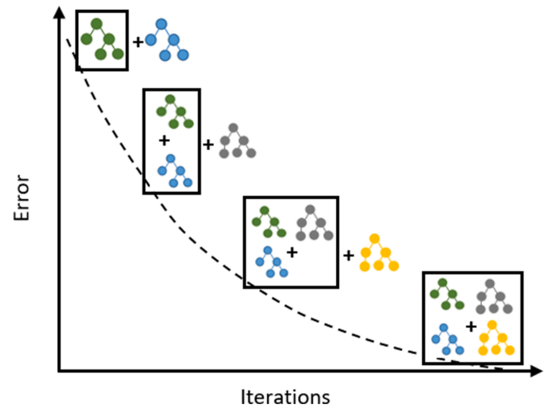

Fig. B2. Gradient Boosting Algorithm.

Table B1
Confusion Metric.

		Predicted	
		Positive	**Negative**
Actual	**Positive**	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Appendix C. Systematic review procedure

The systematic review methodology is implemented to determine the associated ethical implication of wearables and their current state in the health sector. The procedure is described as below:

According to Arksey and O'Malley's (2005) procedure for literature reviews, we perform five-stage for our review flow. For instance, first, the research question is identified, then the related articles from the database are identified and selected. Next, data are visualized, and outcomes are summarised and reported. We have carried out an extensive literature search in ProQuest digital relational database on 01 May 2021. The inspection is restricted to articles published from 2017 to 2021 and had English texts. Besides, the review is narrowed to ethical implications of wearables use in the healthcare field. Keywords for searching inquiry of article's abstract in the databases are included three groups: healthcare (e.g., healthcare, health, health care), wearable devices (e.g., wearables, wearable), and ethical implications (e.g., ethical, ethics, safety, privacy, trust, consent, security, concern, concerns). Fig. C1 illustrates this study's workflow to determine and decide relevant articles, which is strictly followed PRISMA methodological framework for systematic reviews (Page et al., 2021). Many criteria for exclusion and inclusion are applied to determine articles as follows.

- Articles not regarded as original studies, like comments or letters to the editors, are excluded.

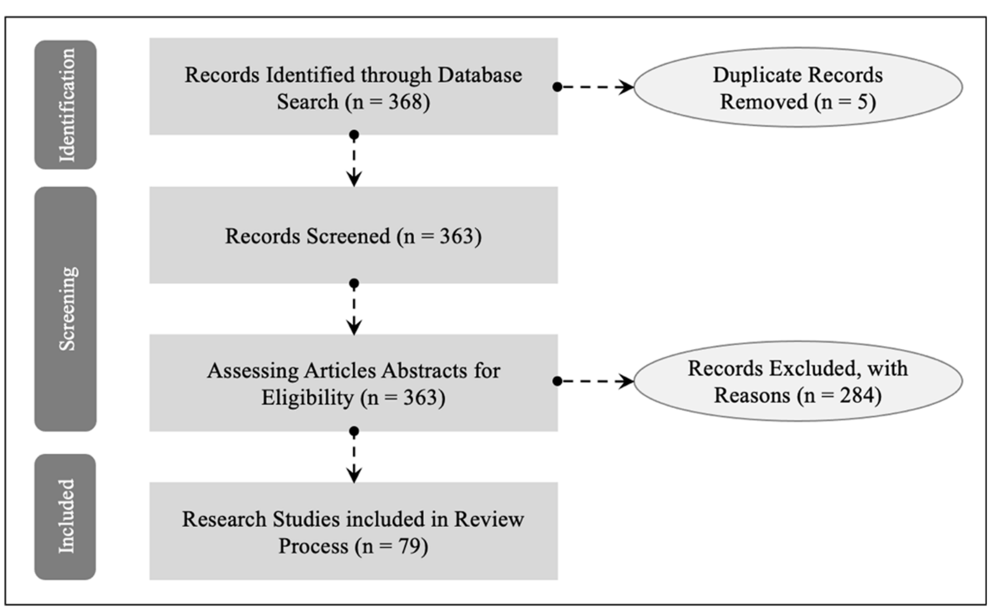

Fig. C1. Research Workflow.

- Only articles that provided theoretical discussion, opinion, or framework about ethical issues of healthcare wearables were included. Those only solely mentioned specific ethical concerns are excluded.
- The review is focused on ethical implications, so completely technical aspect articles are also omitted.

Next, all relevant articles' abstracts are screened for eligibility with the assist of the Natural Language Process (NLP) toolkit. After that, we extract and analyze entities and key concepts. Additionally, the efficiency of the literature corpus' search is ensured by the NLP algorithm advancements aid in automating the process defined the key concepts in the documents. Finally, we implement text analysis applying Power BI, a new and powerful business intelligence tool provided by Microsoft, to visualize the analysis's critical results.

References

Abouzahra, M., & Ghasemaghaei, M. (2020). The antecedents and results of seniors' use of activity tracking wearable devices. *Health Policy and Technology, 9*(2), 213–217. https://doi.org/10.1016/j.hlpt.2019.11.002

Allhoff, F., & Henschke, A. (2018). The Internet of Things: Foundational ethical issues. *Internet of Things, 1–2*, 55–66. https://doi.org/10.1016/j.iot.2018.08.005

American Medical Association. AMA digital health care 2022 study findings. https://www.ama-assn.org/about/research/ama-digital-health-care-2022-study-findings. 2022. (Accessed 13 Nov 2022).

Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology: Theory and Practice, 8*(1), 19–32. https://doi.org/10.1080/1364557032000119616

Azodo, I., Williams, R., Sheikh, A., & Cresswell, K. (2020). Opportunities and challenges surrounding the use of data from wearable sensor devices in health care: Qualitative interview study. *Journal of Medical Internet Research, 22*(10), e19542.

Azoev, G., Sumarokova, E., & Butkovskaya, G. (2019). Marketing communications integration in healthcare industry: Digitalization and omnichannel technologies. In *International Scientific and Practical Conference on Digital Economy (ISCDE 2019)* (pp. 635–640). Atlantis Press.

Babun, L., Denney, K., Celik, Z. B., McDaniel, P., & Uluagac, A. S. (2021). A survey on IoT platforms: Communication, security, and privacy perspectives. *Computer Networks, 192*, Article 108040.

Bijmolt, T. H., Broekhuis, M., De Leeuw, S., Hirche, C., Rooderkerk, R. P., Sousa, R., et al. (2021). Challenges at the marketing–operations interface in omni-channel retail environments. *Journal of Business Research, 122*, 864–874.

Bourreau, M., Caffarra, C., Chen, Z., Choe, C., Crawford, G. S., Duso, T., et al. (2020). *Google/Fitbit will monetize health data and harm consumers*. Centre for Economic Policy Research.

Buchlak, Q. D., Esmaili, N., Leveque, J. C., Farrokhi, F., Bennett, C., Piccardi, M., et al. (2020). Machine learning applications to clinical decision support in neurosurgery: An artificial intelligence augmented systematic review. *Neurosurgical Review, 43*(5), 1235–1253.

Castner, J., & Suffoletto, H. (2018). Emergency department crowding and time at the bedside: A wearable technology feasibility study. *Journal of Emergency Nursing, 44*(6), 624–631.

Chandrasekaran, R., Katthula, V., & Moustakas, E. (2020). Patterns of use and key predictors for the use of wearable health care devices by Us Adults: Insights from a national survey. *Journal of Medical Internet Research, 22*(10), e22443.

Chen, Y., Cheung, C. M., & Tan, C. W. (2018). Omnichannel business research: Opportunities and challenges. *Decision Support Systems, 109*, 1–4.

Chérrez-Ojeda, I., Vanegas, E., Calero, E., Plaza, K., Cano, J.A., Calderon, J.C., Valdano, J., Gutierrez, J.O., & Guevara, J. (2018). What kind of information and communication technologies do patients with Type 2 diabetes mellitus prefer? An Ecuadorian cross-sectional study. *International Journal of Telemedicine and Applications,* 2018.

Cilliers, L. (2020). Wearable devices in healthcare: Privacy and information security issues. *Health information Management Journal, 49*(2–3), 150–156.

Cui, T. H., Ghose, A., Halaburda, H., Iyengar, R., Pauwels, K., Sriram, S., et al. (2021). Informational Challenges in Omnichannel Marketing: Remedies and Future Research. *Journal of Marketing, 85*(1), 103–120.

Dave, R., & Gupta, R. (2020). Mandating the Use of Proximity Tracking Apps During Coronavirus Disease 2019: Ethical Justifications. *Frontiers in Medicine, 7*, Article 590265. https://doi.org/10.3389/FMED.2020.590265

Dahl, A. J., Milne, G. R., & Peltier, J. W. (2021). Digital health information seeking in an omni-channel environment: A shared decision-making and service-dominant logic perspective. *Journal of Business Research, 125*, 840–850.

Dahl, A. J., D'Alessandro, A. M., Peltier, J. W., & Swan, E. L. (2018). Differential effects of omni-channel touchpoints and digital behaviors on digital natives' social cause engagement. *Journal of Research in Interactive Marketing*.

Dahl, A. J., Barber, K., & Peltier, J. (2019). Social media's effectiveness for activating social declarations and motivating personal discussions to improve organ donation consent rates. *Journal of Research in Interactive Marketing*.

Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: Management, analysis and future prospects. *Journal of Big Data, 6*(1), 1–25.

Deep, S., Zheng, X., Jolfaei, A., Yu, D., Ostovari, P., & Kashif Bashir, A. (2022). A survey of security and privacy issues in the Internet of Things from the layered context. *Transactions on Emerging Telecommunications Technologies, 33*(6), e3935.

Deloitte. (2015). *Connected health - How digital technology is transforming health and social care*. https://www2.deloitte.com/uk/en/pages/life-sciences-and-healthcare/articles/connected-health.html.

Dreiseitl, S., & Ohno-Machado, L. (2002). Logistic regression and artificial neural network classification models: a methodology review. *Journal of biomedical informatics, 35*(5–6), 352–359.

El-Masri, M., Al-Yafi, K., & Kamal, M. M. (2022). A task-technology-identity fit model of smartwatch utilisation and user satisfaction: A hybrid SEM-neural network approach. *Information Systems Frontiers, 1–18*. https://doi.org/10.1007/s10796-022-10256-7

Falk, R. F., & Miller, N. B. (1992). A primer for soft modeling. In *A primer for soft modeling.* University of Akron Press.

Farivar, S., Abouzahra, M., & Ghasemaghaei, M. (2020). Wearable device adoption among older adults: A mixed-methods study. *International Journal of Information Management, 55*, Article 102209. https://doi.org/10.1016/j.ijinfomgt.2020.102209

FDA. (2020). *Remote or Wearable Patient Monitoring Devices EUAs | FDA*. https://www.fda.gov/medical-devices/coronavirus-disease-2019-covid-19-emergency-use-authorizations-medical-devices/remote-or-wearable-patient-monitoring-devices-euas.

Frenzel, A., Muench, J. C., Bruckner, M. T., & Veit, D. (2021). Digitization or digitalization?-Toward an understanding of definitions, use and application in IS research. *In AMCIS.* https://aisel.aisnet.org/amcis2021/adv_info_systems_general_track/adv_info_systems_general_track/18.

Fruchter, N., & Liccardi, I. (2018, April). Consumer attitudes towards privacy and security in home assistants. In Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems (pp. 1-6).

Galindo-Martín, M. Á., Castaño-Martínez, M. S., & Méndez-Picazo, M. T. (2021). The role of entrepreneurship in different economic phases. *Journal of Business Research, 122* (June 2020), 171-179.

Giansanti, D. (2021). Cybersecurity and the digital-health: The challenge of this millennium. *Healthcare, 9*(1), 62. https://doi.org/10.3390/HEALTHCARE9010062

Gibson, B., Ishfaq, R., Defee, C., & Davis-Sramek, B. (2018). *Eight annual state of retail supply chain report*. Auburn, AL: Retail Industry Leaders Association.

Goodfellow, I., McDaniel, P., & Papernot, N. (2018). Making machine learning robust against adversarial inputs. *Communications of the ACM, 61*(7), 56–66. https://doi.org/10.1145/3134599

Guha, S., & Kumar, S. (2018). Emergence of big data research in operations management, information systems, and healthcare: Past contributions and future roadmap. *Production and Operations Management, 27*(9), 1724–1735. https://doi.org/10.1111/POMS.12833

Guk, K., Han, G., Lim, J., Jeong, K., Kang, T., Lim, E.-K., et al. (2019). Evolution of wearable devices with real-time disease monitoring for personalized healthcare. *Nanomaterials, 9*(6), 813. https://doi.org/10.3390/NANO9060813

Ha, J., & Park, H. K. (2020). Factors affecting the acceptability of technology in health care among older Korean adults with multiple chronic conditions: A Cross-sectional study adopting the senior technology acceptance model. *Clinical Interventions in Aging, 15*, 1873.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems.*

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in Variance-based Structural Equation Modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Hermes, S., Riasanow, T., Clemons, E. K., Böhm, M., & Krcmar, H. (2020). The digital transformation of the healthcare industry: Exploring the rise of emerging platform ecosystems and their influence on the role of patients. *Business Research, 13*(3), 1033–1069.

HINTS. (2021). *Health Information National Trends Survey*. National Cancer Institute. https://hints.cancer.gov/.

Howard, M. (2021). Wearables, the Marketplace and Efficiency in Healthcare: How Will I Know That You're Thinking of Me? *Philosophy & Technology, 34*(4), 1545–1568.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.

Hughes-Roberts, T. (2015). *Privacy as a secondary goal problem: An experiment examining control*. Information & Computer Security.

Ishfaq, R., Davis-Sramek, B., & Gibson, B. (2022). Digital supply chains in omnichannel retail: A conceptual framework. *Journal of Business Logistics, 43*(2), 169–188.

Jiang, Y., West, B. T., Barton, D. L., & Harris, M. R. (2017). Acceptance and use of eHealth/mHealth applications for self-management among cancer survivors. *Studies in Health Technology and Informatics, 245*, 131.

Jurcut, A., Niculcea, T., Ranaweera, P., & Le-Khac, N. A. (2020). Security considerations for Internet of Things: A survey. *SN Computer Science, 1*(4), 1–19.

Karatas, M., Eriskin, L., Deveci, M., Pamucar, D., & Garg, H. (2022). Big Data for Healthcare Industry 4.0: Applications, challenges and future perspectives. *Expert Systems with Applications, 200*, Article 116912.

Kim, T., & Chiu, W. (2019). Consumer acceptance of sports wearable technology: The role of technology readiness. *International Journal of Sports Marketing and Sponsorship, 20*(1), 109–126. https://doi.org/10.1108/IJSMS-06-2017-0050

Kraus, S., Schiavone, F., Pluzhnikova, A., & Invernizzi, A. C. (2021). Digital transformation in healthcare: Analyzing the current state-of-research. *Journal of Business Research, 123*, 557–567. https://doi.org/10.1016/J.JBUSRES.2020.10.030

Lee, S. Y., & Lee, K. (2018). Factors that influence an individual's intention to adopt a wearable healthcare device: The case of a wearable fitness tracker. *Technological Forecasting and Social Change, 129*, 154–163. https://doi.org/10.1016/j.techfore.2018.01.002

Leone, D., Schiavone, F., Appio, F. P., & Chiao, B. (2021). How does artificial intelligence enable and enhance value co-creation in industrial markets? An exploratory case study in the healthcare ecosystem. *Journal of Business Research, 129*, 849–859.

Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International Journal of Medical Informatics, 88*, 8–17. https://doi.org/10.1016/j.ijmedinf.2015.12.010

Liao, Y., Vitak, J., Kumar, P., Zimmer, M., & Kritikos, K. (2019). In *March). Understanding the role of privacy and trust in intelligent personal assistant adoption* (pp. 102–113). Cham: Springer.

Lynch, S., & Barnes, L. (2020). Omnichannel fashion retailing: Examining the customer decision-making journey. *Journal of Fashion Marketing and Management: An International Journal.*

Marakhimov, A., & Joo, J. (2017). Consumer adaptation and infusion of wearable devices for healthcare. *Computers in Human Behavior, 76*, 135–148. https://doi.org/10.1016/j.chb.2017.07.016

Martinez-Martin, N., Luo, Z., Kaushal, A., Adeli, E., Haque, A., Kelly, S. S., et al. (2021). Ethical issues in using ambient intelligence in healthcare settings. *The Lancet Digital Health, 3*(2), e115–e123.

Merhi, M., Hone, K., & Tarhini, A. (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust. *Technology in Society, 59*, Article 101151.

Min, H. (2021). Exploring omni-channels for customer-centric e-tailing. *Logistics, 5*(2), 31.

Mirzabeiki, V., & Saghiri, S. S. (2020). From ambition to action: How to achieve integration in omni-channel? *Journal of Business Research, 110*, 1–11.

Mitchell, U. A., Chebli, P. G., Ruggiero, L., & Muramatsu, N. (2019). The digital divide in health-related technology use: The significance of race/ethnicity. *The Gerontologist, 59*(1), 6–14.

Mochales, G., & Blanch, J. (2022). Unlocking the potential of CSR: An explanatory model to determine the strategic character of CSR activities. *Journal of Business Research, 140*, 310–323.

Monteith, S., Glenn, T., Geddes, J., Severus, E., Whybrow, P. C., & Bauer, M. (2021). Internet of things issues related to psychiatry. *International Journal of Bipolar Disorders, 9*(1), 1–9. https://doi.org/10.1186/S40345-020-00216-Y

Montgomery, K., Chester, J., & Kopp, K. (2018). Health wearables: Ensuring fairness, preventing discrimination, and promoting equity in an emerging Internet-of-Things environment. *Journal of Information Policy, 8*, 34–77.

Mostaghel, R., Oghazi, P., Parida, V., & Sohrabpour, V. (2022). Digitalization driven retail business model innovation: Evaluation of past and avenues for future research trends. *Journal of Business Research, 146*, 134–145.

Ogbuke, N. J., Yusuf, Y. Y., Dharma, K., & Mercangoz, B. A. (2022). Big data supply chain analytics: Ethical, privacy and security challenges posed to business, industries and society. *Production Planning & Control, 33*(2–3), 123–137.

Ordu, M., Demir, E., Tofallis, C., & Gunal, M. M. (2021). A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. *Journal of the Operational Research Society, 72*(3), 485–500.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. In *The BMJ* (Vol. 372)BMJ Publishing Group. https://doi.org/10.1136/bmj.n71.

Reuveni, E. (2017). *Omnichannel Healthcare & Patient Satisfaction with Microsoft - Microsoft Industry Blogs, Microsoft Industry Blogs*. Available at: https://cloudblogs.microsoft.com/industry-blog/health/2017/09/22/omnichannel-healthcare-patient-satisfaction-with-microsoft/ (Accessed: 5 December 2021).

Ringle, C. M., Wende, S., and Becker, J.-M. (2015). *SmartPLS 3*. SmartPLS. Retrieved from http://www.smartpls.com.

Roni, S. M., & Djajadikerta, H. G. (2021). *Data Analysis with SPSS for Survey-based Research.* Singapore: Springer.

Royakkers, L., Timmer, J., Kool, L., & van Est, R. (2018). Societal and ethical issues of digitization. *Ethics and Information Technology, 20*(2), 127–142.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263–286.

Sharon, T. (2016). The Googlization of health research: From disruptive innovation to disruptive ethics. *Personalized Medicine, 13*(6), 563–574.

Shah, R., & Chircu, A. (2018). IOT and ai in healthcare: A systematic literature review. *Issues in Information Systems, 19*(3), 33–41.

Segura Anaya, L. H., Alsadoon, A., Costadopoulos, N., & Prasad, P. W. C. (2018). Ethical implications of user perceptions of wearable devices. *Science and Engineering Ethics, 24*(1), 1–28. https://doi.org/10.1007/s11948-017-9872-8

Shailaja, K., Seetharamulu, B., & Jabbar, M. A. (2018). Machine Learning in Healthcare: A Review. *Proceedings of the 2nd International Conference on Electronics, Communication and Aerospace Technology, ICECA 2018*, 910–914. Doi: 10.1109/ICECA.2018.8474918.

Sherman, L. D., Patterson, M. S., Tomar, A., & Wigfall, L. T. (2020). Use of Digital Health Information for Health Information Seeking Among Men Living With Chronic Disease: Data From the Health Information National Trends Survey. *American Journal of Men's Health, 14*(1). https://doi.org/10.1177/1557988320901377

Sinha, N., & Gupta, M. (2019). Taxonomy of Wearable Devices: A Systematic Review of Literature. *International Journal of Technology Diffusion (IJTD), 10*(2), 1–17. https://econpapers.repec.org/RePEc:Igg:jtd000:V:10:Y:2019:I:2:P:1-17.

Slepchuk, A. N., Milne, G. R., & Swani, K. (2022). Overcoming privacy concerns in consumers' use of health information technologies: A justice framework. *Journal of Business Research, 141*, 782–793.

Tavakoli, M., Carriere, J., & Torabi, A. (2020). Robotics, smart wearable technologies, and autonomous intelligent systems for healthcare during the COVID-19 pandemic: An analysis of the state of the art and future vision. *Advanced Intelligent Systems, 2*(7), 2000071. https://doi.org/10.1002/AISY.202000071

Tawalbeh, L. A., Muheidat, F., Tawalbeh, M., & Quwaider, M. (2020). IoT Privacy and security: Challenges and solutions. *Applied Sciences, 10*(12), 4102.

Thakare, V., Khire, G., & Kumbhar, M. (2022). Artificial intelligence (AI) and internet of things (IoT) in healthcare: Opportunities and challenges. *ECS Transactions, 107*(1), 7941.

Thompson, T. G., & Brailer, D. J. (2004). *The decade of health information technology: Delivering consumer-centric and information-rich health care*. Washington, DC: US Department of Health and Human Services.

Tsay-Vogel, M., Shanahan, J., & Signorielli, N. (2018). Social media cultivating perceptions of privacy: A 5-year analysis of privacy attitudes and self-disclosure behaviors among Facebook users. *new media & society, 20*(1), 141–161.

Ursachi, G., Horodnic, I. A., & Zait, A. (2015). How reliable are measurement scales? External factors with indirect influence on reliability estimators. *Procedia Economics and Finance, 20*, 679–686.

Van Rossum, G., & Drake, F. L. (2009). *Python 3 Reference Manual*. CreateSpace.

Varadarajan, R., Welden, R. B., Arunachalam, S., Haenlein, M., & Gupta, S. (2021). Digital product innovations for the greater good and digital marketing innovations in communications and channels: Evolution, emerging issues, and future research directions. *International Journal of Research in Marketing*.

Wibawa, K. C. S., Cahyaningtyas, I., & Prabandari, A. P. (2021, October). Reconception of Information Commission Arrangements as a Response to the Digitalization Development of Public Information in Indonesia. In ICOLEG 2021: Proceedings of the 2nd International Conference on Law, Economic, Governance, ICOLEG 2021, 29-30 June 2021, Semarang, Indonesia (p. 458). European Alliance for Innovation.

Wiesner, M., Zowalla, R., Suleder, J., Westers, M., & Pobiruchin, M. (2018). Technology adoption, motivational aspects, and privacy concerns of wearables in the german running community: Field study. *JMIR MHealth and UHealth, 6*(12), e9623.

Williams, M., Nurse, J. R., & Creese, S. (2019). Smartwatch games: Encouraging privacy-protective behaviour in a longitudinal study. *Computers in Human Behavior, 99*, 38–54.

Xie, Z., Jo, A., & Hong, Y. R. (2020). Electronic wearable device and physical activity among US adults: An analysis of 2019 HINTS data. *International Journal of Medical Informatics, 144*, Article 104297. https://doi.org/10.1016/J.IJMEDINF.2020.104297

Zeng, E., Mare, S., & Roesner, F. (2017). End user security and privacy concerns with smart homes. In Thirteenth Symposium on Usable Privacy and Security (SOUPS 2017) (pp. 65-80).

Zhang, M., Luo, M., Nie, R., & Zhang, Y. (2017). Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology. *International Journal of Medical Informatics, 108*, 97–109. https://doi.org/10.1016/j.ijmedinf.2017.09.016

Further reading

Bendoly, E., Blocher, J. D., Bretthauer, K. M., Krishnan, S., & Venkataramanan, M. A. (2005). Online/in-store integration and customer retention. *Journal of Service Research, 7*(4), 313–327.

Bhalla, R. (2014). The omni-channel customer experience: Driving engagement through digitization. *Journal of Digital & Social Media Marketing, 1*(4), 365–372.

Gibson, B. J., Defee, C. C., & Ishfaq, R. (2016). *The state of the retail supply chain*. Center of Supply Chain Innovation-Auburn University.

Jr, H., Joseph, F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced Issues in Partial Least Squares Structural Equation Modeling.* Thousand Oaks: Sage.

HP. (2015). *HP Internet of Things Security Report: Smartwatches*. HP. https://www8.hp.com/us/en/hp-news/press-release.html?id=2037386#.YIyOVLVKg2x.

Kavakiotis, I., Tsave, O., Salifoglou, A., Maglaveras, N., Vlahavas, I., & Chouvarda, I. (2017). Machine learning and data mining methods in diabetes research. *Computational and Structural Biotechnology Journal, 15*, 104–116. https://doi.org/10.1016/J.CSBJ.2016.12.005

Palmaccio, M., Dicuonzo, G., & Belyaeva, Z. S. (2021). The internet of things and corporate business models: A systematic literature review. *Journal of Business Research, 131*, 610–618.

Secundo, G., Shams, S. R., & Nucci, F. (2021). Digital technologies and collective intelligence for healthcare ecosystem: Optimizing Internet of Things adoption for pandemic management. *Journal of Business Research, 131*, 563–572.

Van Baal, S. (2014). Should retailers harmonize marketing variables across their distribution channels? An investigation of cross-channel effects in multi-channel retailing. *Journal of Retailing and Consumer Services, 21*(6), 1038–1046.

Prof. Victor Chang is a Professor of Business Analytics at Operations and Information Management, Aston Business School, Aston University UK, since mid-May 2022. He was previously a Professor of Data Science and Information Systems at the School of Computing, Engineering and Digital Technologies, Teesside University, UK, between September 2019 and mid-May 2022. He has deep knowledge and extensive experience in AI-oriented Data Science and has significant contributions in multiple disciplines. Within 4 years, Prof Chang completed Ph.D. (CS, Southampton) and PGCert (Higher Education, Fellow, Greenwich) while working for several projects simultaneously. Before becoming an academic, he has achieved 97% on average in 27 IT certifications. He won 2001 full Scholarship, a European Award on Cloud Migration in 2011, IEEE Outstanding Service Award in 2015, best papers in 2012, 2015 and 2018, the 2016 European award: Best Project in Research, 2016-2018 SEID Excellent Scholar, Suzhou, China, Outstanding Young Scientist award in 2017, 2017 special award on Data Science, 2017-2022 INSTICC Service Awards, Talent Award Suzhou 2019, Top 2% Scientist 2017/2018, 2019/2020 & 2020/2021, the most productive AI-based Data Analytics Scientist between 2010 and 2019, Highly Cited Researcher 2021 and numerous awards mainly since 2011. Prof Chang was involved in different projects worth more than £14 million in Europe and Asia. He has published 3 books as sole authors and the editor of 2 books on Cloud Computing and related technologies. He published 1 book on web development, 1 book on mobile app and 1 book on Neo4j. He gave 33 keynotes at international conferences. He is widely regarded as one of the most active and influential young scientist and expert in IoT/Data Science/Cloud/security/AI/IS, as he has the experience to develop 10 different services for multiple disciplines. He is the founding conference chair for IoTBDS, COMPLEXIS and FEMIB to build up and foster active research communities globally with positive impacts.

Le Minh Thao Doan is a PhD student, Data Analytics Developer at Industrial Digitalisation Technology Centre, and part-time Lecturer in Computer Science at the School of Computing, Engineering and Digital Technologies, Teesside University, UK. Her research interest is machine learning and building predictive models to solve business problems and support healthcare, business, and technology decision-making. Her research mainly focuses on Explainable Artificial Intelligence (XAI) and how AI and machine learning can assist in early cancer detection and improve patient survival outcomes. She has authored a book chapter on Computational Biology and Machine Learning for Metabolic Engineering and Synthetic Biology and several publications in academic journals, such as Computers and Electrical Engineering, Future Internet, and Decision Analytics Journal.

Qianwen Ariel Xu is a PhD student at Operations and Information Management, Aston Business School, Aston University UK. She was previously a PhD student in Computer Science at the School of Computing, Engineering and Digital Technologies at Teesside University. Her dissertation research focuses on box-office prediction based on techniques of Artificial Intelligence and Data Science. She completed her master's degree in Business Analytics with Distinctions from the University of Liverpool, UK. She is also a member of Prof. Chang's research team. She is a hardworking, dedicated and resourceful student who can make things happen. She has published several publications in refereed academic journals, such as Technological Forecasting and Social change, Information Systems Frontiers, Expert Systems, Journal of Global Information Systems, etc.

Karl Hall is a first year PhD student, early career researcher and Part-time Lecturer in Computer Science at the School of Computing, Engineering and Digital Technologies at Teesside University. His doctoral thesis is concerned with discovering novel biomarkers linking COVID-19 and other diseases by developing an information retrieval framework and systems. His research is primarily focused on artificial intelligence and machine learning systems, focusing on disease diagnosis, bioinformatics, and healthcare analytics. He has authored a book chapter and several papers in academic journals, such as Future Internet, Healthcare Analytics, Decision Analytics and COMPLEXIS. He has also published work on Intrusion Detection systems for Fog and Cloud Computing, and social network analysis.

Dr. Yuanyuan Anna Wang is an Adjunct Lecturer of Department of Public Health and Preventive Medicine, Faculty of Medicine, Nursing and Health Science (FMNHS), Monash University. She is also a Research Fellow of Suzhou Industrial Park Monash Research Institute of Science and Technology, since August 2022. Prior to this, she gained her Ph.D. in Health Economics at the University of Nottingham Ningbo China (UNNC), and her Master's from Liverpool University. She has published several papers in leading peer-reviewed ABS ranked journals, such as Technological Forecasting and Social Change; Industrial Management & Data Systems and Journal of Global Information Systems.

Dr. Muhammad Mustafa Kamal is an Associate Professor of Supply Chain Management, Curriculum Lead in Decision Making (Business Analytics) and Risk Management, and Director of the Transnational Research Degree (TNRD) Programme at the School of Strategy and Leadership. Dr Kamal is a Senior Fellow of HEA and a Certified Management and Business Educator (CMBE). Currently, he is the Deputy Editor for the Journal of Enterprise Information Management (JEIM), Senior Editor for Information Systems Management and on editorial board for Government Information Quarterly. He has published over 70 papers in refereed academic journals, conference proceedings, book chapters, and magazine article. His research work has appeared in several leading ABS ranked journals, such as International Journal of Production Research, Journal of Business Research, Information and Management, Production, Planning and Control, Expert Systems with Applications, Government Information Quarterly, Supply Chain Management: An International Journal, and Journal of the Operational Research Society, International Journal of Information Management, and Information Systems Management. He has also presented his research papers at globally esteemed conferences such as British Academy of Management Conference (BAM), European Conference on Information Systems (ECIS), Americas Conference on Information Systems (AMCIS), and Hawaii International Conference on System Sciences (HICSS). He has also chaired conferences and tracks at leading conferences including AMCIS, ECIS and HICSS. He has worked on several internal and external research grant (including EU Framework 7, Horizon 2020, Qatar National Research Foundation).