OULUN AMMATTIKORKEAKOULU

EMPOWERING HUMAN HEALTH WITH WEARABLES :

EXPLORING THE FEASIBILITY AND EFFICACY OF AI-POWERED HEALTH MENTORING SYSTEMS

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ABSTRACT

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This thesis deals with AI mentoring systems in the medical field especially in wearable technology and how it could be applied to individual health and wellness by studying the feasibility and efficacy of AI health wearable devices on end user perspective. The primary data was collected by employing a quantitative research method, distributing surveys to students of Oulu University of Applied Sciences.

The statistical analysis includes descriptive statistics, correlation analysis, and thematic coding for frequency of use of the wearable, user satisfaction, perceived accuracy, and health impact. The feedback from the respondents says that they are extremely pleased with the ease of use, physical activity tracking and sleep improvement but not quite as much with the ability to motivate behavior and improve health. Users expressed notable concerns over data accuracy, privacy, and device costs, with recommendations for improving AI integration in wearables to better meet health goals. This thesis would show what is coming from the user perspective, what the AI health systems lack, and what improvements need to be made on the AI health mentoring technology.

Keywords: Artificial Intelligence, wearable technology, intelligent systems

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GLOSSARY

concept	definition
AI	(Artificial Intelligence) The simulation of human intelligence processes by machines, especially computer systems, to perform tasks like learning, reasoning, and self-correction.
AIoT	The integration of AI with IoT (Internet of Things) to enable smart devices and systems to process data and make autonomous decisions.
Blockchain	A decentralized, distributed ledger technology that provides secure, transparent, and tamper-proof data sharing, often used in health data management.
FedHealth	A Federated Transfer Learning Framework for wearable healthcare that ensures data privacy while facilitating secure data sharing among devices.
IoMT	(Internet of Medical Things) A network of connected medical devices that enable the collection, exchange, and analysis of health data over the internet.
Smart Wearable Sensors	Sensors embedded in wearable devices that monitor physiological signs, environmental data, or physical activity with biocompatibility and accuracy.
Ubiquitous Sensors	Sensors integrated into everyday devices that enable continuous monitoring and data collection, commonly used in AI-powered health monitoring systems.

1 INTRODUCTION

Health is the foundation of our existence, and preserving well-being ranks among life's most central objectives. Health maintenance is an ongoing requirement irrespective of evolving circumstances, and the traditional adage of 'prevention is better than cure' is as applicable today as ever. But it is a flaccid attitude to the craft of health management in general.

Today's world is a technological world, where everything is done on computers and similar technologies, and devices like mobile phones are available to almost everyone. These changes have opened opportunities for improving human well-being as never before. The power of processing of today's technology dwarfs that of previous generations, and this has led to a profound change in how people think about health and wellness.

Artificial intelligence (AI), which is not truly a creator in its own right, has already shown its enormous power to provide useful knowledge from diverse data streams and sophisticated algorithms. AI will be a significantly good tool for health management and for making people healthy.

How much can AI truly support people on the path to better health, and how effectively can it be plugged into the daily rhythms of health practice?

With these considerations in mind, this research explores the potential of AI through the project titled *"Empowering Human Health with Wearables: Exploring the Feasibility and Efficacy of AI-Powered Health Mentoring Systems."*

2 LITERATURE REVIEW

2.1 Wearable Technology in Healthcare

The advancements in wearable health technology have significantly improved the landscape of healthcare, with the introduction of flexible and stretchable sensors combined with low power silicon based electronics for medical monitoring. These devices have been designed to monitor vital signs such as body temperature, heart rate, respiration rate, blood pressure, pulse oxygenation, and blood glucose (Khan et al., 2016). Apart from medical monitoring, wearable health technology has also been integrated into smart homes for continuous and remote monitoring of elderly health and wellbeing (Majumder et al., 2017). With the introduction of new brands and devices for wrist worn fitness wearables, sensor support has been increasing every year, thus enhancing the potential for physical activity tracking and monitoring (Henriksen et al., 2018).

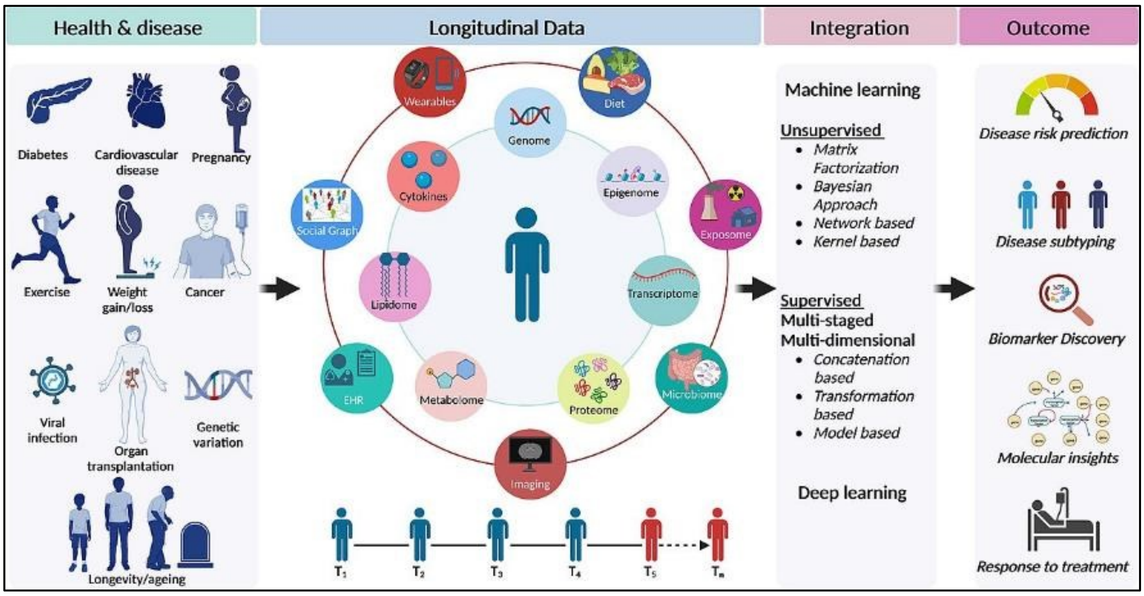

FIGURE 1. Longitudinal multi-omics and wearable data enabled deep pheno-typing for precision health (Mohan Babu, Michael Snyder 2023.)

FIGURE 1 illustrates how health data combined with technology predicts disease risks and aids in treatment.

2.1.1 Flexible and Stretchable Devices

The development of flexible and stretchable devices has been a major focus of advancement in wearable health technology. M. Chen et al. discussed that these devices can accommodate strain and maintain high performance under deformation, driving innovations in wearable devices (M. Chen et al., 2016). In addition, the use of graphene-based sensors has further expanded the capabilities of wearable health technology, allowing for real-time measurement of various health indicators and enabling personalized healthcare (Jara et al., 2013). Moreover, the integration of smart textiles has shown potential for personalized healthcare, allowing for the monitoring of real-time physiologic and movement parameters during training and competitive sports (Libanori et al., 2022).

FIGURE 2. The Palarum PUP Smart Sock uses eTextile biosensors woven into the sock sole (Bbcrossword 2023.)

FIGURE 2 shows the probability of textile wearable for tracking the person's health data in the near future.

2.1.2 Smart Wearable Sensors

The development of smart wearable sensors with excellent bio functionality has been a significant area of progress in wearable health technology. These sensors have been designed for precise monitoring of vital signs of the human body or the surrounding environment, and have exhibited properties such as biocompatibility, biodegradability, and self-healing (Gibson et al., 2019). Furthermore, smart IoT-enabled garments have shown potential in communicating with smartphones to process biometric information, promising a new era for retail and sports medicine (R. T. Li et al., 2016).

2.1.3 Future Research Directions and Knowledge Gaps

While there have been significant advancements in wearable health technology, there are still several knowledge gaps and potential future research directions. Additionally, further research is needed to explore the potential of Internet of medical things (IoMT) for the management of chronic diseases such as diabetic foot ulcers, enabling remote monitoring and personalized care (Shan et al., 2019a).

2.2 AI in Personal Health Monitoring

In recent years, the integration of artificial intelligence (AI) algorithms in personal health monitoring has gained significant attention due to its potential to revolutionize healthcare. This literature review aims to provide a comprehensive overview of the role of AI in health tracking, the impact of machine learning on personal health, and the use of AI for health data analysis.

Sarker discusses the application of AI algorithms in health tracking, emphasizing the importance of machine learning in analyzing health data (Sarker, 2021). The author highlights the potential of AI to track various health parameters and identify patterns that may indicate potential health issues. This finding underscores the significance of AI in providing personalized health monitoring and early detection of health conditions.

Rajpurkar et al. also acknowledge the potential of AI in health and medicine; however, their study did not provide specific findings related to AI algorithms in health tracking (Rajpurkar et al., 2022). This knowledge gap suggests the need for further research to explore the specific applications and impact of AI algorithms in personal health monitoring.

Furthermore, Mohr et al. emphasize the use of AI for health data analysis, particularly in the context of mental health (Mohr et al., 2017). The authors highlight the role of ubiquitous sensors and machine learning in understanding mental health patterns and predicting mental health outcomes. This finding demonstrates the potential of AI in leveraging health data to gain valuable insights and improve personalized health monitoring.

Despite the valuable insights provided by the existing research, there are still knowledge gaps that warrant further exploration. Firstly, there is a need for more comprehensive studies to elucidate the specific algorithms and techniques used in AI-based health tracking. Additionally, future research should focus on evaluating the effectiveness and accuracy of AI algorithms in personal health monitoring to ensure reliable and actionable insights.

Moreover, the integration of AI in personal health monitoring raises ethical and privacy concerns that require careful consideration. Future research should explore the ethical implications of AI in health tracking and develop guidelines to ensure the responsible and secure use of AI technologies in healthcare settings.

In conclusion, the existing literature on AI in personal health monitoring highlights the significant potential of AI algorithms in health tracking and data analysis. However, there is a need for further research to address knowledge gaps, evaluate the effectiveness of AI algorithms, and address ethical considerations, ultimately advancing the field of AI in personal health monitoring.

2.3 Integrating AI and Wearables for Health Mentoring

The integration of artificial intelligence and wearables has shown promising potential in the field of health mentoring. This literature review aims to provide a comprehensive synthesis of existing research findings related to the combination of AI and wearables for personalized health recommendations and technology-assisted health coaching.

Schüll discusses the significance of wearable technology in the design of self-care and its potential impact on health mentoring. The study emphasizes the importance of data for life and how wearable technology can be utilized to facilitate self-care practices. The integration of AI with wearables is highlighted as a crucial aspect of leveraging the data obtained from these devices for personalized health mentoring (Schüll, 2016).

Subramaniyaswamy et al. present an ontology-driven personalized food recommendation system in the context of an IoT-based healthcare system. The study focuses on the use of AI to provide personalized recommendations, particularly in the domain of dietary choices (Subramaniyaswamy et al., 2019). This research finding underscores the potential of AI-driven systems to offer tailored health recommendations based on individual user data, thus contributing to the field of health mentoring.

Shan et al. shed light on the state of the art in digital health technology and mobile devices for the management of diabetes mellitus (Shan et al., 2019b). The study emphasizes the role of technology-assisted health coaching, particularly through the use of wearables, in the context of managing chronic conditions such as diabetes. The findings underscore the potential of wearables and AI-driven technologies in providing real-time health coaching and monitoring, thereby enhancing the effectiveness of health mentoring practices.

While the existing research provides valuable insights into the integration of AI and wearables for health mentoring, there are certain knowledge gaps that warrant further investigation. Firstly, there is a need for more extensive studies that evaluate the long-term effectiveness and user acceptance of AI-driven personalized health recommendations delivered through wearables. Additionally, future research should focus on the development of advanced AI algorithms that can analyze wearable data to provide proactive health coaching and mentoring tailored to individual needs. Moreover, the ethical implications and privacy concerns associated with the use of AI and wearables in health mentoring require thorough exploration in future studies.

In conclusion, the literature review highlights the potential of integrating AI with wearables for personalized health mentoring, as evidenced by the existing research findings. However, there is a need for further research to address the knowledge gaps and propel the field towards more effective and ethical applications of AI and wearables in health mentoring.

2.4 Feasibility of AI-Enabled Wearable Health Systems

The integration of Artificial Intelligence (AI) into wearable health systems has the potential to revolutionize health monitoring, diagnostics, and management. This literature review aims to explore the practical challenges, scalability, and cost analysis of AI-powered wearable health systems.

2.4.1 Practical Challenges in AI and Wearables Integration

Pantelopoulos & Bourbakis conducted a survey on wearable sensor-based systems and highlighted the practical challenges associated with AI and wearables integration. They emphasized the need for efficient data processing, real-time monitoring, and seamless connectivity in wearable health systems. These practical challenges include data accuracy, power consumption, interoperability, and data security. Addressing these challenges is crucial for the successful implementation of AI-enabled wearable health systems. (Pantelopoulos & Bourbakis, 2010.)

2.4.2 Scalability of AI-Based Health Monitoring Devices

Abràmoff et al. conducted a pivotal trial of an autonomous AI-based diagnostic system for the detection of diabetic retinopathy in primary care offices. The study focused on the scalability of AI-based health monitoring devices and demonstrated the potential for widespread adoption of AI in primary care settings. The scalability of AI-based health monitoring devices is a critical factor in ensuring accessibility and affordability, especially in resource-constrained environments. (Abràmoff et al., 2018).

2.4.3 Cost Analysis of AI-Powered Wearable Health Systems

Wang et al. discussed the development of flexible sensing electronics for wearable/attachable health monitoring. While the study did not explicitly address the cost analysis of AI-powered wearable health systems, the advancement of flexible sensing electronics is a crucial step towards reducing the production costs of wearable health devices. Cost analysis of AI-powered wearable health systems is essential to determine the economic feasibility and market affordability of such technologies. (Wang et al., 2017).

2.4.4 Knowledge Gaps and Future Research Directions

In conclusion, the feasibility of AI-enabled wearable health systems is contingent on addressing practical challenges, ensuring scalability, and conducting comprehensive cost analyses. Future research should focus on filling the identified knowledge gaps and exploring the potential of AI in conjunction with emerging technologies for health monitoring and management.

2.5 Efficacy of AI-Powered Health Mentoring Systems

Health behavior change interventions have evolved in recent years due to the advancements in technology. The integration of artificial intelligence (AI) in health mentoring systems has shown promise in promoting behavior change and improving health outcomes. This literature review aims to provide an overview of the effectiveness of AI in health behavior change, outcomes of using AI for health mentoring, and comparative studies on AI-based vs traditional health mentoring.

2.5.1 Effectiveness of AI in Health Behavior Change

Several studies have investigated the impact of AI on health behavior change. Webb et al. conducted a systematic review and meta-analysis to assess the impact of theoretical basis, behavior change techniques, and mode of delivery on the efficacy of internet-based interventions for promoting health behavior change

(Webb et al., 2010). The findings suggested that AI-powered interventions have the potential to effectively promote behavior change, especially when incorporating behavior change techniques and a strong theoretical basis.

Korda & Itani explored the potential of harnessing social media, which often utilizes AI algorithms, for health promotion and behavior change (Korda & Itani, 2013). Their study highlighted the significance of social media platforms in influencing health behavior change, indicating the potential effectiveness of AI-powered health mentoring systems in reaching and engaging a wider audience.

Furthermore, Zhao et al. conducted an evidence review to determine the influence of mobile phone apps, many of which incorporate AI elements, on people's health behavior change (Zhao et al., 2016). The review concluded that mobile apps have the potential to influence health behavior change, suggesting that AI-powered health mentoring systems delivered through mobile platforms could be effective in promoting behavior change.

2.5.2 Outcomes of Using AI for Health Mentoring

The outcomes of using AI for health mentoring have been a subject of interest in recent research. Cossy-Gantner et al. discussed the contribution of AI to global health, particularly in resource-poor settings. The study emphasized the potential of AI in improving health outcomes, indicating that AI-powered health mentoring systems could play a crucial role in addressing health disparities and promoting positive health behavior change. (Cossy-Gantner et al., 2018.)

Liu et al. evaluated the eligibility criteria of oncology trials using real-world data and AI. While the focus of the study was on oncology trials, the findings underscored the potential of AI in optimizing health interventions and improving patient outcomes (Liu et al., 2021). This suggests that AI-powered health mentoring systems could lead to improved health behavior change outcomes in various clinical settings.

2.5.3 Comparative Studies on AI-Based vs Traditional Health Mentoring

In addition to exploring the effectiveness of AI in health behavior change, several studies have compared AI-based health mentoring with traditional approaches. Maher et al. conducted a systematic review to determine the effectiveness of health behavior change interventions that use online social networks (Maher et al., 2014). The study highlighted the potential of online social networks, often utilizing AI algorithms, in promoting health behavior change, suggesting that AI-based health mentoring systems may offer unique advantages over traditional approaches.

Moreover, Milne-Ives et al. conducted a systematic review of mobile apps for health behavior change, which often incorporate AI elements (Milne-Ives et al., 2020). The review encompassed various health domains, including physical activity, diet, drug and alcohol use, and mental health. The findings suggested that mobile apps, particularly those using AI, have the potential to promote positive health behavior change across diverse health domains, indicating the potential superiority of AI-based health mentoring systems compared to traditional interventions.

2.5.4 Knowledge Gaps and Future Research Directions

While the existing literature provides valuable insights into the efficacy of AI-powered health mentoring systems, there are still knowledge gaps that warrant further research. Investigating the impact of AI on specific health behaviors and populations would contribute to a more comprehensive understanding of the potential of AI-powered health mentoring systems.

In conclusion, the literature reviewed demonstrates the potential effectiveness of AI-powered health mentoring systems in promoting behavior change and improving health outcomes. However, ongoing research is essential to address knowledge gaps and fully understand the impact of AI on health behavior change. This will ultimately contribute to the development of more effective and tailored AI-powered interventions for promoting positive health behavior change.

2.6 User Experience and Engagement

2.6.1 Introduction

User interaction with AI-powered wearables, adoption barriers for wearable health technology, and patient engagement in AI-assisted health programs are important aspects of user experience and engagement. The integration of artificial intelligence (AI) in wearables presents both opportunities and challenges, and understanding user behavior and engagement is crucial for successful adoption and sustained use. In this review, the researcher aim to synthesize the research findings on these topics and identify knowledge gaps and future research directions.

2.6.2 User Interaction with AI-Powered Wearables

Xiong et al. explored the use of functional fibers and fabrics for soft robotics, wearables, and human-robot interface, indicating the potential for innovative user experiences with AI-powered wearables (Xiong et al., 2021). The study emphasizes the importance of material design and human-robot interaction in enhancing user engagement and experience with AI-powered wearables.

2.6.3 Adoption Barriers for Wearable Health Technology

Baig et al. conducted a systematic review of wearable patient monitoring systems, highlighting the current challenges and opportunities for clinical adoption (Baig et al., 2017). The study identified several barriers to the adoption of wearable health technology, including technical, organizational, and user-related factors. Understanding and addressing these barriers are essential for improving user experience and engagement with AI-powered wearables.

2.6.4 Patient Engagement in AI-Assisted Health Programs

Fernández-Caramés & Fraga-Lamas reviewed IoT wearables and garments for creating intelligent connected e-textiles, emphasizing the potential for enhancing patient engagement in AI-assisted health programs (Fernández-Caramés & Fraga-Lamas, 2018). The study highlights the role of intelligent connected e-textiles in promoting user engagement and experience through personalized and context-aware interactions.

2.6.5 Knowledge Gaps and Future Research Directions

While the existing literature provides valuable insights into user interaction, adoption barriers, and patient engagement in AI-assisted health programs, several knowledge gaps and future research directions can be identified. Firstly, there is a need for further research on the integration of wearable health technology with electronic health records (Dinh-Le et al., 2019). Understanding the implications of this integration on user experience and engagement is critical for the successful implementation of AI-powered wearables in healthcare settings. Furthermore, exploring the potential of AIoT-enabled applications for enhancing user engagement with wearable health technology, Sun et al. presents an exciting avenue for future research (Sun et al., 2021).

In conclusion, user experience and engagement with AI-powered wearables are complex and multifaceted, influenced by user interaction, adoption barriers, and patient engagement in AI-assisted health programs. By integrating and synthesizing the existing research findings, this literature review highlights the need for further research to address knowledge gaps and drive future advancements in the field.

Overall, these findings underscore the importance of understanding user experience and engagement to inform the design and implementation of AI-powered wearables in healthcare and other domains. Further research is needed to address the identified knowledge gaps and explore the potential of AI-powered wearables for enhancing user experience and engagement.

2.7 Ethical, Legal, and Privacy Concerns in AI and Health Technology

2.7.1 Introduction

Artificial Intelligence (AI) and wearable health technology have become increasingly prevalent in the healthcare industry, offering numerous benefits for patient care and monitoring. However, the integration of AI and wearable health technology also raises crucial ethical, legal, and privacy concerns that must be addressed. This literature review aims to provide a comprehensive overview of the existing research findings on these concerns and highlight potential future research directions.

2.7.2 Ethical Implications of AI in Health Mentoring

Rajpurkar et al. emphasize the ethical implications of AI in health and medicine, highlighting the need for ethical considerations in the development and use of AI technologies in healthcare (Rajpurkar et al., 2022). The authors underscore the importance of ensuring that AI systems prioritize patient well-being and safety, and do not compromise the ethical principles of medical practice. This finding underscores the critical need for further research into the ethical implications of AI in health mentoring, particularly in the context of patient-provider relationships and the potential impact on patient autonomy.

2.7.3 Data Privacy in Wearable Health Technology

Y. Chen et al. focus on data privacy in wearable health technology, emphasizing the importance of protecting sensitive health data collected from wearables (Y. Chen et al., 2020). The authors propose a Federated Transfer Learning Framework, FedHealth, to address data privacy concerns and facilitate secure data sharing among wearable healthcare devices. This research finding underscores the need for robust data privacy measures in wearable health technology and suggests the potential for future research to explore advanced encryption and data anonymization techniques to enhance privacy protection.

2.7.4 Regulatory Aspects of AI in Healthcare

Gao et al. conduct an empirical study on wearable technology acceptance in healthcare, shedding light on the regulatory aspects of AI in healthcare (Gao et al., 2015). The authors highlight the importance of regulatory frameworks to govern the use of AI in healthcare and ensure compliance with legal and ethical standards. This finding underscores the need for further research into the development of comprehensive regulatory frameworks for AI in healthcare, encompassing data privacy, security, and ethical considerations.

2.7.5 Data Security and Privacy in Wireless Body Area Networks

M. Li et al. provide insights into data security and privacy in wireless body area networks, highlighting the importance of securing sensitive health data transmitted wirelessly (M. Li et al., 2010). The authors emphasize the need for robust data security measures to protect health data from unauthorized access and breaches. This finding underscores the significance of addressing data security and privacy concerns in the context of wearable health technology, calling for future research to explore encryption protocols and secure communication mechanisms for wireless body area networks.

2.7.6 Integrating Blockchain for Data Sharing and Collaboration in Mobile Healthcare Applications

Liang et al. propose the integration of blockchain for data sharing and collaboration in mobile healthcare applications, aiming to enhance data security and privacy (Liang et al., 2017). The authors highlight the potential of blockchain technology to provide a secure and immutable platform for sharing sensitive health data. This finding suggests the potential for future research to explore the application of blockchain in ensuring data privacy and integrity in the context of AI and wearable health technology.

2.7.7 Conclusion

In conclusion, the literature review highlights the critical ethical, legal, and privacy concerns associated with the integration of AI and wearable health technology in the healthcare industry. The findings from the reviewed research underscore the need for further investigations into ethical implications, data privacy, regulatory frameworks, and data security measures to address the existing gaps in knowledge. Future research directions should focus on developing comprehensive ethical guidelines, privacy-enhancing technologies, and regulatory frameworks to ensure the responsible and ethical deployment of AI and wearable health technology in healthcare settings.

2.8 Future Trends and Potential in AI and Wearable Health Technology

The intersection of artificial intelligence (AI) and wearable health technology is an area of growing interest and innovation. In this literature review, the researcher synthesize and integrate research findings from the literature to provide insights into the emerging trends and future potential of AI in personal health management and wearable health technology.

2.8.1 Emerging Innovations in Health Wearables and AI

Boxall et al. highlighted the emerging innovations in health wearables and AI, emphasizing the need to address the environmental implications of pharmaceuticals and personal care products (Boxall et al., 2012). While the focus of the study was on environmental health, the findings underscore the increasing relevance of health wearables and AI in addressing personal health management. The study suggests the need for further research to understand the potential impact of these emerging innovations on personal health and well-being.

2.8.2 Future Potential of AI in Personal Health Management

Dash et al. discussed the future potential of AI in personal health management, particularly in the context of big data in healthcare (Dash et al., 2019). The study emphasized the role of AI in the management and analysis of healthcare data, pointing towards the future prospects of AI-driven solutions in personalized health interventions. This highlights the need for continued research to explore the full potential of AI in improving personal health management and healthcare delivery.

2.8.3 Predicting Trends in Wearable Health Technology

Dias & Cunha focused on predicting trends in wearable health technology, particularly in vital sign monitoring systems and technologies (Dias & Cunha, 2018). The study provided insights into the advancements in wearable devices for health monitoring and the potential implications for personalized healthcare. This research underscores the need for further investigation into the integration of AI with wearable health technology to enhance real-time health monitoring and intervention strategies.

2.8.4 Knowledge Gaps and Future Research Directions

While the existing literature has shed light on the emerging trends and potential of AI and wearable health technology, several knowledge gaps and future research directions are apparent. Rai highlighted the concept of "Explainable AI" and the need to transition from black box to glass box AI systems (Rai, 2020). This presents an opportunity for future research to explore transparent and interpretable AI solutions in the context of wearable health technology.

Similarly, Yigitcanlar et al. emphasized the contributions and risks of AI in building smarter cities, providing insights that can be extrapolated to the development of AI-driven health wearables and personalized health management systems (Yigitcanlar et al., 2020). Future research should explore the ethical, social, and technical implications of integrating AI into wearable health technology.

Moreover, Lu et al. and Shen et al. provided valuable insights into wearable health devices and AI-assisted network-slicing for next-generation wireless networks (Lu et al., 2020) (Shen et al., 2020). These findings underscore the need for interdisciplinary research to develop AI-enabled wearable health devices and network infrastructure that can support seamless health monitoring and intervention.

In conclusion, the literature reviewed provides a comprehensive understanding of the emerging trends and potential of AI and wearable health technology. However, future research should address the highlighted knowledge gaps and explore the interdisciplinary collaboration needed to realize the full potential of AI in personalized health management and the development of advanced wearable health devices.

3 RESEARCH METHODOLOGY

This part summarizes the research approach used, and explains how the empirical work was conducted. It's on a research methodology, non-probability purposive sampling, quantitative approach. The data collection process involved distributing surveys to students at Oulu University of Applied Sciences, and the survey design included multiple-choice and scale-based questions focused on AI-powered health mentoring systems. And then, finally, the chapter on quality and validity of the study, so that the data it has generated is robust and can be meaningfully used to analyze the ways that students use and experience wearable health technologies.

3.1 Research Type

This paper takes a non-probability purposive sampling strategy, with quantitative research methods aiming at a targeted understanding of AI-driven health mentoring systems. This strategy is especially appropriate for this study because it enables the inclusion of participants of interest, thus ensuring that the data gathered is relevant, and the analysis of the feasibility and effectiveness of these systems is focused.

Quantitative Methods

Quantitative studies are about gathering and analyzing numerical data in order to detect patterns, relationships and trends. This approach is used for measuring attitudes, opinions, behaviors, etc., and other specified variables, and allows for generalization of the results to a defined sample population. In this study, structured data was gathered using surveys aimed at assessing participant experiences and perceptions of AI-powered health mentoring systems. They also used multiple-choice and scale questions, so that the responses could be counted quickly. The collected data was analyzed using descriptive statistics to summarize key findings, correlation analysis to identify relationships between variables, and comparative analysis to highlight significant differences among participant groups. This method allowed for an in-depth and specific understanding of the data.

3.2 Theoretical frameworks

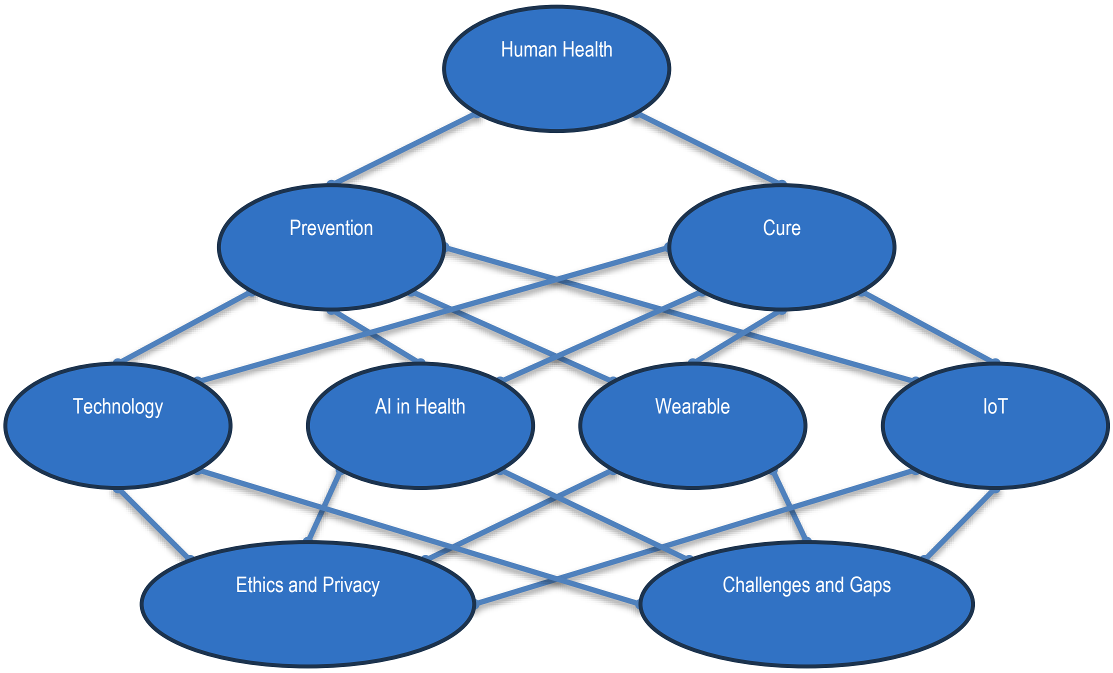

FIGURE 3. Theoretical frameworks

FIGURE 3 diagram shows a conceptual framework for how technology can be integrated to improve human health. It lumps the health system into Prevention and Cure, with each linked to a central technological field such as AI in Health, Wearable Technology and IoT (Internet of Things). These technologies are part of the answer to ethics, privacy, and bridging gaps and challenges in healthcare systems. The connections highlight the holistic perspective required to enhance human health through prevention, treatment and the ethical use of new technologies.

3.3 Methods Used for Data Collection and Analysis

3.3.1 Data Collection:

Questionnaires were sent to students of the Oulu University of Applied Sciences (OAMK) in email through the student mail system, which contained a link leading to the Webropol survey. These surveys asked about the use and experience of AI-powered health-coaching interfaces. The population of choice was chosen because students have the potential to wear a wearable device or use a phone app on a daily basis, because they are not expensive, and because they are also comfortable with technology. This approach aided the development of a relevant and focused sample for the study, and allowed for the gathering of useful information on the use of health-related technology.

3.3.2 Data Analysis:

The quantitative analysis of the data required the use of descriptive statistics to summarize and describe the information on the survey and correlation analysis to examine and quantify the relationships between the main variables of interest and comparative analysis to identify the differences between the various groups of the respondents. This mixed-methods approach allowed a more nuanced analysis of patterns and trends in the data, guaranteeing that conclusions were drawn not only from aggregate summaries, but also from the interaction between variables, and from comparisons between different groups of the respondents. Using these exacting analytical techniques, the study offers a comprehensive, well-rounded analysis of the quantitative data that it collected

3.4 Sources of Data

3.4.1 Primary Data

The main data was sourced from surveys sent out to students at Oulu University of Applied Sciences (OAMK). The surveys gave quantitative feedback on how people experienced and perceived AI-driven health coaches. This strategy enabled the gathering of useful, targeted information and a sense of how wearable devices and health technology might be used, and might play a role, in students' everyday lives.

3.4.2 Secondary Data

The secondary data was collected through a systematic literature search of peer-reviewed articles, academic books, journals and respected online publications. This information helped to give crucial background and context to the general significance and prior knowledge of AI-driven health mentoring systems. The literature review highlighted critical themes (wearable technology, AI in healthcare, the ethics of health data collection, among others) and provided a context for interpreting the study's findings against the backdrop of the broader literature.

3.5 How Data Were Collected

The researcher adopted a rigorous, quantitative approach to data collection, seeking a focused, targeted sense of what sorts of impacts AI-powered health mentoring systems can have on students' health behavior. Questionnaires were sent by post to the students at Oulu University of Applied Sciences (OAMK) during the period of 24th Sept. to 5th Oct. These surveys included multiple choice and scale based questions designed to quantify experiences of the respondents and perceptions of wearable devices and health related technologies. The Webropol platform was utilized for the distribution and collection of the survey responses, in order for ensuring efficient and organized data management.

Using surveys, the researcher got certain quantitative information, the type that can be used to study general trends and relationships between variables. This targeted data-collection strategy meant that the study collected only the data necessary to identify both the adoption and effectiveness of AI-driven health mentor programs, and thus improved the trustworthiness and replicability of the study's results.

3.6 How Questionary Were Designed

TABLE 1. Categorization of survey questions and response types

Category	Question no.	Response type
Demographic	1 - 4	Single choice
Device usage	5 - 7	Text field and single choice
Ease of use and satisfaction	8 - 9	NPS
Effectiveness and Impact	10 - 13	NPS
Health Behavior Changes	14	Multiple choice
Perception and Future of AI	15 - 16	NPS
Potential and Barriers	17 - 18	Multiple choice
Privacy and Security Concerns	19 - 20	NPS and single choice
Data Sharing	21	Single choice
Open-Ended Feedback	22	Text field

TABLE 1 presents a spreadsheet, which transformed answers to survey questions into themes from demographics to device use to user experience. Questions were phrased as single-choice, multiple-choice or Text field to suit different types of data. Net Promoter Score (NPS) questions, under Ease of Use and Satisfaction, measure the user's willingness to recommend the user experience on a scale of 0 to 10. They are divided into Promoters (9-10), Passives (7-8) and Detractors (0-6). The NPS score is simply the subtraction of the number of Detractors from the number of Promoters, a tidy way of summarizing user satisfaction and loyalty. -100 to 0 consider poor NPS, 0 to 30 consider average to good, 30 to 70 consider very good and 70 to 100 consider excellent score.

3.7 Population and Sampling

The subjects of this study were students at Oulu University of Applied Sciences (OAMK), who were expected to range widely in their prior experience with wearable technology and health-oriented technologies. The study sought to find a sample that would be informative about the use of AI-based health-mentoring systems.

The survey was delivered by email to around 5,000 potential participants. Of those, 220 participants first entered the survey, but 115 of them didn't proceed to the questions because they hadn't used AI wearables. Ultimately, 105 participants fully completed the survey. Although this meant a smaller sample size, the respondents' experience with wearable technology and health tech made their input worthwhile. The sampling technique was non-probability purposive sampling, enabling the selection of students most likely to have certain experience of relevance.

This approach made it possible to keep the collected data focused and useful, and to glean certain important insights from the ways that students do and might use AI-powered health mentoring systems.

3.8 Who Respondents Were Selected and Why

The recruitment of respondents for this study was purposefully planned to facilitate the provision of useful and informative data on the use of AI-based health mentoring systems by students. Selection criteria and sampling procedures were carefully designed to seek out people who were likely to have used wearable or health technologies, thus ensuring that the data collected would be informative about how they are used and how they affect people on a day-to-day basis.

3.9 Criteria for Selection

The main qualification to be a respondent was an exposure to and experience with wearable technologies and health technologies. It was important to obtain expert views and understandings of how AI-driven health mentoring systems might be applied and the consequences of their use. Participants were selected for their probability of using these technologies in their everyday lives, so that the data collected would represent actual and significant experiences.

Also, the research looked at students at Oulu University of Applied Sciences (OAMK) because they are a population that's probable to use wearable health technology because of their accessibility and because they are familiar with tech. This student-centric approach gave the researcher a wide and representative sample to study the effects of AI-powered health mentors in actual life.

4 ANALYSIS OF RESULTS

This survey screened out the people so that only the ones of interest would actually take the survey. One of the first questions in the survey, as shown in FIGURE 4, asked whether or not the participant uses an artificial intelligence health care system. If they clicked "No", meaning they didn't use a system similar to that one, then the survey would terminate for them, and they would not have to answer any more questions. A total of 220 participants initially responded, with 105 (or 47.7% selecting "Yes," indicating they used AI-powered health systems, while 115 (or 52.3% selected "No" and exited the survey at that point. This screening mechanism allowed only those 105 participants with a certain level of background to proceed to the remainder of the survey, thus facilitating a more targeted exploration of the use of and attitudes towards AI supported health mentoring systems.

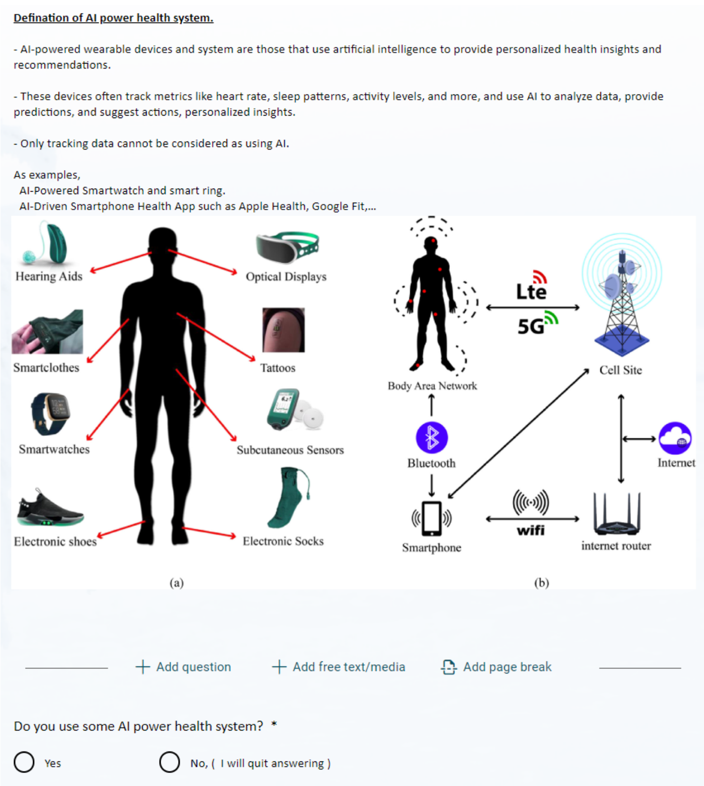

FIGURE 4. Filtering process of questioning

4.1 Demographic of the respondents

TABLE 2 presents demographic data of various traits of the surveyed participants. In terms of gender, 71.4 percent of participants were female, and 28.6 percent were male. The majority of the respondents, around 73.3 percent, were between the ages of 18 and 34, with 39 percent in the 18 to 24 age group and 34.3 percent in the 25 to 34 age group. Smaller proportions were found in older age groups, with 10.5 percent aged 35 to 44, 11.4 percent aged 45 to 54, and only 4.8 percent aged 55 to 64. There were no respondents under 18 or over 65.

Regarding educational background, most of the respondents, 68.6 percent, held a Bachelor's degree, while 21.9 percent had a Master's degree, and 9.5 percent had completed high school. In terms of overall health, the majority rated their health as Good, with 64.8 percent, followed by 20 percent who rated it as Fair, and 11.4 percent who considered their health Excellent. Three point eight percent reported their health being Poor.

That is a fairly comprehensive sociodemographic description of the subjects and it is important to know where they are coming from in order to examine their experiences and opinions of AI health coaching systems.

TABLE 2. Demographic of the respondents

Variable	Category	Frequency	Percentage
Gender	Male	30	28.6%
	Female	75	71.4%
Age	Less than 18 years	0	0.0%
	18-24	41	39.0%
	25-34	36	34.3%
	35-44	11	10.5%
	45-54	12	11.4%
	55-64	5	4.8%
	65+	0	0.0%
Education level	High school	10	9.5%
	Bachelor	72	68.6%
	Master	23	21.9%
Overall Health	Poor	4	3.8%
	Fair	21	20.0%
	Good	68	64.8%
	Excellent	12	11.4%

4.2 Familiarity of AI power health system

For a deeper understanding of the usage of AI-powered health systems, the researcher developed the questions to know the types of devices which are participants use, the frequency of their usage, and the duration for which they have been using them. The key questions here asked were: "What AI-powered health applications or wearables are you using now?", "For how long have you been using them?", and "How often do you wear your device?". These type of questions help to researcher to provide insight into participants' experiences and engagement in AI-powered health technologies.

TABLE 3. The frequency of devices and applications used by the respondents.

Category	Frequency	Percentage
Smart watch	81	83.51%
Smart Application	9	9.28%
Smart ring	5	5.15%
Smart band	2	2.06%

TABLE 3 presents the summary of the different AI-aided medical devices and applications used by the respondents (n=97), which was with the text field. Some of the respondents answered two or three devices and application at the same time. So the researcher used thematic analysis and refined the answer to only 4 category. The majority of participants, 83.51 percent, reported using smart watches, including brands such as Apple, Samsung, Polar, Garmin, and Amazfit. In addition to smart watches, 9.28 percent of the respondents used smart applications like Apple Health, Samsung Health, Flo, Gentler Streak and Clue. A smaller portion, 5.15 percent, used smart rings, with Oura being the most popular choice. Mean-while, 2.06 percent of the respondents reported using smart bands, including Google Fit and Whoop.

Also, it was noted that those who used "smart" items also used "smart" health applications on their phones. That must be a trend wearable tech and Iphone apps all in one for the ultimate health tracking.

TABLE 4. Usage duration and frequency of AI-powered health devices

Variable	Category	Frequency	Percentage
For how long?	Less than 6 months	8	7.6%
	6-12 months	13	12.4%
	1-2 years	22	21.0%
	Over 2 years	62	59.0%
How often?	Daily	81	77.1%
	Sometime (only when need)	24	22.9%

TABLE 4 presents the average amount of time and how often the participants used their AI health machine. 59% responded that they used their device for over 2 years, 21% for 1-2 years. A smaller portion, 12.4 percent, indicated using these devices for six to twelve months, and only 7.6 percent have been using them for less than six months.

In terms of frequency, the majority of the respondents which is 77.1 percent, use the devices daily as normal. Meanwhile, 22.9 percent use their devices occasionally, typically only when they feel the need of it. According to this information, the majority of participants are veterans of AI health peripherals and applications, using them multiple times a day.

4.3 Ease of Use and Satisfaction

Questions 8 and 9 were designed to measure ease of use and satisfaction with accuracy. These issues are important for user acceptance and trust in the technology. Both questions were phrased on a Net Promoter Score (NPS) scale, in which participants were asked to report their experiences on a scale ranging from 0 (not at all easy/satisfied) to 10 (extremely easy/satisfied). Based on their responses, users were categorized as Promoters (those who gave a rating of 9 or 10), Passives (ratings of 7 or 8), and Detractors (ratings from 0 to 6). This approach makes it possible to make a standardized comparison of ease of use and satisfaction with the accuracy of health data.

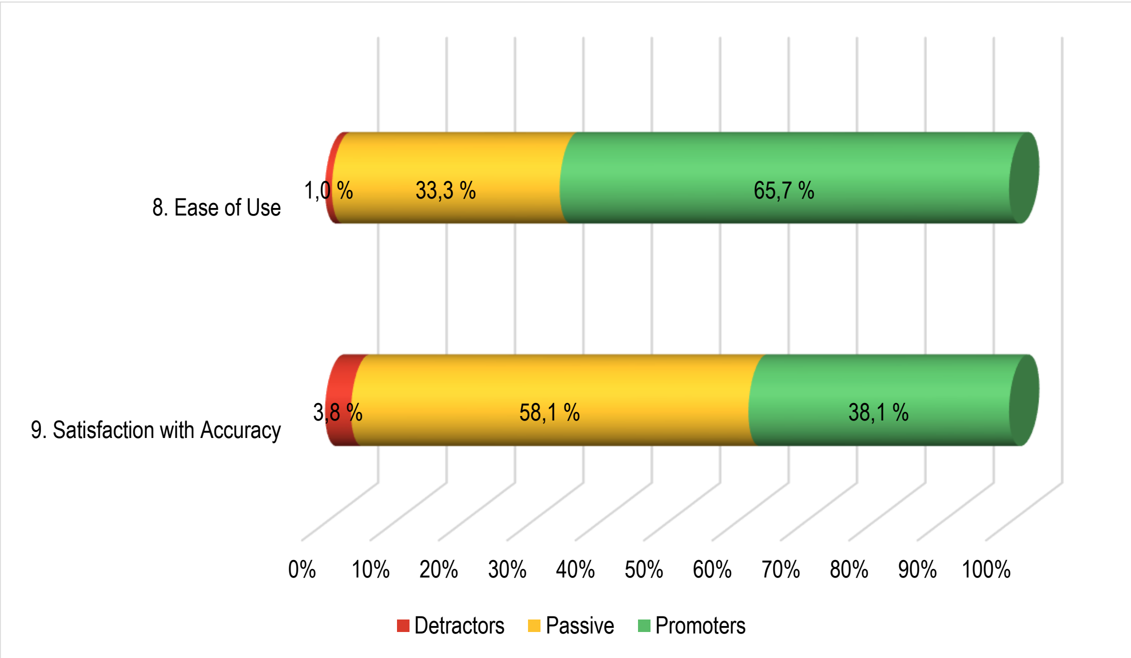

FIGURE 5. Ease of use and satisfaction

Satisfaction with usability and accuracy are among the most dramatic differences. In the FIGURE 5, 65.7 percent of the respondents rated the AI-powered health systems very easy to use, putting them in the promoter category. A further 33.3 percent were passives, they thought the devices were relatively easy to use, but still thought they could be improved. Only one in 100 participants were detractors, indicating that certain individual found the devices were hard to use. That means a high score, and an excellent Net Promoter Score (NPS) of 65, in that health monitoring is generally easy to use.

Satisfaction with accuracy, by contrast, showed a more even pattern. While 38.1 percent of the respondents were promoters, meaning they were highly satisfied with the accuracy of the data, a larger portion of 58.1 percent were passives, indicating that while the accuracy was acceptable, improvements could still be made. A minority, 3.8 percent, were detractors, who disliked the accuracy. The NPS for satisfaction with accuracy was lower, at only 34, meaning that, despite their ease of use, certain users doubt the accuracy of the health information the devices report.

In general, users reported no trouble using the devices, although there is more variability in their satisfaction with how accurate the data they record is.

4.4 Effectiveness and Impact

Questions 10-13 were used to test users' perceptions of the effectiveness, accuracy and power of AI-powered health systems. These questions sought to understand how well the AI systems are doing at encouraging healthier behavior, at predicting health outcomes, at enhancing health overall, and at giving useful advice. All the questions used a Net Promoter Score (NPS) scale, with respondents asked to rank their experiences on a scale from 0 (not at all) to 10 (very). The answers were coded as Promoters (9 or 10), Passives (7 or 8) and Detractors (0 to 6), so the answers could be broken down to see how satisfied users were, and what kind of influence they had.

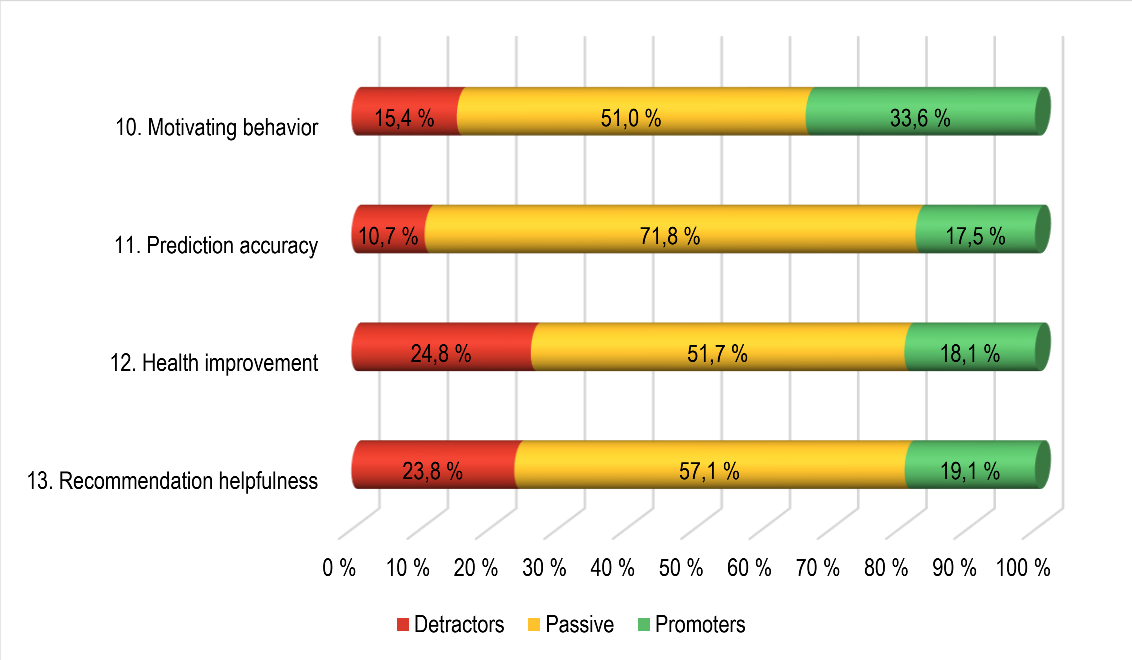

FIGURE 6. User perceptions of AI-powered health systems: motivation, accuracy, health improvement, and helpfulness

The results for Question 10: Motivating Behavior 33.6 percent of the respondents were promoters, who reported that the AI systems were very effective in motivating them to healthier behavior. 51 percent were passive, meaning they were moderately motivated, while 15.4 percent were detractors, meaning that the system didn't work for them in this regard. NPS score is 18.

For Question 11: Prediction Accuracy, only 17.5 percent of the respondents were very satisfied with the accuracy of health predictions, with the majority of 71.8 percent being passive. 10.7 percent were detractors, unhappy with the accuracy of the system's predictions. NPS score is 7.

In Question 12: Health Improvement, 18.1 percent reported that the systems driven by the AI had made a big difference to their general health. 51.7 percent were passive, which implies certain degree of recovery, but 24.8 percent were detractors, meaning they did not think the systems made them healthier. NPS score is -7.

Finally, for Question 13: Advice Usefulness, 19.1 percent of the respondents rated the AI-provided health advice as very useful in enhancing their daily practices. While 57.1 percent were passive, 23.8 percent were detractors, unhappy with the system's recommendations. NPS score is -5.

Taken together, as FIGURE 6, AI-powered healthcare systems were considered moderately effective by users in terms of promoting behavior and improving their health, but there were clear concerns about the accuracy of predictions and the usefulness of recommendations, as evidenced by the lower percentages of promoters.

4.5 Health Behavior Changes

Question 14 was intended to test which particular aspects of participants' lives they felt most changed by the advice given by their AI-enabled health wearables. They ranged from components of health, like exercise, nutrition, sleep, psychological health, and tracking of medical status. This question also reveals which areas of health are most impacted by AI-powered devices, and so provides the researcher with an insight into the practical benefits that users believe they get from using the technology.

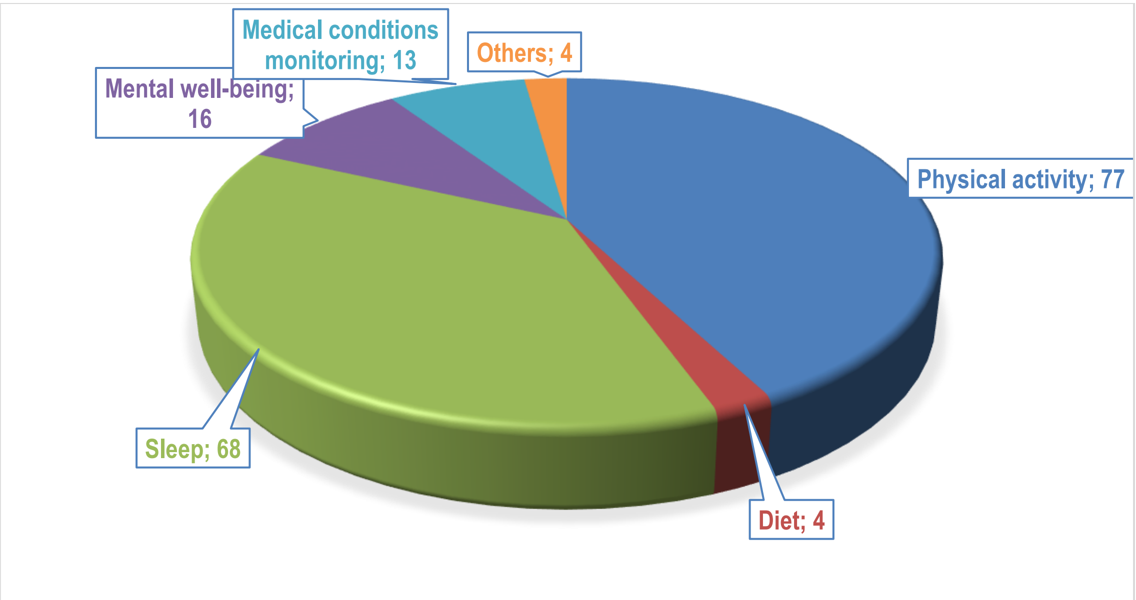

FIGURE 7. Impact of AI-powered wearables on various health areas as reported by the respondents

On all these, as shown in FIGURE 7, the respondents reported benefits through their AI-powered health wearables, according to this pie chart. 73.3 percent (n 77) noted the most noticeable improvements in physical activity and 64.8 percent (n 68) in sleeping. They cited improvements in their mental state in 15.2 percent (n 16) and improvements in medical condition monitoring in 12.4 percent (n 13). Less than 4 percent (n 4) reported a better diet, and 3.8 percent selected the others.

In the others section, the respondents provided a range of responses, including "menstrual cycle prediction with skin care," while one respondent noted that they did not experience any changes, stating, "Nothing. I found it myself because the AI didn't. Another response was simply "None really," and one respondent mentioned "Activity".

It is important to note that this question allowed for multiple selections, meaning the respondents could select more than one area of improvement. Percentages are also relative to the proportion of overall responses, not to the number of the respondents. This explains why the total percentage exceeds 100 percent.

That finding suggests that wearables powered by AI are especially effective at boosting physical activity and improving sleep (and have more modest, though still significant, impacts on tracking mental health and medical condition).

4.6 Perception and Future of AI in Healthcare

Items 15 and 16 were used to assess users' beliefs about the long-term utility of AI in medicine, and their long run willingness to wear AI-enabled wearables. Question 15 asks quiz-takers how confident they are that AI will 'play a significant role in healthcare in five years' and Question 16 how likely they are to use their AI-powered wearable health monitor over the next year. Both inquiries employed the Net Promoter Score (NPS) scale, asking the respondents to indicate how confident they were, or how likely they were, on a scale ranging from 0 (not at all) to 10 (extremely). Responses were classified as Promoters (ratings of 9 or 10), Passives (ratings of 7 or 8) and Detractors (ratings of 0 to 6), making it possible to analyze the respondents' future likelihood to recommend the place, and their likely future engagement with it, in one analysis.

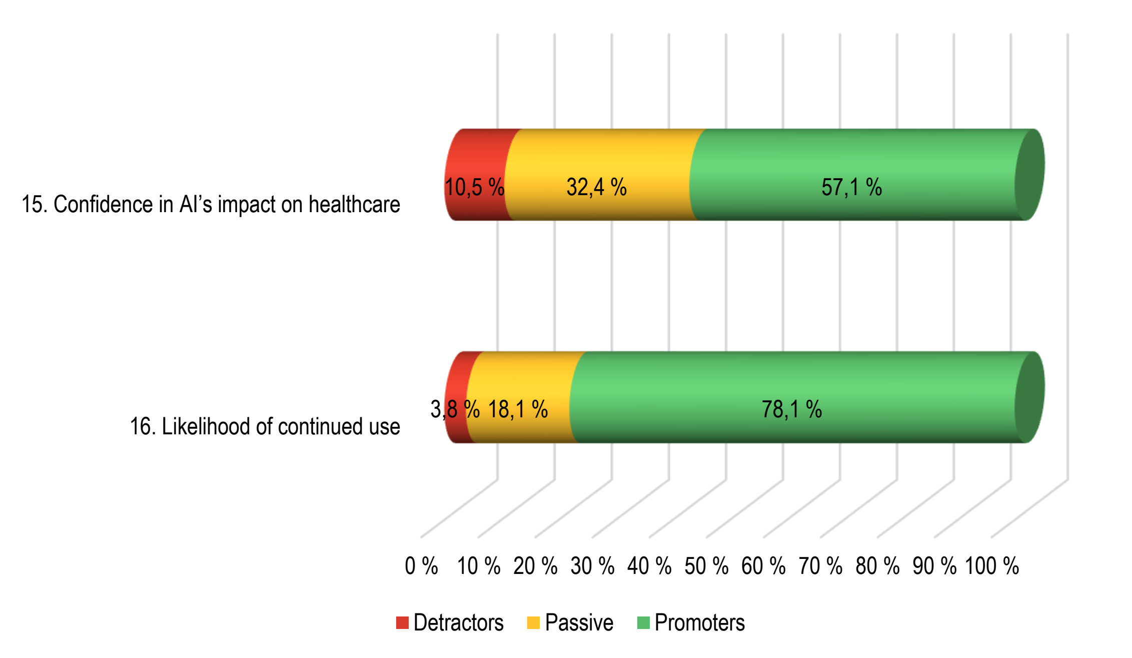

FIGURE 8. User confidence in ai's future impact on healthcare and likelihood of continued wearable use

For Question 15: Belief in the Impact of AI on Healthcare, 57.1 percent are defined as promoters, who are highly confident that AI will have a very significant impact on improving the quality of healthcare in five years' time'. 32.4 percent are in the passive camp, reporting a moderate level of confidence, and 10.5 percent are detractors, expressing a low level of confidence in the ability of AI to make a difference. These findings are representative of an overall optimistic view of the contributions of AI to healthcare. NPS score is 47.

In Question 16: 'Probability of Future Use', an important 78.1 percent of the respondents are 'advocates', meaning they intend to use AI-powered health wearables for tracking their health in the next year. 18.1 percent are passives, showing a moderate likelihood of continued use, while only 3.8 percent are detractors, expressing a low likelihood of continuing use. This sort of sustained commitment of continued use indicates that most users still derive an ongoing benefit from their AI-equipped health wearables. NPS score is 74.

Taken together, as shown in FIGURE 8, the findings reflect considerable user optimism about the future role of AI in health, as well as a strong likelihood of continued use of AI-enabled wearables.

4.7 User Perspectives on the Promising Applications of AI in Health Systems

Number 17 was designed to see what users thought the most exciting potentials of AI-driven health systems are. Participants were given a list of possible responses from personalized health advice, enhanced fitness and activity tracking, early detection and diagnosis, mental health care and real-time health monitoring and were allowed to choose more than one. This methodology sought to paint a wide canvas of user values and needs concerning AI in medicine.

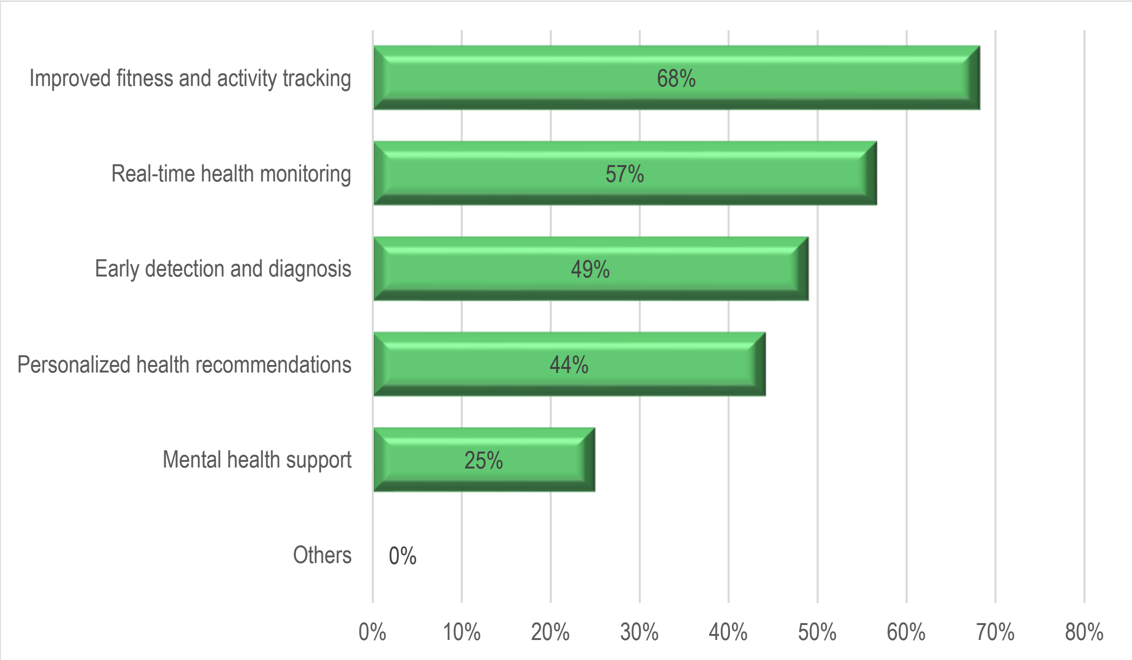

FIGURE 9. Most promising aspects of AI-powered health systems as perceived by users

The horizontal bar chart of FIGURE 9 shows how members of each group answered each category, and where they find the greatest potential for intelligent health systems. The most common was Better fitness and exercise tracking (68 percent), which likely reflects its promise in improving fitness.

Next was Real-time health monitoring (57 percent). That means many people enjoy the vision of AI continuously tracking health markers and providing timely information and interventions.

Early detection and diagnosis trailed at 49 percent, but captured the sense that AI could be particularly useful in identifying hints of disease.

44 percent of the users found health recommendations on demand to be of value, an indication of interest in the power of AI to provide specific advice based on personal health information.

Finally, Mental health support came in fourth, being chosen by a quarter of the respondents, which suggests a more muted but still significant interest in what AI might do to advance mental wellbeing.

The 'Others' box remained empty, suggesting that the preprogrammed options did pick up the most common worries of the respondents. This information also shows that, while patients imagine a wide range of uses for AI in their lives, right now the most highly rated features they want are health, fitness-tracking and real-time monitoring.

4.8 Barriers to Frequent Use of AI-Powered Health Wearables

Question 18 was tasked with identifying the primary barriers that prevent users from using AI-powered health wearables on a daily basis. They spanned the usual roadblocks, from cost, battery life, data accuracy, complexity, privacy and lack of interest. There was also an 'Other' box to fill in if the respondents thought there were other barriers that were important to them but not included in the list. The question sought to understand the difficulties that users experience as they try to incorporate AI-driven health technology into their lives.

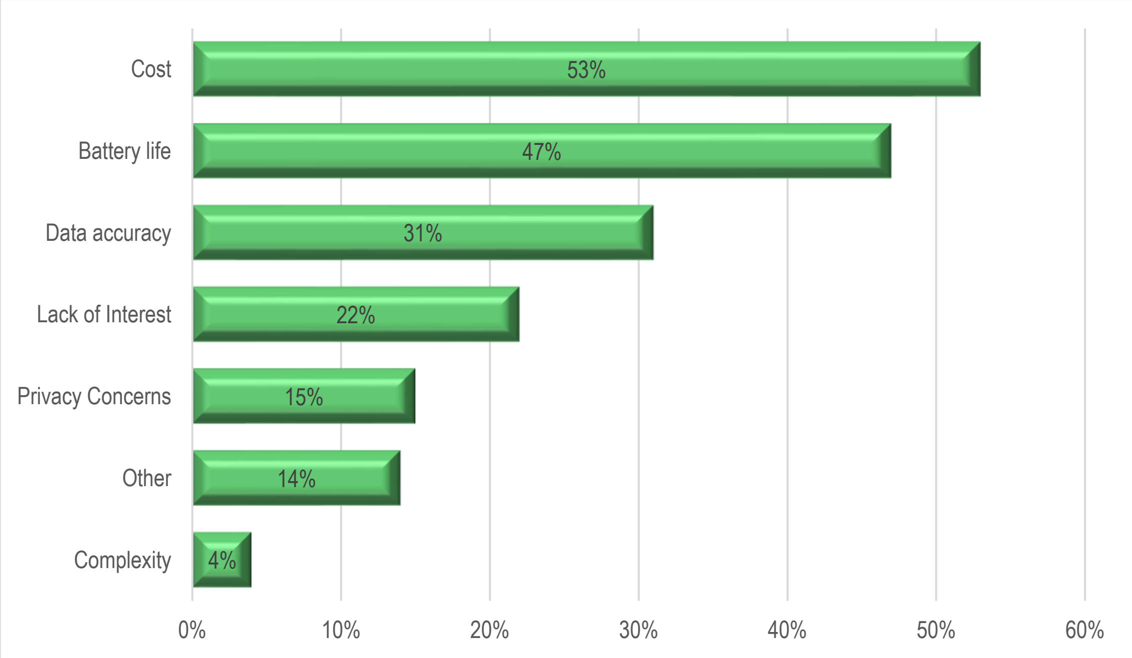

FIGURE 10. Primary barriers to frequent use of AI-powered health wearables

The bar chart across the bottom in FIGURE 10 shows the breakdown of responses for each barrier to wearable use. The most commonly mentioned barrier was price (53 percent of the respondents), which suggests that, for people to use these devices consistently, they need to be affordable. Battery life was the next big stumbling block, with 47 percent of the respondents citing the hassle of regular recharging.

Accuracy of data was the top answer, chosen by 31 percent, which may signal users' uncertainty about the accuracy of health data from such devices. 22% cited lack of interest, which, for certain users, can come down to not caring enough to use AI-enabled wearables on a regular basis. Privacy concerns were a barrier for 15% of the respondents, underscoring worries about data security in health monitoring. The Other option was the most common response, at 14 percent, followed by complexity, the most unpopular barrier, at 4 percent, suggesting that usability of the device is not a major issue.

The answers in the 'Other' column give further insight into the obstacles listed. A few users raised issues about the weight and hygiene of wearables, the possible adverse effects of wireless devices, and sensitivity to strap materials. Others expressed a lack of necessity or a preference for listening to their own body instead of relying on technology, with certain individuals noting that wearables affect mental health by creating pressure to meet specific goals. Some of the respondents cited workplace limitations, such as not being permitted to wear devices at work, such as for healthcare professionals. Moreover, users reported device errors, including inaccurate step counting and heart rate monitoring, both of which can engender a skepticism of the information that wearables offer.

4.9 Privacy and Security Concerns

Questions 19 and 20 were two questions that were aimed at measuring user apprehension and experience about the privacy and security of the data of their wearable device. Question 19 aimed to measure respondents' level of concern about data privacy, using the Net Promoter Score (NPS) scale to categorize users as Detractors, Passives, or Promoters. Question 20 asked if the respondents had actually experienced any problems with data security, offering a 'Yes' or 'No' response, as well as the possibility to explain the specific problem.

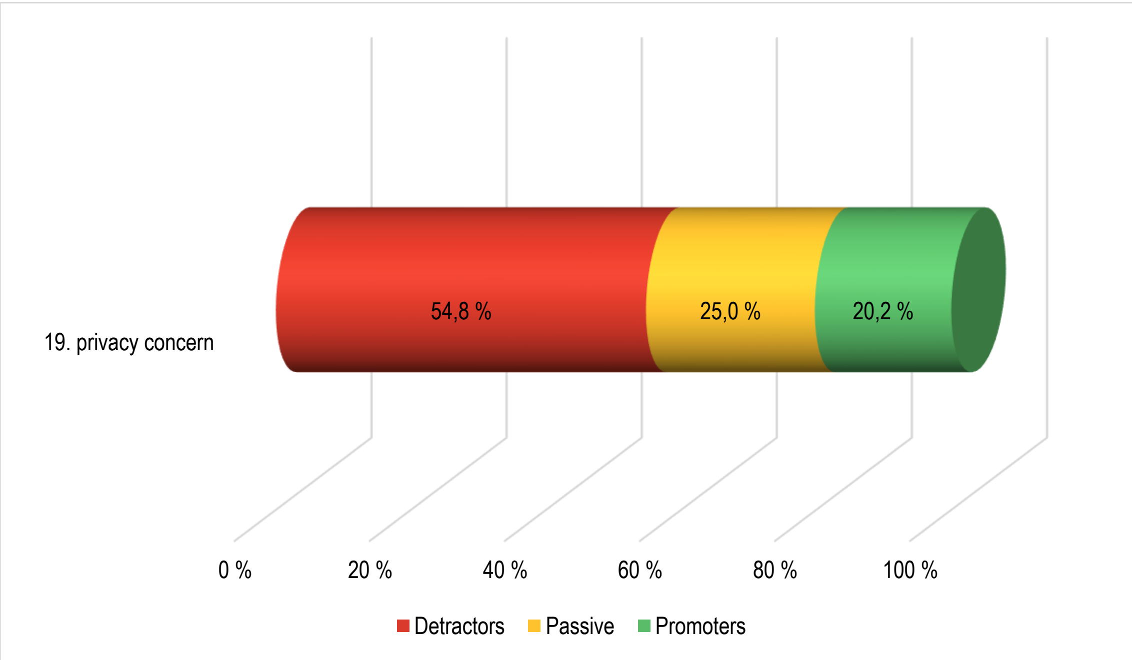

FIGURE 11. User concern levels regarding privacy of wearable device data

For the Question 19, as shown in FIGURE 11, the results indicate a fairly high degree of concern regarding data privacy, with 54.8 percent falling in the Detractor category (low on unconcerned), 25 percent in the Passive category, and only 20.2 percent in the Promotor category (low on concern). This distribution gives an overall Net Promoter Score (NPS) of -35, indicating a net negative attitude to data privacy confidence in wearable health devices. The large share of detractors indicates that data privacy is actual issue for most users.

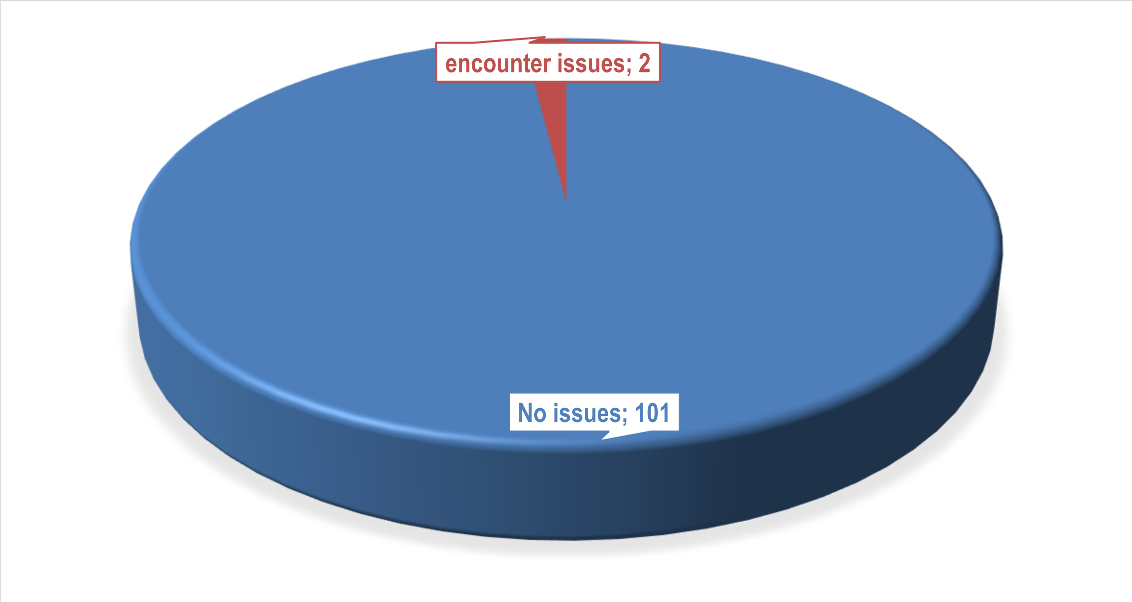

FIGURE 12. User-reported security issues encountered with wearable device data

Question 20 inquired whether the respondents had encountered any security concerns regarding their wearable's data. FIGURE 12 show a substantial 98.1% (n=101) reported having encountered no issues, while a small 1.9% (n=2) reported experiencing problems.

The responses in the "Yes" category provide additional insight. A user reported problems with ATK, with updates or loading or something. Another respondent noted that they experienced focused marketing related to a specific health condition they had, suggesting possible targeted ads based on their health data.

4.10 Data Sharing

And question 21 was created to figure out how often users submit data from their AI-equipped wearables to their doctors. Respondents were given four options—Never, Rarely, Sometimes, and Often—to indicate how regularly they share this data. The question is designed to measure the degree of engagement between wearable users and healthcare professionals regarding data sharing, and to understand whether users feel that sharing their health data is useful to receive professional healthcare advice.

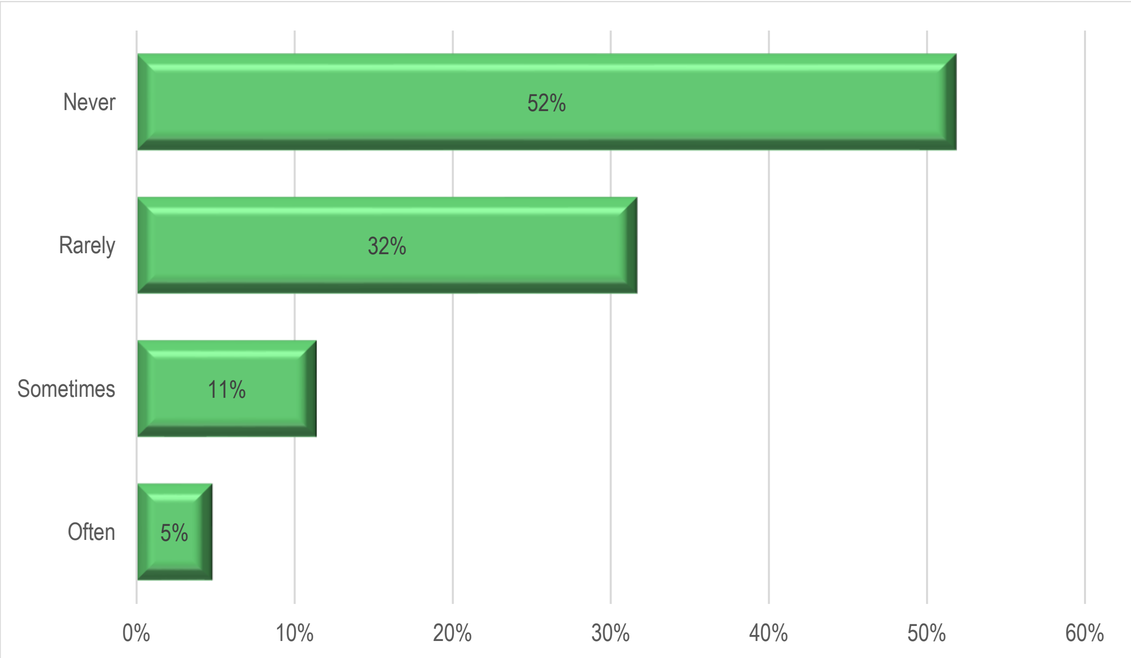

FIGURE 13. frequency of data sharing from AI-powered wearables with healthcare providers.

Results indicate, as shown in FIGURE 13, that most users are not consistently sharing wearable data with clinicians. 52% of the respondents selected Never, indicating that more than half do not share any data with healthcare providers. 32 percent selected 'Rarely', meaning that they sometimes share data, but still at a low level of activity. 11% indicated that they Sometimes share data, while only 5% reported sharing data Often.

These results show that while AI-powered wearables are ubiquitous for monitoring personal health, they are not well connected or interacting with professional health systems. The extremely high percentage of the respondents who never or only sometimes share data might signal a missed opportunity in users' habits, or in healthcare providers' interest, or in privacy concerns that could keep people from sharing more often. This pattern provides an example of how wearable device developers and health clinicians could work together to encourage more frequent, relevant data sharing, and ultimately, better health monitoring and outcomes.

4.11 Feedback on AI-powered wearable

In Question 22, the respondents were invited to answer an open-ended question, and in their own words describe how their AI-equipped wearable has affected their health and wellbeing. This qualitative data collection sought to capture rich and personal information beyond the confines of the survey questions. They were asked for their thoughts via an online survey sent to them, for them to respond to in a quantified, considered way. This method enabled a range of experiences and senses to be captured, and provided a much fuller sense of how the wearables impacted people's lives.

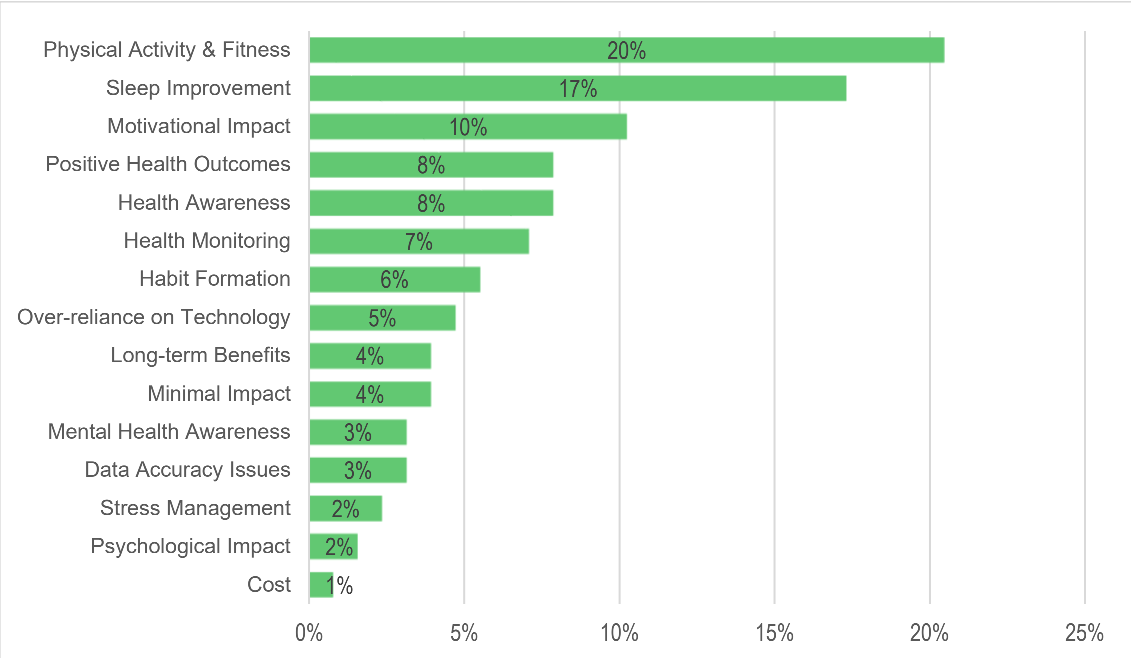

FIGURE 14. Distribution of thematic codes from user responses on AI-powered wearables' impact

This chart, as shown in FIGURE 14, summarizes the thematic analysis of respondents' views on the impact of AI-driven wearables on their health and well-being. The most commonly reported effect was on physical activity and fitness, 20 percent of the respondents reporting increased incentives to exercise and get fit. Better sleep was another recurring message, with 17 percent of the respondents reporting improved sleep and awareness through the use of wearable technology. 10 percent of users reported a motivational effect from the devices, which they found helpful in encouraging healthier behavior. Another 8 percent of those surveyed reported improved health, and 8 percent reported greater health consciousness. 7 percent cited tracking health as a notable advantage, since users could check their health metrics on a recurring basis. Other themes included habit formation, over reliance on technology, and concerns about data accuracy, with smaller percentages of the respondents highlighting these aspects. And this analysis, therefore, offers a rich picture of how users understand the application of AI-powered wearables to monitor users' health and wellbeing.

TABLE 5. Summary of codes and categories for AI-powered wearables' impact analysis

Code	Category	Frequency	Percentage
Health Awareness	Behavioral and Lifestyle Changes	10	7,9 %
Habit Formation	Behavioral and Lifestyle Changes	7	5,5 %
Motivational Impact	Behavioral and Lifestyle Changes	13	10,2 %
Sleep Improvement	Impact on Physical Health	22	17,3 %
Physical Activity & Fitness	Impact on Physical Health	26	20,5 %
Health Monitoring	Impact on Physical Health	9	7,1 %
Cost	Limitations and Concerns	1	0,8 %
Data Accuracy Issues	Limitations and Concerns	4	3,1 %
Over-reliance on Technology	Limitations and Concerns	6	4,7 %
Psychological Impact	Limitations and Concerns	2	1,6 %
Positive Health Outcomes	Perceived Effectiveness	10	7,9 %
Minimal Impact	Perceived Effectiveness	5	3,9 %
Long-term Benefits	Perceived Effectiveness	5	3,9 %
Mental Health Awareness	Impact on Mental Well-being	4	3,1 %
Stress Management	Impact on Mental Well-being	3	2,4 %

Here is the complete dataset from the thematic analysis of the answers to Question 22, as shown in TABLE 5, which describes the effects of AI-equipped wearables on users' health and well-being. The data is organized by Code, Category, Frequency, and Percentage.

The Codes are topics that emerge from the responses, and the Categories are ways of grouping the Codes into larger domains. 'Health Awareness', 'Habit Formation' and 'Motivational Impact', for instance, all fall under a general heading of Behavioral and Lifestyle Changes and describe how wearables influence users' daily habits and behavior. Under Impact on Physical Health are subheadings such as 'Physical Activity Fitness', 'Sleep Improvement' and 'Health Monitoring', which highlight concrete health outcomes, such as getting fitter or sleeping better.

Limitations and Concerns encompass issues such as "Data Accuracy," "Over reliance on Technology," and "Cost," highlighting users' perceived drawbacks or challenges. The Perceived Effectiveness lists 'Positive Health Outcomes' and 'Long term Benefits', reflecting the perceived worth of wearables to improve overall health. Finally, Impact on Mental Well-being lists 'Mental Health Awareness' and 'Stress Management', which deal with the psychological value of wearables.

The Frequency and Percent columns tell the researcher how many times each theme was mentioned, and thus how common these experiences are among the respondents. For example, 'Physical Activity Fitness' was the most frequently cited benefit, with 20.5 percent of the respondents citing it, while 'Cost' was the least, at 0.8 percent. This deep dataset reveals a detailed portrait of the user experience of AI-powered wearables - the positive experiences they afford, and the negative experiences they generate.

5 DISCUSSION

The researcher is pleased to present these findings, as the findings of this study has given a new outlook on AI today. As a result of the research, the researcher has accepted the nature of AI as it is today. This research is also hoping that it will make people think of AI in a more positive light and that it will also lead to further developments and experimentation in the field.

It is acknowledged that there are hundreds of personal opinions about AI all over the world, but this research is based on the answers of 100 plus technologically advanced students in a first world country, at least that's what the population statistics in TABLE 2 indicate. Most of the respondents were in the 18-24 age range, with a background in bachelor's degree programs or as recent graduates, and reported good health. Their familiarity with AI wearables is evident, as seen in the responses to questions about what devices they use and how they use them. Most of the respondents indicated that they have been using smartwatches for over two years on a daily basis, lending credibility to the reliability of the findings.

AI-powered wearable devices were generally reported as easy to use, and the respondents expressed satisfaction, as evidenced by a high NPS score, which falls within the "very good" range for both usability and satisfaction. But the AI seemed to be pretty moderate in its effectiveness, somewhere between average and good. The accuracy of these devices was also somewhat questionable, bordering on the lower end of the satisfaction scale.

The most intriguing finding, at least for the researcher, is the low belief among the respondents in the ability of AI wearables to improve overall health. Most answerers found the AI-suggested health recommendations did not significantly help their everyday lives. They were mainly used for exercise tracking and sleep monitoring, so although AI wearables can collect data, it is not necessarily going to improve one’s health significantly. This highlights the need to reconsider the purpose of AI in health it should extend beyond tracking to actively contribute to health improvement.

However, even with these restrictions, there is hope for the future as shown by the answers in FIGURE 8. The goal should be to enhance AI wearables so that they serve as more than only tracking tools. Continued research is needed to develop practical use cases. Many of the respondents hope for improved tracking accuracy and personalized health recommendations, as AI in other sectors has shown considerable progress.

Challenges remain, however, including the high cost, short battery life, and data accuracy issues of AI wearables. Some users already feel disinterested in the trend of using AI wearables in healthcare, as seen in FIGURE 10. This raises a future research question: Is it considerably worth it to track these trends of technology that will never live up to our expectations of feedback that is tailored to our own health?

Privacy concerns around health data are also significant. Many users are not fully aware of the potential privacy risks associated with AI wearables, even though there have not been many security issues reported yet. However, as technology advances, the associated risks may grow. Privacy will become a critical concern as AI wearables evolve to provide real-time, personalized health recommendations, which require synchronized access to biological health data, psychological information, and medical history. More research is needed on how to inform users of privacy issues and possible dangers in an understandable and brief way, and also what type of security precautions must be taken to ensure secure real-time data synchronization.

The responses from the free-text field highlight more insightful perspectives on AI health devices, as about half of the respondents were willing to provide additional insights. The research will include these responses in the APPENDICES, as most of the feedback is worth reviewing. These responses reveal the current reality of AI in health devices. According to the results from the thematic analysis of all responses, the majority of the respondents use AI wearable devices for physical activity tracking and sleep improvement. This same pattern was also highlighted in FIGURE 7. This prompts the research to consider more clearly the role of AI in healthcare. Is it limited to activity tracking?

Although the majority of the respondents provided feedback on activity tracking and sleep improvement, only a small number offered more thoughtful perspectives. Comments like “It's my responsibility to react to the information I see, and usually I make the choice to act and do the work (for example, reduce drinking when I see how it affects my sleep, or exercise more frequently when I see a decreased VO2 max score)” lead the research to consider another direction and raise more questions about AI usage in our health devices.

How can human achieve the use of AI in the healthcare system if there is already a lack of successful integration even within health devices themselves? Is the use of AI in health wearable devices only for marketing purposes? How long do the human need to wait to fully integrate AI into devices so that they can provide generative responses based on the data collected? A further question is, when will human be able to use a healthcare system integrated with AI to synchronize all health data from multiple different sources? How far are human progressing, and where are human currently? We should conduct more research on the user perspective to look beyond marketing strategies that use the term 'AI' on new devices to align with current trends.

Advanced technological inventions by humans should be beneficial to humanity rather than merely generating profits by exploiting resources. AI holds promise in various ways to affect our daily lives in the coming years, and human are currently experiencing one of the most significant movements in human evolution. We should not fall behind in effectively integrating AI technology into our healthcare system, as health is the most valuable asset.

In conclusion, as human advance in AI technology, it is essential to harness its potential thoughtfully, ensuring it truly serves to enhance our health and well-being rather than merely capitalizing on trends, paving the way for a more meaningful integration of AI in future healthcare.

REFERENCES

Abràmoff, M. D., Lavin, P. T., Birch, M., Shah, N., & Folk, J. C. (2018). Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. *Npj Digital Medicine*, *1*(1). https://doi.org/10.1038/s41746-018-0040-6

Baig, M. M., GholamHosseini, H., Moqeem, A. A., Mirza, F., & Lindén, M. (2017). A Systematic Review of Wearable Patient Monitoring Systems – Current Challenges and Opportunities for Clinical Adoption. *Journal of Medical Systems*, *41*(7). https://doi.org/10.1007/s10916-017-0760-1

Bbcrossword 2023. PUP Smart Sock biosensors detect floor contact when a fall-risk inpatient is out of bed and walking unassisted. Search Date 24.3.2024. Wikimedia Commons,CC BY-SA 4.0. https://commons.wikimedia.org/wiki/File:The_Palarum_PUP_Smart_Sock_uses_eTextile_biosensors_woven_into_the_sock_sole.png

Boxall, A. B. A., Rudd, M. A., Brooks, B. W., Caldwell, D. J., Choi, K., Hickmann, S., Innes, E., Ostapyk, K., Staveley, J. P., Verslycke, T., Ankley, G. T., Beazley, K. F., Belanger, S. E., Berninger, J. P., Carriquiriborde, P., Coors, A., DeLeo, P. C., Dyer, S. D., Ericson, J. F., … Van Der Kraak, G. (2012). Pharmaceuticals and personal care products in the environment: What are the big questions? In *Environmental Health Perspectives* (Vol. 120, Issue 9). https://doi.org/10.1289/ehp.1104477

Case, M. A., Burwick, H. A., Volpp, K. G., & Patel, M. S. (2015). Accuracy of smartphone applications and wearable devices for tracking physical activity data. In *JAMA - Journal of the American Medical Association* (Vol. 313, Issue 6). https://doi.org/10.1001/jama.2014.17841

Chen, M., Ma, Y., Song, J., Lai, C. F., & Hu, B. (2016). Smart Clothing: Connecting Human with Clouds and Big Data for Sustainable Health Monitoring. *Mobile Networks and Applications*, *21*(5). https://doi.org/10.1007/s11036-016-0745-1

Chen, Y., Qin, X., Wang, J., Yu, C., & Gao, W. (2020). FedHealth: A Federated Transfer Learning Framework for Wearable Healthcare. *IEEE Intelligent Systems*, *35*(4). https://doi.org/10.1109/MIS.2020.2988604

Cossy-Gantner, A., Germann, S., Schwalbe, N. R., & Wahl, B. (2018). Artificial intelligence (AI) and global health: How can AI contribute to health in resource-poor settings? *BMJ Global Health*, *3*(4). https://doi.org/10.1136/bmjgh-2018-000798

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). https://doi.org/10.1186/s40537-019-0217-0

Dias, D., & Cunha, J. P. S. (2018). Wearable health devices—vital sign monitoring, systems and technologies. In *Sensors (Switzerland)* (Vol. 18, Issue 8). https://doi.org/10.3390/s18082414

Dinh-Le, C., Chuang, R., Chokshi, S., & Mann, D. (2019). Wearable health technology and electronic health record integration: Scoping review and future directions. In *JMIR mHealth and uHealth* (Vol. 7, Issue 9). https://doi.org/10.2196/12861

Fernández-Caramés, T. M., & Fraga-Lamas, P. (2018). Towards the internet-of-smart-clothing: A review on IoT wearables and garments for creating intelligent connected E-textiles. In *Electronics (Switzerland)* (Vol. 7, Issue 12). https://doi.org/10.3390/electronics7120405

Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. In *Industrial Management and Data Systems* (Vol. 115, Issue 9). https://doi.org/10.1108/IMDS-03-2015-0087

Gibson, A. L., Wagner, D. R., & Heyward, V. H. (2019). Advanced Fitness Assessment and Exercise Prescription. In *Advanced Fitness Assessment and Exercise Prescription*. https://doi.org/10.5040/9781718220966

Hassanalieragh, M., Page, A., Soyata, T., Sharma, G., Aktas, M., Mateos, G., Kantarci, B., & Andreescu, S. (2015). Health Monitoring and Management

Using Internet-of-Things (IoT) Sensing with Cloud-Based Processing: Opportunities and Challenges. *Proceedings - 2015 IEEE International Conference on Services Computing, SCC 2015*. https://doi.org/10.1109/SCC.2015.47

Henriksen, A., Mikalsen, M. H., Woldaregay, A. Z., Muzny, M., Hartvigsen, G., Hopstock, L. A., & Grimsgaard, S. (2018). Using fitness trackers and smartwatches to measure physical activity in research: Analysis of consumer wrist-worn wearables. *Journal of Medical Internet Research*, *20*(3). https://doi.org/10.2196/jmir.9157

Jara, A. J., Zamora-Izquierdo, M. A., & Skarmeta, A. F. (2013). Interconnection framework for mHealth and remote monitoring based on the internet of things. *IEEE Journal on Selected Areas in Communications*, *31*(9). https://doi.org/10.1109/JSAC.2013.SUP.0513005

Khan, Y., Ostfeld, A. E., Lochner, C. M., Pierre, A., & Arias, A. C. (2016). Monitoring of Vital Signs with Flexible and Wearable Medical Devices. In *Advanced Materials* (Vol. 28, Issue 22). https://doi.org/10.1002/adma.201504366

Korda, H., & Itani, Z. (2013). Harnessing Social Media for Health Promotion and Behavior Change. *Health Promotion Practice*, *14*(1). https://doi.org/10.1177/1524839911405850

Li, M., Lou, W., & Ren, K. (2010). Data security and privacy in wireless body area networks. *IEEE Wireless Communications*, *17*(1). https://doi.org/10.1109/MWC.2010.5416350

Li, R. T., Kling, S. R., Salata, M. J., Cupp, S. A., Sheehan, J., & Voos, J. E. (2016). Wearable Performance Devices in Sports Medicine. In *Sports Health* (Vol. 8, Issue 1). https://doi.org/10.1177/1941738115616917

Liang, X., Zhao, J., Shetty, S., Liu, J., & Li, D. (2017). Integrating blockchain for data sharing and collaboration in mobile healthcare applications. *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC*, *2017-October*. https://doi.org/10.1109/PIMRC.2017.8292361

Libanori, A., Chen, G., Zhao, X., Zhou, Y., & Chen, J. (2022). Smart textiles for personalized healthcare. In *Nature Electronics* (Vol. 5, Issue 3). https://doi.org/10.1038/s41928-022-00723-z

Liu, R., Rizzo, S., Whipple, S., Pal, N., Pineda, A. L., Lu, M., Arnieri, B., Lu, Y., Capra, W., Copping, R., & Zou, J. (2021). Evaluating eligibility criteria of oncology trials using real-world data and AI. *Nature*, *592*(7855). https://doi.org/10.1038/s41586-021-03430-5

Lu, L., Zhang, J., Xie, Y., Gao, F., Xu, S., Wu, X., & Ye, Z. (2020). Wearable health devices in health care: Narrative systematic review. In *JMIR mHealth and uHealth* (Vol. 8, Issue 11). https://doi.org/10.2196/18907

Maher, C. A., Lewis, L. K., Ferrar, K., Marshall, S., De Bourdeaudhuij, I., & Vandelanotte, C. (2014). Are health behavior change interventions that use online social networks effective? A systematic review. In *Journal of Medical Internet Research* (Vol. 16, Issue 2). https://doi.org/10.2196/jmir.2952

Majumder, S., Aghayi, E., Noferesti, M., Memarzadeh-Tehran, H., Mondal, T., Pang, Z., & Deen, M. J. (2017). Smart homes for elderly healthcare—Recent advances and research challenges. In *Sensors (Switzerland)* (Vol. 17, Issue 11). https://doi.org/10.3390/s17112496

Mantua, J., Gravel, N., & Spencer, R. M. C. (2016). Reliability of sleep measures from four personal health monitoring devices compared to research-based actigraphy and polysomnography. *Sensors (Switzerland)*, *16*(5). https://doi.org/10.3390/s16050646

Metcalf, D., Milliard, S. T. J., Gomez, M., & Schwartz, M. (2016). Wearables and the internet of things for health: Wearable, interconnected devices promise more efficient and comprehensive health care. *IEEE Pulse*, *7*(5). https://doi.org/10.1109/MPUL.2016.2592260

Middleton, K. R., Anton, S. D., & Perri, M. G. (2013). Long-Term Adherence to Health Behavior Change. *American Journal of Lifestyle Medicine*, *7*(6). https://doi.org/10.1177/1559827613488867

Milne-Ives, M., LamMEng, C., de Cock, C., van Velthoven, M. H., & Ma, E. M. (2020). Mobile apps for health behavior change in physical activity, diet, drug and alcohol use, and mental health: Systematic review. *JMIR MHealth and UHealth*, *8*(3). https://doi.org/10.2196/17046

Mohan Babu, Michael Snyder 2023. Longitudinal multi-omics and wearable data enabled deep phenotyping for precision health. Search Date 25.3.2024. Wikimedia Commons, CC BY-SA 4.0. https://commons.wikimedia.org/wiki/File:Longitudinal_multi-omics_and_wearable_data_enabled_deep_phenotyping_for_precision_health.jpg

Mohr, D. C., Zhang, M., & Schueller, S. M. (2017). Personal Sensing: Understanding Mental Health Using Ubiquitous Sensors and Machine Learning. *Annual Review of Clinical Psychology*, *13*. https://doi.org/10.1146/annurev-clinpsy-032816-044949

Pantelopoulos, A., & Bourbakis, N. G. (2010). A survey on wearable sensor-based systems for health monitoring and prognosis. In *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews* (Vol. 40, Issue 1). https://doi.org/10.1109/TSMCC.2009.2032660

Prestwich, A., Sniehotta, F. F., Whittington, C., Dombrowski, S. U., Rogers, L., & Michie, S. (2014). Does theory influence the effectiveness of health behavior interventions? Meta-analysis. *Health Psychology*, *33*(5). https://doi.org/10.1037/a0032853

Rai, A. (2020). Explainable AI: from black box to glass box. In *Journal of the Academy of Marketing Science* (Vol. 48, Issue 1). https://doi.org/10.1007/s11747-019-00710-5

Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. In *Nature Medicine* (Vol. 28, Issue 1). https://doi.org/10.1038/s41591-021-01614-0

Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. In *SN Computer Science* (Vol. 2, Issue 3). https://doi.org/10.1007/s42979-021-00592-x

Schüll, N. D. (2016). Data for life: Wearable technology and the design of self-care. *BioSocieties*, *11*(3). https://doi.org/10.1057/biosoc.2015.47

Shan, R., Sarkar, S., & Martin, S. S. (2019a). Digital health technology and mobile devices for the management of diabetes mellitus: state of the art. In *Diabetologia* (Vol. 62, Issue 6). https://doi.org/10.1007/s00125-019-4864-7

Shan, R., Sarkar, S., & Martin, S. S. (2019b). Digital health technology and mobile devices for the management of diabetes mellitus: state of the art. In *Diabetologia* (Vol. 62, Issue 6). https://doi.org/10.1007/s00125-019-4864-7

Shen, X., Gao, J., Wu, W., Lyu, K., Li, M., Zhuang, W., Li, X., & Rao, J. (2020). AI-assisted network-slicing based next-generation wireless networks. *IEEE Open Journal of Vehicular Technology*, *1*. https://doi.org/10.1109/OJVT.2020.2965100

Subramaniyaswamy, V., Manogaran, G., Logesh, R., Vijayakumar, V., Chilamkurti, N., Malathi, D., & Senthilselvan, N. (2019). An ontology-driven personalized food recommendation in IoT-based healthcare system. In *Journal of Supercomputing* (Vol. 75, Issue 6). https://doi.org/10.1007/s11227-018-2331-8

Sun, Z., Zhu, M., Zhang, Z., Chen, Z., Shi, Q., Shan, X., Yeow, R. C. H., & Lee, C. (2021). Artificial Intelligence of Things (AIoT) Enabled Virtual Shop Applications Using Self-Powered Sensor Enhanced Soft Robotic Manipulator. *Advanced Science*, *8*(14). https://doi.org/10.1002/advs.202100230

Wang, X., Liu, Z., & Zhang, T. (2017). Flexible Sensing Electronics for Wearable/Attachable Health Monitoring. In *Small* (Vol. 13, Issue 25). https://doi.org/10.1002/smll.201602790

Webb, T. L., Joseph, J., Yardley, L., & Michie, S. (2010). Using the Internet to promote health behavior change: A systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. *Journal of Medical Internet Research*, *12*(1). https://doi.org/10.2196/jmir.1376

Xiong, J., Chen, J., & Lee, P. S. (2021). Functional Fibers and Fabrics for Soft Robotics, Wearables, and Human–Robot Interface. In *Advanced Materials* (Vol. 33, Issue 19). https://doi.org/10.1002/adma.202002640

Yigitcanlar, T., Desouza, K. C., Butler, L., & Roozkhosh, F. (2020). Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. In *Energies* (Vol. 13, Issue 6). https://doi.org/10.3390/en13061473

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*. https://doi.org/10.1016/j.ijmedinf.2017.09.016

Zhao, J., Freeman, B., & Li, M. (2016). Can mobile phone apps influence people's health behavior change? An evidence review. In *Journal of Medical Internet Research* (Vol. 18, Issue 11). https://doi.org/10.2196/jmir.5692

APPENDICES

INFORMATION SHEETS FOR QUESTIONNAIRE APPENDIX 1

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Information sheet

Nature of the Research

This research explores the practical applications and impact of AI-powered health mentoring systems integrated with wearable technology. These systems utilize artificial intelligence to provide personalized health recommendations and monitor individual health metrics in real-time. The research will examine how these AI-powered wearables are being used to support health behavior changes, their effectiveness in improving health outcomes, and the potential benefits and challenges they present in modern healthcare.

Researcher

The researcher is Zaw Ye Tun who is a master student from the Data Analytics and Project Management program at Oulu University of Applied Sciences (OAMK) , supervised by principal lecturer Jukka Jauhiainen.

Funding / Sponsors

This research is conducted as part of an academic thesis at OAMK and is not sponsored by any external organizations.

Population, Sampling, Sample Size

The population for this research includes individuals who use AI-powered health mentoring systems and wearable technology to monitor and improve their health. The sampling method will involve convenience sampling through social media and OAMK student network, targeting individuals who actively use these systems. Given the accessibility and potential reach, the sample size will aim to collect a minimum of **50 to 100 participants** to ensure a diverse and representative sample, accounting for potential data cleaning and the need for statistical significance. Measures will be taken to ensure only one response per participant by using features of Webropro software.

Data collection methods and types of data collected

Data collection methods for the research include surveying individuals who use AI-powered smartwatches and apps. The types of data collected will be:

- Participants' demographic and personal information
- Information about the type of AI-powered devices used
- Participants' experiences with AI-powered wearables
- Participants' views and opinions
- Privacy and security concerns

Duration and the number of takes of the survey

3 minutes to answer the survey, plus **2 minutes** for reading, making the overall time commitment around **5 minutes**.

Participation in the research

Participating in the research is entirely voluntary.

Data Privacy and Participants' Control

For this study, participants will complete a quantitative survey, which will be conducted online. No audio or video recordings will be involved. All responses will be collected anonymously, and no personal identifying information will be tied to any data. Participants are free to skip any questions they do not wish to answer and may choose to withdraw from the survey at any point. All data collected will be securely stored and used solely for research purposes. Participants' privacy and confidentiality will be protected throughout the study.

Possible Consequences, Risks, and Benefits

Participants may feel a minor inconvenience due to the time spent answering the questions, which is estimated to be around 5 minutes. Participation involves minimal risk, with potential benefits of participating include contributing to important research on the feasibility and efficacy of AI-powered health mentoring systems.

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Anonymity and Confidentiality

All survey responses will be anonymized to ensure that participants cannot be identified. Confidentiality will be strictly maintained throughout the research process. The data will be used solely for the purpose of this research study and will not be shared with third parties.

Access to Data

Restricted to the research, with findings to be aggregated for analysis and reporting.

Dissemination of Results

Results will be shared through academic channels, including publications and conferences, with participants receiving a summary of the findings.

Data destruction

After the study is complete, all survey data will be securely destroyed. Only anonymized results, which do not contain any personal identifying information, will be preserved for research purposes.

Contact information

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Data Analytics and Project Management, OAMK

OULUN AMMATTIKORKEAKOULU

AI power health system questions

Mandatory questions are marked with a star (*)

This research, conducted by Zaw Ye Tun, a master's student at OAMK under the supervision of Jukka Jauhiainen, explores AI-powered health mentoring systems integrated with wearables, focusing on their impact on health behavior, effectiveness, and challenges. It is part of an academic thesis with no external sponsorship. Your responses are anonymous, and no personally identifiable information will be collected. Participation is voluntary, and the estimated completion time is 3-5 minutes.
For more information... Click here

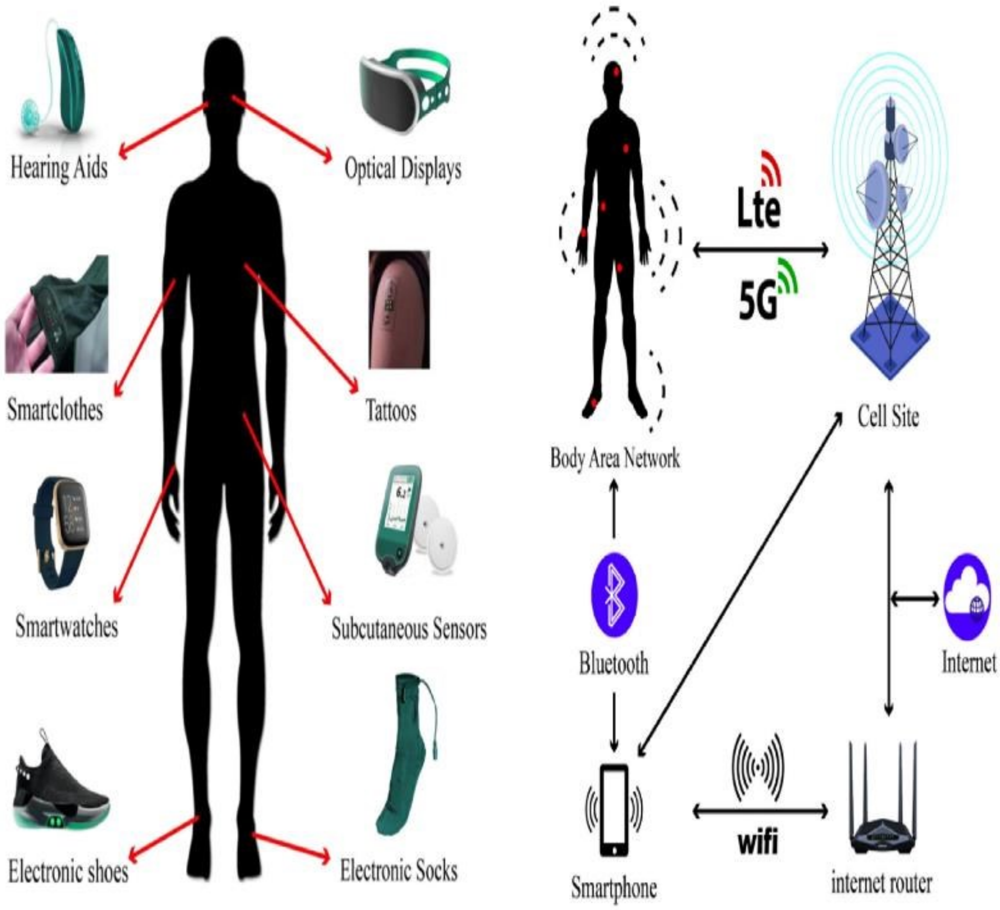
Defination of AI power health system.

- AI-powered wearable devices and system are those that use artificial intelligence to provide personalized health insights and recommendations.

- These devices often track metrics like heart rate, sleep patterns, activity levels, and more, and use AI to analyze data, provide predictions, and suggest actions, personalized insights.

- Only tracking data cannot be considered as using AI.

As examples,
AI-Powered Smartwatch and smart ring.
AI-Driven Smartphone Health App such as Apple Health, Google Fit,...



(a) (b)

Do you use some AI power health system? *

◯ Yes ◯ No, (I will quit answering)

	less than 18 years	18-24	25-34	35-44	45-54	55-64	65+
1. Your age?	◯	◯	◯	◯	◯	◯	◯

	Male	Female
2. Are you male of female?	○	○

	High school	Bachelor	Master	Doctor
3. Your highest education level? (including any degree you're currently pursuing)	○	○	○	○

	Poor	Fair	Good	Excellent
4. How would you describe your overall health?	○	○	○	○

5. What AI-powered health applications or wearables are you using now?

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	Less than 6 months,	6-12 months,	1-2 years,	Over 2 years
6. For how long have you been using?	○	○	○	○

7. How often do you wear your device?

○ Daily ○ Sometime (only when needed)

8. how easy is it to use for health monitoring?

Not at all easy

Extremely Easy

9. How satisfied are you with the accuracy of the health data provided by your wearable device?

Not at all satisfy

Extremely satisfy

10. Rate the effectiveness of the AI system in motivating you to engage in healthier behavior.

Not at all effective

Extremely effective

11. How accurate do you find the health predictions made by the AI system?

Not at all accurate

Extremely accurate

12. How much do you believe AI-powered health applications have improved your overall health?

Not at all believe

Extremely believe

13. How helpful do you find AI-generated health recommendations in improving your daily routines?

Not at all helpful

Extremely helpful

14. which area was most noticeable changes due to recommendations from your AI-powered wearable?

☐ Physical activity, ☐ Mental well-being

☐ Diet, ☐ Medical conditions monitoring

☐ Sleep, ☐ Others ____________

15. How confident are you that AI can significantly improve healthcare in the next 5 years?

Not at all likely

Extremely likely

16. How likely are you to continue using your AI-powered wearable for health tracking over the next year?

Not at all likely

Extremely likely

17. What aspect of AI-powered health systems do you believe holds the most promise?

- [ ] Personalized health recommendations
- [ ] Improved fitness and activity tracking
- [ ] Early detection and diagnosis
- [ ] Mental health support
- [ ] Real-time health monitoring
- [ ] Others ____________

18. What are the main reasons preventing you from using AI-powered health wearables more frequently?

- [ ] Battery life,
- [ ] Data accuracy,
- [ ] Cost,
- [ ] Complexity,
- [ ] Privacy Concerns,
- [ ] Lack of Interest,
- [ ] Other ____________

19. How concerned are you about the privacy of your health data collected by the wearable device?

Not at all concern

Extremely concern

20. Have you ever encountered any issues regarding the security of your wearable's data?

○ No ○ Yes ____________________

21. how often do you share the data from your AI-powered wearable with your healthcare provider?

◯ Never, ◯ Rarely, ◯ Sometimes, ◯ Often

22. In your own words, how has your AI-powered wearable impacted your health and well-being?

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Figure reference:
Darius Nahavandi, Roohallah Alizadehsani, Abbas Khosravi, U Rajendra Acharya,
Application of artificial intelligence in wearable devices: Opportunities and challenges,
Computer Methods and Programs in Biomedicine,
Volume 213,2022,106541,ISSN 0169-2607,https://doi.org/10.1016/j.cmpb.2021.106541.

Thank you for your time.

22. In your own words, how has your AI-powered wearable impacted your health and well-being?

Number of respondents: 52

Responses
Increase awareness
Maybe in the sense that my device reminds me to take small breaks and walk a little during the workday. This keeps me from sitting for hours on an end. Sleep data also helps me navigate my routines and understand my physical feelings of the day better. Additionally, liking the additional suggested solutions for meditating and falling asleep, though these are not free features in the app.
It helps a lot when i needed.
I can track my sleep and steps and make changes if needed.
Monitoring heart rate, so that I don't start working out too enthusiastically.
Yes, it has improved but also made it worse from time to time.
I have had healthy lifestyle already before using a smartwatch, so there have been quite small effects. One is that I don´t drink almost any alcohol due to the smartwatch showed how alcohol impacts my sleep.
Olen alkanut urheilla tavoitteellisemmin ja useammin
It has been easier to have trainings in desired efficiency.
With my watch I can see when I´m getting too tired and need longer resting time, I can also see quite clearly what daily actions affect my good night sleep making it better (or worse).
it is rewarding to get feedback
I think that the overall effect has been mainly positive. It has motivated me exercise more and helps me specially with the gym. For example, it's easy to set timer between breaks in the gym with your watch. You also see how many calories you have burnt and how many steps you have taken during the day. There is also downsides..for example you can get hooked with tracking your health too much. I want to keep exercising in the side of joy and not to ruin it with monitoring too much.
it has helped me have a general view of my health (it doesn't have to be completly accurate)
It makes me think about my health more frequently and sometimes gets me activated better than without it.
The impact of my smart watch is quiet small to myoverall wellbeing. It is interesting to save data about gym workouts and running. I also use to look how was my sleep and activity of the day. But I suppose that my habits would be the same without the watch.
Sometimes ut can help me walk more steps daily and I can monitore my heartbeat while exercusing etc.
Not at all!! AI today is useless due to the fact that the data behind is still too shorthanded, narrow and not fact based. AI will though be a great asset in the future, when we let them loose and they really start to "eat" data. AI is still to confined to be taken seriously.
I have improved my fitness level, since as for instance, the application fitness is very encouraging in completing my daily goal
More physical activity.
It's good for tracking my heart rate, since I have a heart condition, and I've learned what is too stresful for me to do in the evening to cause me lack of sleep.
I can better predict my period and how it affects to my daily life for example mental health, sleep, nutrition and sports. With knowing how it affects every day, I can plan my days to support my overall well being. I also feel more compassion for myself and that's how I can better accept me and go through hard days.
Sleep tracking has helped me to plan my daily schedule proper recovery in mind. Better sleep helps studying too.
In the beginning it was exiting and probably inspired me to get more exercise. Now it's mainly for monitoring and collecting data about my jogging routes. One good thing was that I noticed how easily I can get my sleeping habits disturbed, and also followed up how they were fixed. This helps me do better in the future.
It helps keep track of my counted steps which can encourage me to do better or to take it easy depending on my progress. It also has helped me tracking my stress levels and heart rate and make changes in my daily life if I have had alot of stress. Yet I'm a little sceptical how accurate the stress tracking can be. Still I feel that it has helped me to improve my mental health if I notice that my stress levels haven't been so low and do something differently.
My smartwatches help me to track my run regularly, i am a runner, and track the number of steps I take. It's really motivating, especially when I earn achievements for my progress. Additionally, I monitor the quality and duration of my sleep, as well as my stress levels. All of this helps me better understand my condition and maintain good well-being.
It knows before any symptoms that I'm catching a flu and asks me to slow down which I do. I know I'm prepared to take it easy.
Improved tracking
My AI-powered smartwatch has improved my health by tracking my activity, and heart rate, helping me stay more active, set fitness goals, and maintain better overall well-being.
It helps to track the health
I know my sleep quality better
I started walking and running. I can see my exercise improvements, so it motivates to work towards better health and keep exercising. Not really much impact what non-AI powered wearable could not do. Expecting AI to further improve to actually make a bigger difference in my health.
It depands, sometimes it's very useful but sometimes it affects my mental health.

Responses
I track my sleep routines and heartbeat. Also whenever I exercise I want to now the effect and impact of training on my body.
Boosted activity level
mayde inspires to move
I think using watches is great for tracking the effectiveness of a workout. Seeing results after a workout is rewarding but I wouldn't say its the sole reason I exercise. AI will improve and adapt even more to hopefully diagnose and prevent health problems, being what mostly interests me regarding the issue.
Maybe
Not significantly
It helps me not to concern about every aspect of my sport life
I strive for better sports performance as well as better sleep.
I have been able to track my sleep (amount, quality, sleep stages (REM etc.)) and calory/fat burn. I have also been able to monitor my heartbeat.
I've been able to track my sleeping and activity better, but I don't think it has benefited my overall health and well-being. It's been the same wether or not I have used these wearables.
I do watch my sleeping pattern and heart rate every now and then.
I'm motivated to be more actice and sleep better (regularly, more)
It has impacted my well-being positively. Before its use I was already healthy, but it has helped me improving and maintaining my health and healthy habits, especially my physical activity. It could help me improving in other areas, but the main purpose of my purchase was increasing my daily physical activity, so I am content with the results. Good luck with your work, it is a great and interesting topic!
I take more steps every day and I my sleep has improved
It is nice to track sleep and recovering statistics and get some ideas what to do if statistics are not that good.
Seeing the step counter is encouraging (although inaccurate, the connected phone app shows more accurate number). Heart rate is not reliable enough to use for diagnosis, but it gave me reassurance that my pulse is not too high all the time. Mostly I just use it as basic wrist watch
No notable difference really, just tracking my sleep.
Motivates me to be more active
It's merely a tool for me to see how I'm doing, it's not doing anything for me and I think it's a silly marketing tool to say that something like an Oura or Apple Watch actively does anything. It's my responsibility to react to the info I see, and usually I make the choice to react and do the work (for example, reduce drinking when I see how it affects my sleep, or exercise more frequently when I see a decreased VO2 max score).
It makes me more aware and helps to remember things more accurately. Like when I had worse sleep etc, if I have to explain it to a Dr for instance.