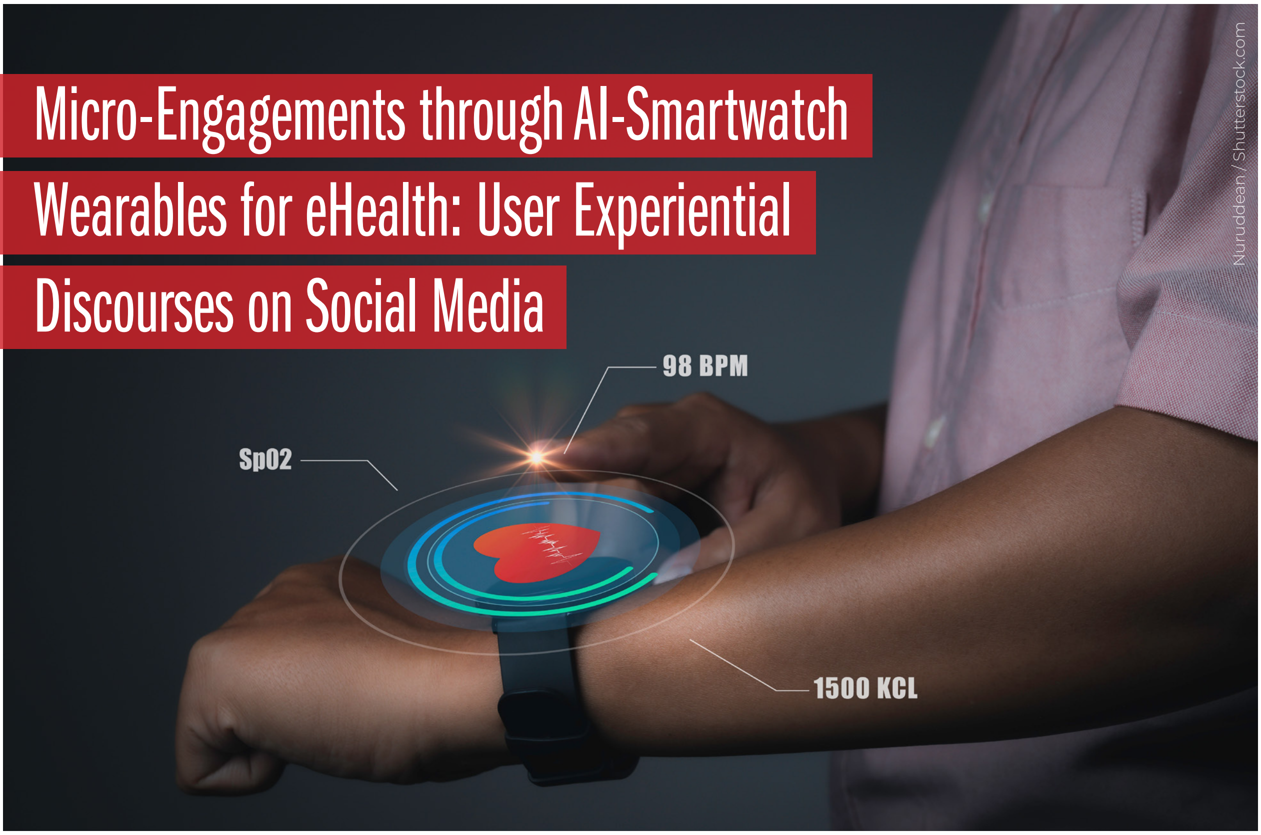
Micro-Engagements through AI-Smartwatch Wearables for eHealth: User Experiential Discourses on Social Media



Nuruddean / Shutterstock.com

By Ireen Mmatlou Manyuha and Elizabeth Lubinga

Abstract

Globally, the use of Artificial Intelligence (AI) wearables including smartwatches has gained traction. AI-Smartwatches have emerged as powerful communication tools and their increased use for personal eHealth is driven by capabilities to facilitate micro-engagements with users. Micro-engagements enhance user experience and active interaction by providing real-time feedback that triggers the user to act. While smartwatches have the potential to effectively drive positive user health behaviour through instant communication, it is imperative to examine the strategic use of communication of these devices by smartwatch users. The purpose of this study was to examine AI-Smartwatch user experiences, specifically micro-engagement perceptions. Theoretically, the study was underpinned by The Unified Theory of Acceptance and Use of Technology. A qualitative approach, using a netnography design provided results from online discourses expressed on X (formerly known as Twitter), in response to a question tweeted about the effectiveness of smartwatches. Results indicate that the use of AI-smartwatches has propelled active personal engagement with health. Users reported tracking various aspects of their health due to instantly available data that is in turn used to seek solutions from health professionals. Conversely, it is unclear whether lay people who are not health professionals are skilled in interpreting the instant data that they are exposed to. This study provides much-needed insight into user experiences of strategic use of communication through AI-powered smartwatch devices using data-driven micro-engagements. It will inform Health Professionals, Health Service Organisations and AI Technology Developers among others regarding practice as well as improvement of technological services for digital public health.

Introduction

Artificial Intelligence (AI) is increasingly pervading human lives including personal health and well-being. In recent years, AI has revolutionised health (Ivancovic et al. 2023), affecting the way human beings conduct their lives, creating a customised, health data-driven ecosystem (Stevens et al. 2022). This data-driven ecosystem has become pivotal to enabling individuals to attain, manage and sustain good health as well as supplement and facilitate better health outcomes, previously the sole domain of healthcare providers. Most importantly, whereas health and well-being in general have always been central to human beings, personalised AI appears to have elevated individual human consciousness about health, subsequently influencing decisions to improve individuals' quality of life. Personalised AI has elevated the quality of human health from a state of well-being defined as a state of general health and happiness to wellness where individuals actively strive to achieve and maintain good health (Ometov et al. 2021).

The functions of wearables, namely, screening, monitoring, detection and prediction drive public use (Canali et al. 2022). Monitoring facilitates continuous data collection through tracking physiological metrics making remote health monitoring more efficient. Screening uses passive sensors that measure motion, steps, light, pressure, and sound, and as Contini et al. (2021) found, wearable clothing efficiently screened sleeping disorders. Additionally, through detection, wearables detect health conditions and alert users, and Perez et al., (2019) indicated that some smartwatches are multifunctional with capabilities of simultaneously fulfilling monitoring, screening and detecting functions. Wearables have also been used for the prediction of disease as Singh et al. (2020) established that a respiratory rate detector could predict the seriousness of respiratory diseases.

Apart from these functional benefits, from a communicative perspective, AI-powered wearables have facilitated micro-engagements between technology and people, ensuring subsequent communication with individuals about their wellness statuses through data collation by algorithms (Contini et al. 2021). Furthermore, AI has enabled the instant communication of such crucial data between healthcare providers and patients, reducing the time spent collecting data through face-to-face consultations, facilitating timeous diagnosis and enabling health-saving decision-making. This AI-facilitated multi-functional communication of health has altered and revolutionised the interpersonal context of health communication as well as interactions between health providers and patients. To a large extent, AI wearables are fulfilling the traditional roles of screening, monitoring, detecting and predicting health problems. Kang and Exworthy (2022) point out that health systems in many countries acknowledge the potential of wearables to improve health care. From a viewpoint of the intrapersonal communication context, individuals are able to monitor and make informed decisions about their personal health, increasing agency.

> "...smartwatches have the potential to effectively drive positive user health behaviour through instant communication..."

The article acknowledges that AI wearables have and are constantly changing personal health by facilitating customized services. However, despite the many benefits these technologies are conversely disadvantaging marginalized communities due to digital and technological divides.

Multiple Implications of Wearable Technologies for eHealth

Despite the benefits accruing from wearable technology developments, there are various emergent concerns. Questions arise about what the proliferation of wearables means in resource-constrained settings such as South Africa. As Meier et al. (2020) specify, the advancement of wearables is largely driven by profit, with healthcare providers, insurers, and global technology companies constantly developing more sophisticated wearable devices embedded with medical technology to target a global consumer market.

Globally, different societies are operating at different levels of AI for personal eHealth and well-being, with some determinants being device sophistication, availability, and most importantly individual affordability of AI gadgets for personal use. At a societal level, the disparities between resource-slack and resource-constrained settings determine who benefits most from wearable technologies. Resource-constrained societies still lag behind resource-slack ones. Statista (2024) indicates for instance that even though the fitness-tracker market in South Africa is expected to grow to US$212.70m in 2024, with a projected US$278.60m by 2029, most revenue will be generated in the United States (US$10,990.00m in 2024).

Furthermore, at an individual level, while researchers acknowledge that wearables provide individuals with health-related agency, they emphasise that these technologies are instruments of empowerment. To some extent, wearables shift power in health provider-patient relationships to the latter, by assisting them to contribute to their health and to take greater control of their lives, also termed as patient empowerment by Kang and Exworthy (2022). However, Bravo et al. (2015) view patient empowerment as specific activities that foster self-management. Conversely, disempowerment arises for the poor and rural populations that cannot exercise wearable-enabled agency, and remain disadvantaged through a lack of access to technologies that facilitate self-management and health literacy as Denecke et al. (2021) argue. These researchers refer to the concept of participatory health informatics that attributes the role of technology as enhancing individual's self-management and health management leading to greater involvement in personal health and care.

In South Africa, while the average revenue per user on fitness trackers is expected to amount to US$38.73/R670, this amount is unaffordable for most South Africans. Therefore, nine million unemployed people who survive on a monthly

> "AI-powered wearables have facilitated micro-engagements between technology and people, ensuring subsequent communication with individuals about their wellness statuses through data collation by algorithms *(Contini et al. 2021)*"

R350 Special Social Relief of Distress Grant and potentially more than 26 million South Africans who receive social assistance per month (South African Government, 2024) are disempowered. The lack of disposable income to spend on buying wearables, especially among the poor, leaves these individuals who most need healthcare without access to technological advancement benefits. Even though individuals can afford to buy basic wearables, they may lack Internet access in remote areas or money to buy data, to enable connection between devices and data banks compounding marginalised populations' exclusion (Boloka and Ngoepe 2024).

In developing countries such as South Africa, it is mostly elite users and ardent health-conscious individuals who benefit from wearable technologies for individual and personalised ehealth-related use to the exclusion of the majority of the population. This is largely because health companies in South Africa subsidise buying wearable technologies or the use thereof, in a bid to stimulate and grow their use. By 2022, only 15.8% of South Africans were members of medical aid schemes (Statista 2023). Conversely, the lack of access to private healthcare compounded by the inability to pay membership to health companies that offer these subsidies ostracises approximately 52 million South Africans (84.2%) who depend on public healthcare. Meanwhile, a new generation of wearables powered by artificial intelligence has emerged and is rapidly growing, in which smartphones are used as gateways to transmit data directly to the cloud.

Understanding Wearable Technologies

A rudimentary definition by Pataranutaporn et al. (2019), is that wearable technology refers to AI-enabled devices that can be worn on the user's body. This implies that any electronic devices that can be worn on a person's body can be classified as wearables since they have wireless communication capabilities that can be integrated into gadgets, accessories, or clothing (Nahavandi, et al., 2021). However, Zhu and Cahan (2016) build on this definition by referring to wearable devices based on their built-in sensors that track users' movements, location and provide biometric identification. This is in addition to wearable technology capabilities to capture and transfer data to cloud storage through wireless communication synched with the smartphone (Mishra et al. 2020). However, Bhushan and Agrawal (2020) argue that wearables also refer to devices that users can carry because they have multiple functions and connectivity to the outside world.

> "Globally, different societies are operating at different levels of AI for personal eHealth and well-being, with some determinants being device sophistication, availability, and most importantly individual affordability of AI gadgets for personal use."

Meier et al. (2020) conclude that the terms wearable technologies, wearable devices and wearables all refer to accessorised items and clothing that facilitate the collection and self-monitoring of personal health. This article uses the terms interchangeably. Based on the above, the definition of a modern wearable health device appears to be more complex based on functionality, access, aesthetics, ease of use, dynamic technological advancement and capabilities among a plethora of identifiers driven by AI. It is evident that AI has significantly transformed the design and capabilities of wearable technology in many ways. The use of AI algorithms enables wearables to process and interpret sensor data in real-time, allowing for more accurate insights.

Micro Engagements through the Use of Wearable Technologies

Communicatively, micro engagement, also termed as micro interaction, facilitates engagement generated when people use wearable technological devices (Saffer 2013). The prompts contained within the user interface of a digital device or system (Ntosti 2018) constitute interpersonal communication. In the context of artificial intelligence-embedded wearables such as smartwatches, micro engagements may be minimal yet purposeful interactions that take place within the user interface.

These micro engagements are also triggered when users interface with technological devices or systems, through various communicative message formats, such as notifications, indicators, or even in-situ assistance (Ntosti 2018). In terms of user responses, the use of micro engagements facilitates response user actions on digital devices by guiding users through complex processes, providing them with real-time feedback and support to enhance the overall user experience (Saffer 2013; Ntosti 2018). The communication environment in which micro engagements happen assists users in understanding the functionality of a digital device or system and ultimately creates an engaging and interactive digital environment for users. Furthermore, Motti and Caine (2015), posit that micro engagements should be seen as building blocks that enable an effective flow of communication between the end-user and wearable device, which makes user experience more interactive and personalised.

A form of customised eHealth marketing takes place with AI-integrated machine learning algorithms and sensors enabling the generation of tailored micro engagements which is crucial in enhancing user experience (Wu, & Luo, 2019). Additionally, through a form of persuasive communication, micro engagements attract users' attention, by presenting pertinent details, with the outcome of streamlining user activities efficiently and effectively (Motti and Caine 2015). These could include various forms of fitness milestones, haptic feedback to signal an incoming message, illustrations showcasing progress towards daily activity goals, or subtle animations when a task is completed successfully.

The feedback in the entire communication process includes various forms of engagement through smartwatches user activity, tracking progress, and engaging in healthy behaviours from the delivered personalised feedback. According to Saffer (2013), micro engagements can effectively capture user attention and influence behaviour, a feature that is crucial in the field of health and fitness wearables. By delivering timely and contextually relevant information, they can drive users towards healthier routines and behaviours.

Benefits and Limitations of AI Wearable Devices for eHealth

The advent of AI wearable devices for eHealth has created several benefits enabling active personal interaction with the management of personal health but conversely highlighting various functional and other limitations.

Unprecedented active micro engagements versus digital health inequities

The tailored approach to engaging with personal health-related data that is availed by AI wearables appears to have motivated individuals to take an active interest in their health (Bhushan and Agrawal 2020). Passive potential patients have been moved to a state of active alertness to ensure good health which Kang and Exworthy (2022) refer to as patient empowerment. On the other hand, these technologies have led to digital health inequities with a lack of affordability by large members of the South African population for instance to buy wearables, smartphones to run them and data. The optimal use of AI wearables requires the affordability of wearable devices that range from over R700 – R10,000. Predel and Steger (2020) argue that wearables are consumer goods leading to greater disparities between the rich and the poor. Furthermore, these devices need to connect to other systems using Bluetooth or the Internet. Internet penetration is low or non-existent in most rural areas and even though the Internet is available in some rural areas, people do not own smart devices because they live on the breadline (Aruleba and Jere 2022).

Shortened healthcare processes versus Interpersonal health communication contexts

Accessing healthcare globally is a process that has traditionally been lengthy involving collection of health data to enable healthcare providers to determine what the health problem is. Traditionally, the collection of basic health data would involve taking relevant health tests depending on the nature of reported health problems. The tests would have to be interpreted by knowledgeable health personnel before diagnosis of health problems and prescription of relevant drugs took place. However, due to the capabilities of AI wearables including the constant collection and transmission of information, healthcare processes that inform lifesaving decisions have been shortened (Dias and Cunha 2018). A combination of constant personalised health tracking by AI wearables together with instant transmission of health-related data to healthcare providers has activated remote patient monitoring (Ivankovic et al. 2023). Additionally, constant monitoring of individuals' health statistics by AI wearables has enabled a personal move to sustainable wellness (Wu and Luo 2019). Yet Predel and Steger (2022) warn that self-management of care may lead to poor health provider-patient relationships and that individuals still need professional interpretation of AI generated data. Furthermore, these authors question whether systems have adequately been established to train data and study cohorts.

Data drives insights for Personalised Diagnosis versus Data Interpretation and Contextualisation

Instant access to individuals' personalised health data by both individuals and healthcare

> If the device is not sophisticated enough, it will perform basic functions, incorrect use by the wearer as well as incorrect formatting or required information will affect the quality of information that accrues from the device *Dias and Cunha 2018)*, which makes smartwatch wearables subject to manipulation.

professionals provides early detection and insights into individuals' wellness, making it possible for optimisation of diagnosis as well as velocity (Steven et al 2022). The insights that individuals garner from AI health-related data enable them to make decisions including seeking healthcare in time and avoiding the escalation of diseases to serious illnesses. On the contrary, other researchers argue that the quality of data may lack accuracy and may deter use by producing unreliable data (Canali et al. 2022; Kang and Exworthy 2022).

The interpretation of health data has always been the domain of trained healthcare professionals. The average person is not literate enough to correctly interpret the meaning of the data. And data by itself is meaningless until it is correctly interpreted with contextualisation of the individual's health over a certain period. In developing countries such as South Africa with a majority of (semi) illiterate populations, correct interpretation of data, even if smartwatch devices were accessible, would be difficult. Zhang et al. (2022) argue for more contextual information as well as coherence for data quality. This is because the lack of contextual information about the data collected also makes it difficult for individuals to interpret it and may ultimately lead to mistrust of the technology. Sharon and Lucivero (2019) propose the expansion of the health data ecosystem for better contextualisation and interpretation.

Facilitated Tracking of Health Behaviour versus Data Privacy and Security

Both individuals and healthcare professionals as well as related organisations benefit from tracking health behaviour. Various health problems are caused by poor health behaviour as well as risky lifestyles (Shi et al. 2020). Sophisticated AI wearables can track whether an individual has drunk enough water and is exercising optimally based on age, weight, and gender among others. However, some researchers argue that wearables have also led to a lack of privacy and have facilitated intrusiveness (Canali et al. 2022). As Predel and Steger (2022) also argue, individuals' private information is easily accessible to private organisations exacerbating privacy risks and raising legal and ethical concerns.

As the case is with data that is available on the cloud, data privacy may become compromised. Health-related information has always been rendered private with concerned medical personnel having access to patient "files". Given that online data leaves a permanent digital footprint that is accessible to multiple end users, not limited to the primary healthcare provider, data privacy and security may be compromised.

Variations of accuracy and reliability of data versus Data Quality

The extent to which smartwatch wearables are rendered active and whether data is reliable as collected by the user varies depending on the level of sophistication, correct use by the wearer and formatting of the type of information that is required to enable the device to collect the correct data, among others. If the device is not sophisticated enough, it will perform basic functions, incorrect use by the wearer as well as incorrect formatting or required information will affect the quality of information that accrues from the device (Dias and Cunha 2018), which makes smartwatch wearables subject to manipulation. Canali et al. (2022) argue that variations in wearable sensors and lack of consistency in data collection may compromise the quality of data. They propose that local standards of data quality should be established in individual countries to counter the poor quality of data.

Therefore, as the use of wearable devices in developing societies for eHealth increases, it is important for health communicators to gain an understanding of user experiences and how users interpret their experiences. While studies prevail about the use of AI wearables in developed societies (Ivancovic et al. 2023), studies about user experiences of wearable technologies for eHealth in resource-constrained countries are minimal. Yet it is important for healthcare professionals and health-related organisations to gain a better understanding of user experiences for purposes of improving machine learning and AI capabilities for maximisation of use (Lee 2018). And as Hu et al. (2024) also argue, user experiences and usability of wearable health devices play a crucial role in determining user acceptance.

The purpose of this study was to examine user experiential online discourses regarding micro-engagements on AI Smartwatch wearables for eHealth.

The following questions were asked:

1. How do users experience micro-engagements on AI Smartwatch wearables for eHealth?
2. What are user perceptions about micro-engagements on AI Smartwatch wearables for eHealth?

Theoretical Framework

The second Unified Theory of Acceptance and Use of Technology (UTAUT2) by Venkatesh et al. (2012) aptly applies to this study. UTAUT2 combines a plethora of other theories, some of which have been used to gain insight into health-related behaviour including the Technological Acceptance Model by Davis (1989). Venkatesh et al. (2003 and 2012) argue that behavioural intentions determine the actual use of technology, adding that the effects of the four variables suggested by the model are in turn influenced by age, gender, experience and voluntariness of use.

The model is composed of 4 variables namely: performance expectancy which is the extent to which individuals believe that using the system, in this case AI technology, will help them to attain specific gains such as health-related gains. Social influence is the extent to which an individual perceives that others who are important believe he or she should use the system (Venkatesh et al. 2003). Effort expectancy is the degree of ease associated with the use of technologies and finally facilitating conditions which is the technical infrastructure put into place to support the use of the system. UTAUT2 introduced price value and habits to the acceptance and use of technologies. In application, this study examines how users shared experiences about how to use wearables and emergent experiences through health patterns which relate to social influence. Furthermore, how users shared experiences in online discourses about how wearables assist them to achieve their health-related goals in relation to performance expectancy. Additionally, the study assesses how users shared their effort expectancy through perceived ease of use of various wearables from their shared experiences.

Research approach

A qualitative research approach was employed for this study. The advantage of using a qualitative approach is that it allows researchers to gain insight through detailed observations, which can provide a fruitful and constructive analysis of the data (Minowa and Belk 2020). And Creswell and Cresswell (2018), point out that qualitative research is only best suited to provide insights into the opinions of a small sample, so its results cannot be generalised.

Research Design

The research design applied to this study was netnography. Netnography focuses on the interactions that take place through an online community such as social media platforms to gain insight into opinions, behaviours, or attitudes of individuals within those communities (Kozinets 2002, 2015 and 2020). As a method of observation, netnography is advantageous because it can be completely unobtrusive, making access to a large amount of data possible (Rachoane 2019) and it helps provide insights into the unique experiences of individuals (Sitto and Lubinga 2020). Furthermore, the use of netnography allows researchers to gain a better understanding or insights into how people interact online (Varis, 2016). However, to successfully conduct a netnography study, Kozinets (2010) purports that researchers should identify an online community that is relevant, active, interactive, substantial, heterogeneous and data rich. Based on the guidelines provided by Kozinets, X platform is a suitable online community for conducting netnography studies for several reasons as follows:

- **Relevance** – X is a widely used social media platform, as of April 2023, the platform had over 372.9 million users across the world (Statista 2023).
- **Interactivity** – X platform is known for its high level of activity and interactivity. Users frequently post tweets, engage in discussions, share opinions, and participate in conversations in real-time. This dynamic nature of X provides researchers with a wealth of data to observe, analyse, and engage with.
- **Substantial** – X as a social media platform boasts a substantial user base with diverse demographics, including individuals from various cultures, and backgrounds. This diversity allows researchers to study different communities, subcultures, and user groups.
- **Heterogeneity** – the user base of X consists of individuals from different demographics and regions which makes X as an online community to be highly heterogeneous.
- **Data Richness** – X platform is a rich source of data for netnographic studies. Tweets are posted in various forms of data elements that offer researchers multiple dimensions to explore and analyse.

Data collection and analysis method

Immersion data was collected through X (Twitter) online conversations. Immersion enables researchers to immerse themselves in an online community to develop an depth understanding of the data (Kozinets 2015). As Kozinets (2020) posits, when people interact on an online public platform, they leave online traces which can be collected and used by netnographers.

The study used thematic content analysis to analyse the public sentiments expressed in response to the question tweeted about the effectiveness of smartwatches. The process involved two phases: initial coding and selective coding. During the initial coding phase, the data was systematically examined to identify common codes or categories (Creswell and Cresswell 2018). This coding process involved comparing and categorising the data based on its content, such as themes, topics, or patterns. The purpose was to organise the raw data into meaningful units that could be further analysed. Following the initial coding, the selective coding phase was conducted. This phase involved a more focused analysis, where specific codes were selected for further exploration. The selected codes were analysed in depth to identify overarching themes within the data. This process allowed the researchers to uncover meaningful insights and patterns within the online community's discussions and interactions.

Ethical standards were observed by maintaining the confidentiality and anonymity of informants. To ensure confidentiality, the identities of participants were protected, with their names, handles, or usernames removed from the data.

Findings and Discussion

A total of 174 tweets were posted under the question tweeted about the practical use of AI-smartwatch wearables were coded and analysed. Respondents replied to the question by sharing their experiences about the usefulness of smartwatches for personal health and wellness. The following themes emerged from the recurring tweets and sentiments expressed by users:

Sharing User Experiences about Tracked Health Patterns

Users expressed the view that AI-smartwatch wearables are valuable gadgets to track their overall health and wellness. The capabilities and functionalities of smartwatch wearables in monitoring different health parameters were appreciated by users. Users specifically mentioned the benefits of monitoring heart rate levels, sleep quality patterns, blood oxygen, stress level and blood pressure measurements amongst others. Users also highly rated smartwatches for their capabilities to detect heart risks or conditions such as abnormal heart rate, sleep apnea, low or high blood pressure, and heart attack symptoms before the actual testing or face-to-face medical assessment.

The quantity and quality of sleep is one of the most crucial indicators of a healthy lifestyle. Long periods of poor sleep can lead to a variety of health issues such as high levels of anxiety and stress, depression, diabetes and high blood pressure (Chen et al. 2013). This is an indication of the importance of monitoring sleep patterns which may assist in early detection of any potential sleep disorders. Users shared these experiences regarding using smartwatch devices to track their overall health patterns (see Table 1 below):

Table 1: Tweets about smartwatch usage to track health patterns

Tweets
"I sleep with my watch, so it tracks my sleep and lets me know how many hours of deep, I light and REM sleep I've had".
"I like that it measures BP, heart rate, blood oxygen, body composition, calories burnt, steps taken and stress levels"
"Mine measures my stress levels when my stress is too high it tells me what to do".
"Really helps keep track of your health, sleeping patterns, oxygen levels, blood pressure, stress levels. It's the most helpful tech purchase I have had regarding health".
"Alert me when my stress levels are too high, and it directs me on how to relax with a breathing exercise on my phone".

Enabling Early Detection

Smartwatch users expressed that smartwatch wearables can be a life-saving tool due to its ability to detect health conditions or risks in advance (Zhu and Cahan 2016). This shows that the data collected by smartwatches can track health patterns and identify early signs of serious medical conditions for users. During COVID-19 pandemic, smartwatch wearables have proven to be a useful tool to detect early signs of infection which were crucial in effectively mitigating the transmission of the virus (Mishra et al. 2020). A user shared a similar experience on how a smartwatch has saved his or her life during COVID-19.

> "*When covid hit me, it was my smartwatch that notified me when my oxygen level dropped below 90%, that's when I knew it's getting real and had to rush to hospital".*

Wearables provide real-time data of users' health patterns which is crucial in identifying potential diagnoses before a patient seeks professional medical care or before they even start showing symptoms (Zhu and Cahan 2016). Users' testimonials bear true to this important feature of smartwatch wearables in detecting medical conditions such as sleep apnea, heart attack, influenza 2 and irregular heartbeat of an unborn baby. These are some of the tweets posted:

Table 2: Tweets about smartwatch usage for early detection of ill-health

Tweets
"The heart rate detector saved my friend's husband. He was about to have a heart attack and it was detected. He knew a couple of minutes before he collapsed and called his wife".
"2017, via my Fitbit, noticed erratic heart rate all night at gigs, though feeling fine! Went to ER and they found I had influenza 2… straight to ICU and isolated for almost a week!!! My current Garmin does 500 more things! Only need to charge it twice a week. Sometimes even once!"
"The apple watch was able to detect an irregularity in unborn babies' heartbeat and save it, it is truly out of this world live saving tech".
"When I bought my Apple Watch It was mostly the sync between my watch and phone, being able to get notifications, calls etc. It then detected my sleep apnea 1st before actual testing happened. I like that it tracks when my habits change and it's my personal cheerleader".
"My one helped just the other day I woke up in the middle of the night feeling unwell when I put it on. My heart rate was way too fast and so was my BP at least I then knew what to do".

Instant Transmission of communication to health systems

Users positively expressed that smartwatch wearables are useful for detecting emergency incidents, and they provide instant alerts to emergency healthcare systems or services for rapid response in saving lives. Crime levels continue to rise in most countries and personal safety has become a priority for everyone. According to Statistics South Africa, theft and hijacking of cars are among the leading common crimes experienced by citizens. In 2022, over 137 000 hijackings were reported (Stats SA 2022). Users took to Twitter (X) to share their lived experiences on how their smartwatch wearables saved their lives during emergency situations. These are some of the tweets posted:

See Table 3 on page 40.

Table 3: Tweets about smartwatch usage for instant transmission of communication to health systems

Tweets
"I live alone abroad, one time i fell because of exhaustion and my watch called 911, and I was taken to ER, it can warn you of a possible heart attack"
"Mine notified my emergency contacts when I collapsed from a panic attack. Funny that the watch notified me a few minutes prior "abnormal heart rate detected" & that time I'm feeling proper".
"A cyclist once had a heart failure in Cape Town while cycling in a non-busy area and the watch contacted the emergency number".
"I had a bad fall while alone in the house. It immediately informed my sister and emergency services about the fall".
"I was in an accident last year and my Apple Watch sent a crash alert to my insurer and emergency services who came to the scene within seconds thought that was pretty impressive"

Active Optimisation of Wellness

The online testimonials of users reveal that smartwatch wearables provide active optimisation of wellness through a combination of sensors, data analysis, and software features. Smartwatches continuously monitor physical activities of users throughout the day and track metrics such as steps taken, distance travelled, calories burned, and heart rate. Users find this information helps in managing their wellness and staying motivated to achieve their health and fitness goals. Some of the online discourse includes the following:

Table 4: Tweets about smartwatch usage for active optimisation of wellness

Tweets
"I am a runner. I bought mine to keep tabs on my running progress and overall fitness and or health. To me personally my smart watch is very important and special as you put it".
"I'm a data person and being able to look at my fitness data and be able to track my exercise routines, steps, runs, and hikes is very useful for motivation and for keeping fit; but that's why I use Garmin watches instead of the Apple or Samsung one".
"I enjoy mine for the Daily reminders for my water intake, breathing exercises & stress level notifications".
"It's perfect for my active lifestyle as it tracks gym and running activities, stress & sleep patterns, respiration, and even VO2 max".
"My smartwatch motivates you to keep fit and healthy".

Discussion and Conclusion

The findings of this study reveal that smartwatches offer a wide range of functionalities that enhance users' quality of life and contribute to their overall well-being. One useful pattern identified by users in this study is the enhancement of tracking health patterns and early detection facilitated by smartwatches. Participants acknowledged the capability of these wearables to continuously monitor vital signs and provide timely alerts for potential health concerns. By tracking metrics such as heart rate, abnormal heart rhythms, and other health indicators, smartwatches offer users the opportunity for early detection of potential health issues. In line with (Stevens et al. 2021) smartwatch wearables are at the forefront of driving a customised, health ecosystem where users have become active participants in their personal health.

However, while the self-tracking function removes individuals' health responsibility from health professionals in terms of tracking well-being, the burden of interpreting large amounts of data moves to a public that may not be literate enough to meaningfully sustain health. Nonetheless, this feature empowers individuals to take proactive measures and to seek immediate medical attention, when necessary, potentially leading to early intervention and improved health outcomes (Steven et al. 2022). The ability of smartwatches to serve as a personal health assistant, constantly monitoring and providing insights into health patterns, adds a significant dimension to their practical use.

Sleep tracking also emerged as another valuable feature of smartwatches. Participants appreciated the ability to monitor their sleep patterns, including sleep duration, different sleep-promoting wellness and preventive care. It is evident that smartwatches not only offer convenience and connectivity but also contribute to overall health and well-being. This information empowers users to make informed decisions about their sleep habits and take steps towards improving the quality and duration of their rest (Chent et al. 2013). Stress management capabilities were highlighted as a significant advantage of smartwatches. By leveraging heart rate variability data and providing guided breathing exercises or relaxation techniques, smartwatches help users manage stress levels and promote well-being (Nahavandi 2022).

An emerging disadvantage is the exclusion and disempowerment of people who cannot afford to buy the devices or cannot receive concessions from healthcare organisations such as medical aid organisations, some may not have smartphones to link devices to applications or may not afford to buy data (Kang and Exworthy 2022). Therefore, while there are benefits, certain populations are unable to tap into them and their experiences remain unshared. Future research should continue to explore the long-term impact of smartwatch wearables on individuals' health behaviours and overall well-being. AI Smartwatches are tools that ensure sustainable and optimised health (Davenport and Kalakota 2019) and ensure patient empowerment. Their features, including activity tracking, sleep monitoring, stress management, fitness coaching, and integration with health apps, provide users with valuable insights and tools to actively optimise their well-being (Dias and Cunha 2018). As technology continues to advance, smartwatches are expected to evolve further, incorporating more sophisticated features and capabilities.

References

Aruleba, K. and Jere, N. (2022). Exploring digital transforming challenges in rural areas of South Africa through a systematic review of empirical studies. *Scientific African*, 16, pp. 2468-2276.

Bhushan, D. and Agrawal, R. (2020). Security challenges for designing wearable and IoT solutions. In: Valentina, E. B., Vijender, K. S., Raghvendra, K. and Ahad, M.A.R,. eds. *A handbook of internet of things in biomedical and cyber physical systems.* New York: Springer International Publishing, pp.109-138.

Canali, S., Schiaffonati, V., and Aliverti, A. (2022). Challenges and recommendations for wearable devices in digital health: Data quality, interoperability, health equity, fairness [online]. *PLOS Digital Health* 1(10). Available from: e0000104. https://doi.org/10.1371/ journal. Pdig.0000104 [accessed 27/11/24]

Chent, Z., Lint, M., Chent, F., Lanett, N.D., Cardone, G., Wangt, R. Lit, T., Chen, Y., Choudhury, T. and Campbell, A.T. (2013). Unobtrusive sleep monitoring using smartphones. In: *2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops 2013, Venice* [online], pp.145-152. Available from: https://ieeexplore.ieee.org/document/6563918 [accessed 27/11/24].

Contini, M., Sarmento, A., Gugliandolo, P., Leonardi, A., Longinotti-Buitoni, G., Minella, C. et al. (2021). Validation of a new wearable device for type 3 sleep test without flowmeter. *PLoS ONE* [online], 16(4). Available from: https://doi.org/10.1371/journal.pone.0249470 [accessed 27/11/24].

Creswell, J. W. and Cresswell, J.D. (2018). Research design: qualitative, quantitative and mixed methods. Thousand Oaks, CA: Sage.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3): pp.319–340.

Davenport, E. and Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, 6(2): pp. 94–98.

Denecke, K., Gabarron, E., Petersen, C., and Merolli, M. (2021). Defining participatory health informatics – a scoping review. *Informatics for Health and Social Care*, 46(3): pp. 234–43.

Hu, L., Chen, Y., Cao, E., and Hu, W. (2024). User experience & usability of wearable health device: a bibliometric analysis of 2014–2023. *International Journal of Human–Computer Interaction* [online], pp. 1–20. Available from: https://doi.org/10.1080/10447318.2024.2357905 [accessed 27/11/24].

Ivankovic, D., Garel, P., Klazinga, N. and Kringos, D. (2023). Data-driven collaboration between hospitals and other healthcare organisations in Europe during the covid-19 pandemic: an explanatory sequential mixed-methods study among mid-level hospital managers. *International journal of integrated care*, 23(1): pp. 28-41.

Kang, H.S., and Exworthy, M. (2022). Wearing the future-wearables to empower users to take greater responsibility for their health and care: scoping review. *JMIR mHealth and uHealth,* 10(7). Available from: https://doi.org/10.2196/35684 [accessed 27/11/24].

Kozinets, R.V. (2002). The field behind the screen: Using netnography for marketing research in online communities. *Journal of Marketing Research*, 39(1): pp. 61-72.

Kozinets, R.V. (2010). *Netnography. Doing ethnographic research online*. Thousand Oaks, CA: Sage Publications.

Kozinets, R.V. (2015). *Netnography: Redefined*. London: Sage Publication Limited.

Kozinets, R.V. (2020). *Netnography: The essential guide to qualitative social media research.* London: Sage Publication Limited.

Laricchia, F. (2024). Smartwatch statistics and facts. *Statista* [online], 2 August 2024. Available from: https://www.statista.com/topics/4762/smartwatches/ [accessed 27 November 2024].

Minowa, Y. and Belk, R.W. (2020). Qualitative approaches to life course research: Linking life story to gift giving. *Journal of Global Scholars of Marketing Science*, 30(1), pp. 60-75.

Mishra, S., Mishra, B.K., Tripathy, H.K. and Dutta, A. (2020). Analysis of the role and scope of big data analytics with IoT in the healthcare domain. In: Balas, V.E., Solanki, V.K., Kumar, R., and Khari, M., eds. *A Handbook of Data Science Approaches for Biomedical Engineering.* Academic Press, pp. 1-23.

Mishra, T., Wang, M., Metwally, A.A., Bogu, G.K., Brooks, A.W., Bahmani, A., Alavi, A., Celli, A., Higgs, E., Dagan-Rosenfeld, O., Fay, B., Kirkpatrick, S., Kellogg, R., Gibson, M., Wang, T., Hunting, E.M., Mamic, P., Ganz, A.B., Rolnik, B., Li, X., and Snyder, M.P. (2020). Pre-symptomatic detection of COVID-19 from smartwatch data. *Nature Biomedical Engineering*, 4(12), 1208–1220.

Motti, V. G. and Caine, K. (2015). Micro interactions and multi-dimensional graphical user interfaces in the design of wrist worn wearables. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* [online], 59(1), pp.1712-1716. Available from: https://doi.org/10.1177/1541931215591370 [accessed 27 November 2024].

Nahavandi, D., Alizadehsani, R., Khosravi, A. and Acharya, U.R. (2022). Application of artificial intelligence in wearable devices: Opportunities and challenges. *Computer Methods and Programs in Biomedicine*, 213, pp. 106541.

Ntosti, A. (2018). Why micro-interactions are important for UX. *Medium* [online], 24 July 2018. Available from: https://uxdesign.cc/why-micro-interactions-matter-318e1409a6b2 [accessed 27 November 2024].

Ometov, A., Shubina, V., Klus, L., Skibinska, J., Saafi, S., Pascacio, P., Flueratoru, L., Quezada-Gaibor, D., Chukhno, N., Chukhno, O., Ali, A., Channa, A., Svertoka, E., Qaim, W.B., Marqués, R.C., Holcer, S., Torres-Sospedra, J., Casteleyn, S., Ruggeri, G., Araniti, G., Burget, R., Hosek, J., & Lohan, E.S. (2021). A Survey on Wearable Technology: History, State-of-the-Art and Current Challenges. *Computer Networks,* 193*,* pp.108074.

Pataranutaporn, P., Jain, A., Johnson, C.M., Shah, P. and Maes, P. (2019). Wearable lab on body: combining sensing of biochemical and digital markers in a wearable device. In: *41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society* July [online], pp. 3327-3332. Available from: https://pubmed.ncbi.nlm.nih.gov/31946594/ [accessed 27 November 2024].

Perez, M.V., Mahaffey, K.W., Hedlin, H., Rumsfeld, J.S., Garcia, A., Ferris, T., Balasubramanian, V., Russo, A.M., Rajmane, A., Cheung, L., Hung, G., Lee, J., Kowey, P., Talati, N., Nag, D., Gummidipundi, S.E., Beatty, A., Hills, M.T., Desai, S., Granger, C.B., Desai, M., Turakhia, M.P., and Apple Heart Study Investigators (2019). Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation. *The New England journal of medicine,* 381(20), 1909–1917. https://doi.org/10.1056/NEJMoa1901183 [accessed 27 November 2024].

Predel, C., and Steger, F. (2021). Ethical challenges with smartwatch-based screening for atrial fibrillation: putting users at risk for marketing purposes? *Frontiers in cardiovascular medicine* [online], 7, pp. 615927. Available from: https://doi.org/10.3389/fcvm.2020.615927 [accessed 24 November 2024].

Saffer, D. 2013. *Micro-interactions: Designing with Details*. O'Reilly Media, Inc.

Sharon, T., and Lucivero, F. (2019). Introduction to the special theme: The expansion of the health data ecosystem–Rethinking data ethics and governance. *Big Data and Society,* 6. Available from: doi: 10.1177/2053951719852969 [accessed 24 November 2024].

Shi, J., Liu, S., Zhang, L., Yang, B., Shu, L., Yang, Y., Ren, M., Wang, Y., Chen, J., Chen, W. and Chai, Y. (2020). Smart textile-integrated microelectronic systems for wearable applications. *Advanced Materials*, 32(5), pp. 1901-958.

Singh, G., Tee, A., Trakoolwilaiwan, T., Taha, A., and Olivo, M. (2020). Method of respiratory rate measurement using a unique wearable platform and an adaptive optical-based approach. *Intensive Care Medicine Experimental,* 8(15). Available from: https://doi.org/10.1186/s40635-020-00302-6 [accessed 24 November 2024].

Sitto, K. and Lubinga, E. (2020). Gendered myths, risks and the social amplification of male rape: online discourses. *Communitas*, 25, pp. 1-24.

South African Government 2024. *SoNA-in-Numbers – 2024* [online]. Available from: https://www.gov.za/news/sona-numbers-2024 [accessed 24 November 2024].

Statista. (2024). Fitness trackers – South Africa. *Statista* [online]. Available From: https://www.statista.com/outlook/hmo/digital-health/digital-fitness-well-being/fitness-trackers/south-africa [accessed 27 November 2024].

Steven, G., Haulson, L., Larmuseau, M. and Verdonck, P. (2022). A human-centred, health data-driven ecosystem. *Discover Health Systems* [online], 1(10). Available from: https://link.springer.com/article/10.1007/s44250-022-00011-9 [accessed 27 November 2024].

Varis, P. (2016). Digital ethnography. In: Georgakopoulou, A. and Spilioti, T. eds. *The Routledge handbook of language and digital communication.* London: Routledge, pp. 55-68.

Venkatesh, V., Morris, M.G., Davis, G.B., and Davis, F.D. (2003). Unified theory of acceptance and use of technology (UTAUT). *MIS Quarterly*, 27 (3), pp. 425-478.

Venkatesh, V., Morris, M.G., Davis, G.B., and Davis, F.D. (2003). User acceptance of information technology: towards a unified view. *MIS Quarterly*, 27, pp. 425-478.

Venkatesh, V., Thong, J.Y.L., and Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), pp. 157–178.

Wu, M., and Luo, J. (2019). Wearable technology applications in healthcare: a literature review. *Online Journal of Nursing Informatics*, 23(3), pp. 1-11.

Zhang, J., Symons, J., Agapow, P., Teo, J.T., Paxton, C.A., Abdi, J., Mattie, H., Davie, C., Torres, A. Z., Folarin, A., Sood, H., Celi, L.A., Halamka, J., Eapen, S., and Budhdeo, S. (2022). Best practices in the real-world data life cycle. *PLOS digital health*, 1(1), e0000003. https://doi.org/10.1371/journal.pdig.0000003

Zhu, X., and Cahan, A. (2016). Wearable technologies and telehealth in care management for chronic illness. In: Weaver, C., Ball, M., Kim, G., Kiel, J. (eds). *Healthcare information management systems. health informatics*. Cham: Springer.