PUBLIC HEALTH AND SMART WATCHES TECHNOLOGY

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Abstract:

Smartwatches have become more popular in recent times due to their ability to track various health indicators, including heart rate, sleep patterns, and physical activity. The objective of this scoping review is to explore the use of smartwatches in the healthcare sector. A systematic search was conducted in PubMed/Medline, Scopus, Embassy, Web of Science, ERIC and Google Scholar, following the methodology of Arksey and O'Malley. It is seen that the use of smartwatches is effective in diagnosing the symptoms of various diseases. In particular, the smartwatch promises to detect early symptoms of heart disease, movement disorders and Covid-19. Nevertheless, it should be emphasized that there is an ongoing debate about the reliability of smartwatch diagnostics in the healthcare system. Despite the potential benefits of using smartwatches for disease detection, it is imperative to approach the interpretation of their data with caution. Inconsistencies between smartwatches and their algorithms have significant implications for healthcare use. The accuracy and reliability of the algorithm used is important, as well as the high accuracy in detecting changes in health status through smartwatches. This requires developing medical watches and creating AI-hospital assistants. These assistants will be designed to assist with patient monitoring, appointment scheduling, and medication management tasks. These can educate patients and answer common questions, freeing healthcare providers to focus on more complex tasks.

Keywords: Health, technology, healthcare, Smart watches Wearable devices, Monitoring

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As wearable technology and medical devices come together to monitor personal health in real-time, including cardiovascular health metrics, smartwatches are witnessing phenomenal growth in the mobile technology sector [1, 2]. With these gadgets, consumers can now obtain a personalized medical data report that may help with disease prevention and treatment [3]. an formula called the Framingham Risk Score was created to evaluate a person's 10-year risk of cardiovascular disease [4]. These clever gadgets will assist caretakers in being more vigilant and implementing more suitable comfort measures, as many patients are unable to explain their situation to their friends or family members. The concept of comfort measures has garnered noteworthy interest in nursing and medical literature, as it represents a methodical strategy that encompasses both proactive involvement and deliberate limitation [5].

Clinical smartwatches that capture and process data as well as detect medically relevant events have been approved by the FDA [06]. The European Union (EU) does not currently have any authorized direct-address smartwatches. However, makers of smartwatches have to navigate a number of frameworks, including the Medical Device Regulation 2017/745 and the Radio Equipment Directive 2014/53/EU, in order to comply with EU rules. These laws address important topics such as electromagnetic compatibility and effective radio spectrum usage, with a focus on safety standards [07, 08].

Smartwatches often have advanced features such as a heart rate monitor. These high-tech devices use a technique called photo plethysmography to accurately measure the user's heart rate. Using the light rays and special sensors of the smart watch, changes in the blood flowing from the wrist can be accurately measured. This process produces a PPG waveform that provides valuable information for determining human heart rate [09, 10]. This smartwatch provides physiological information to monitor vital signs and alerts that help save lives, as on-scene presence is associated with fewer serious injuries and deaths [11]. It is important to note that these smart watches are based on algorithmic interpretations of clinical results, and their predictive power ultimately depends on the support and strength of these algorithms [12,13]. In this review, we discuss the applications of these mobile devices in patient health and Health Works educational initiatives. This article seeks to answer several questions, such as whether smart watches can be trusted in clinical measurements and what could contribute to the development of trust in these devices.

METHOD REASON

for scoping review

The scope was made because artificial intelligence and machine learning algorithms are emerging technologies applicable to smartwatches. In addition, research evaluations are useful for evaluating the effectiveness of large-scale or new studies [14]. The purpose

of research reviews is to identify and map relevant evidence on a topic, content, context, or question that meets predefined inclusion criteria [19, 20]. A research review can gather a variety of evidence from different domains, including empirical and non-empirical sources [21]. This type of review is suitable for exploring, identifying, presenting, reporting or discussing features or concepts in several different sources of evidence [22]. Scoping is particularly useful when comparing measures is not practical or possible due to cost or time constraints. Although they often involve review of multiple sources, they do not require or permit statistical aggregation, formal risk assessment, or quality assessment [23].

The methodology of Tisa's study was based on the scoping methodology developed by Arksey and O'Malley [20], using Levac et al. (2010) [24]. As described in this framework, research reviews have six steps: (1) identification of the research question; (2) identify relevant studies; (3) choice of studies; (4) map the data; (5) compile, summarize and report results and (6) consult with stakeholders

Step 1: Identify the research question

The overall main research question, which was developed in collaboration with the research team and key stakeholders, is: "Can all smart watches be trusted in clinical measurements and what could contribute to trusting these devices?

Stage 2: Identifying relevant studies

SEARCH STRATEGY AND INFORMATION SOURCES

The first step to identify articles related to this topic was a limited search of PubMed/Medline, SCOPUS, Embassy, Network of Sciences and ERIC. To develop a comprehensive search strategy, the text words in the titles of the relevant articles and the index terms used to describe the articles were analysed (see Table 1). Depending on the database and/or data source, the search strategy was adjusted to include all identified keywords and index terms. Additional studies were screened from a reference list of all included sources of evidence. We also searched various grey literature sources to ensure that all relevant information was obtained. The review team searched relevant grey literature databases (eg, Grey Literature Report, Google Scholar, Open Grey, and Web of Science Conference Proceedings) for studies, reports, and conference abstracts of interest. A research librarian developed a search strategy and modified it based on stakeholder feedback. To avoid bias, the research team blinded stakeholders to the initially developed search strategy. Considering that the medical applications of smart watches have only recently been introduced to the market, the application period was limited to the period after 2017. After the search, all the citations found were collected in the EndNote 8 database and duplicates were removed.

Stage 3: Study selection Inclusion/exclusion criteria

• Research types include case studies, correlational studies, longitudinal studies, experimental and quasi-experimental studies, controlled clinical trials, randomized

controlled trials (RCT and CT), and any kind of study design. There were no restrictions on the study's design or its geographical scope.

• Participant Types: Everyone who interacts with the healthcare system

• Intervention types: Wearable movement sensors, fitness-bound wristbands, smartwatches, and wireless watches were the main topics of the study.

• Any of the following topics were covered by the included studies: (a) development; (b) implementation; (c) evaluation; or (d) comparative validation of such measures.

• Types of outcomes: the outcomes of interest were satisfaction, knowledge, skills, attitudes, and behaviours.

The review process involved two screening stages: an evaluation of the title and abstract, and a review of the entire text. First, M.M.H and T.M.H independently examined all citations received to see if they met a set of minimum inclusion criteria. Before beginning the abstract review, a sample of abstracts was tested to make sure the criteria were strong enough to capture any articles about smartwatches. The full-text review included any articles that both reviewers found to be relevant. Finally, in the scoping review, the search results and the inclusion process were thoroughly reported, along with a few diagrams representing Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for reviews (PRISMA-ScR) (Fig. 1).

Stage 4: Data collection

Data extraction was performed using the PRISMA-ScR checklist consisting of 22 items developed by IBJ [25]. To ensure that the form accurately captured data, the research team reviewed the form and tested all raters prior to implementation. Characteristics of the included studies, including year of publication, publication type (eg, original research or review type), study design, country, participant population characteristics, intervention setting, description of quality measures including definition, readership, dominant, psychometrics of measures (frontal validity, reliability, construct validity, risk adjustment). the data extraction process was performed twice by two reviewers who independently extracted data from all included studies.

Stage 5: Data summary and synthesis of results

Quality assessment is not an integral part of the scope assessment, but this assessment used the quality control developed in BEME Guideline 11 [26]. Based on the checklist provided, high-quality studies met at least eight set criteria. Moderately rated studies met six or seven indicators, while poor quality studies met five or fewer criteria. Each study received either 0 or 1 for each index measure. Studies that met the index received a positive score, while studies that did not meet the index or were vaguely described

received a score of zero. Selected articles were analysed and themes extracted using the IBJ checklist as a guide.

Step 6: Consultation

It is a proposal of Leva et al. the consultation phase offers opportunities for stakeholder participation that can provide insights beyond what is described in the literature. Integral to the health-focused approach of the study was the involvement of stakeholders, including a patient partner who acted as a consultant and information user during the study.

RESULT

Descriptive

After assessing the quality of the articles, 32 studies were analysed for information. Most of the studies were conducted in the United States (N=10), three in China, three in Taiwan, three in the United Kingdom (UK), Finland, Germany, Norway and Spain, two studies each and one study in other countries (Greece, Switzerland, Slovenia, Canada, Australia, Belgium, Brazil and France). 13 studies were experimental, four were cohort studies, and one study of each design (longitudinal cohort study, longitudinal observational study, multicentre study, randomized controlled trial (RCT), randomized, accelerometric data, combined method, feasibility study, observational study, prospective. , non-randomized and refereed blinded study , Prospective, single-arm, cross-sectional, prospective comparative and prospective study Figure 2 shows the distribution of these studies graphically Analysis of the keywords used in these studies shows that most were related to smart watches, Covid-19 and digital health. A visual representation of their distribution is given in Figure 3.

STRESS LEVEL

Affective computing is one of the leading branches of human-computer interaction and uses technology to detect a person's emotional state [27]. A stress detection system can be used for many different purposes, such as monitoring driver stress, detecting and alleviating passenger stress, monitoring employee stress levels, and assisting psychologists in online therapy sessions [28]. Stress detection occurs in various environments such as laboratories, hospitals, clinics, offices, schools, cars and everyday situations. When the brain receives sensory signals from the eyes, nose and ears, it triggers a stress response. As a result of the stress reaction, the heart rate increases, muscles tighten, blood pressure increases, breathing speeds up, blood sugar levels increase and the senses become heightened. Perceived stress is the way a person interprets and analyses stress. Photo plethysmography (PPG) is an inexpensive optical method to measure the blood volume pulse by blood light absorption. BVP features can be used directly or to extract heart rate or IBI functions. A portable physiological

measurement device must produce high-quality data that is complete, relevant, timely, sufficiently detailed, properly presented, and contains enough contextual information to facilitate decision-making and provide accurate results. A study by Muhammad Ali Faust [29] compared three stress detection learning strategies. All three strategies used logistic regression (LR) as a machine learning model. Unlike individual learning, this learning strategy relies on a central server that combines data and trains an integrated model. the user's devices only need to detect the stress and derive its cause, while the server is responsible for feature extraction and model training. This study compares individual, focused and blended learning with smart watch-based stress detection. Individual learning offers greater accuracy and privacy than centralized and connected learning. the results of this study show that peer learning has a relatively moderate effect on the detection of stress. average precision was 0.8575, average precision was 0.9892, average recall was 0.5208, and average F1 measure was 0.6339. In his research, faze proposed an app that could monitor the physiological signals of healthcare workers to detect work-related stress. smart watches collect data from individual sensors such as heart rate and skin temperature to detect changes in physiological signals. the data would then be used to create individual classifiers and taxa to identify stress levels. In addition, the experiment revealed that these ratings can be used to effectively monitor the stress levels of hospital staff in real time.

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BLOOD PRESSURES

Hypertension is a major risk factor for heart disease, and discontinued devices cannot be used in clinical practice. More studies in both normotensive and hypertensive subjects are needed to increase the reliability of smartwatch-based blood pressure measurements. In the study by Falter [33], consecutive patients scheduled for 24-hour ambulatory blood pressure monitoring were recruited from an outpatient cardiology clinic. Validated devices were used for measurement, including an automatic upper arm blood pressure monitor with a cuff and a Samsung Galaxy Watch Active 2 smart watch that was calibrated. Patients took multiple measurements using both traditional blood pressure monitors and smart watches over at least 24 hours to ensure accuracy. In a total of 40 patients, the smart watch overestimated blood pressure up to 140 mmHg, then underestimated blood pressure, illustrating relative and differential bias. Smartwatch measurements are more accurate at higher blood pressure readings, while the gold standard method is less accurate at lower blood pressure readings. Smartwatch measurements taken during the day were accurate for a blood pressure reading of 135/85 mmHg. sensitivity and specificity were 84.6 and 88.9%, respectively. Blood pressure variability was higher with ABPM measurements compared to smartwatch measurements, and CV was significantly lower with smartwatch measurements. The results of this study indicate that the smart watch currently suffers from a set point set in device calibration that causes overestimation of lower BP values and underestimation of higher BP values. The Samsung Galaxy Watch Active 2 is systematically biased towards the calibration, overestimating low and underestimating high blood pressure, and is not ready for clinical use.

HEART DISEASE

Cardia Band is an Apple Watch accessory that can diagnose atrial fibrillation (AF) using an automatic algorithm. In a non-randomized study [34], patients with AF used KB before and after elective CV procedures. The accuracy of the automatic KB algorithm was evaluated by comparing its results with physician-interpreted KB rhythm strips and simultaneous ECGs. The study found that automated interpretation of KB had high sensitivity and specificity in diagnosing AF compared with physician-interpreted 12-lead ECG and KB rhythm strip. the algorithm correctly diagnosed AF with 93% sensitivity, 84% specificity, and a K-factor of 0.77 compared with electrophysiologist-interpreted ECGs. The doctor's interpretation showed similar results: 99% sensitivity,

83% specificity, and a K-factor of 0.83 to assess the quality of KB traces produced by smart watches. PPG technology is used to passively and continuously monitor AF detection algorithms using modern handhelds. The algorithm should have low computational cost and memory requirements to provide better diagnosis. The study evaluated the accuracy of the AF detection algorithm by obtaining ECG waveforms and PPG signals from patients undergoing AF catheter ablation while accounting for the effects of other arrhythmias. The study included 116 patients with paroxysmal AF and 40 patients with persistent AF. Various PPG properties were analysed, including PPI time and frequency domain analyses, PPG peak height analyses, and PPI ACF properties. Most of these characteristics showed significant differences between AF and SR signals in univariate analysis. The results suggest that using a longer length (25 beats) to analyse PPG data provides better accuracy in differentiating AF from SR compared to using only 10 beats. In addition, repeated PVCs/PACs can reduce the accuracy of the AF detection algorithm [35].

COVID PANDEMIC

A recent study carried out at the Scripps Research Translational Institute investigated the potential of data from wearable sensors to predict patterns of the spread of the coronavirus in 2019. The research team analysed data consisting of 333 participants who actively used the smartphone program DETECT. The It app allowed people to enter their symptoms and test results while collecting additional biometric data, such as heart rate and sleep patterns, using commercially available mobile devices. By incorporating symptom-based indicators and sensor-generated data into the analytical model, researchers achieved significantly higher accuracy in distinguishing between positive and negative cases compared to models based only on symptoms [36]. The Iota-based system was developed to collect signals from Samsung Gear Sport smart watches every two hours for 12 minutes. PPG signals were used to extract parameters related to heart rate and heart rate variability. During the study, physical activity and sleep were measured using a Samsung watch, and TST and WASO were calculated for each night. The Stats Model Python package was used for data analysis, and HRV, physical activity and sleep measures were the dependent variables. The results of this study showed that pandemic-related restrictions were associated with increased heart rate variability, stress levels, physical activity and decreased sleep duration. Pregnant women benefit from using Internet of Things (Iota) technologies to track their daily well-being patterns [37]. The occurrence of lung damage and possible post-treatment injuries is a major concern in the context of the widespread COVID-19 epidemic. Thus, both patients with this disease and the medical professionals involved in their care benefit from monitoring for possible complications even after recovery. A valuable tool that can help with such monitoring is the use of smart watches. In Hunter's study [38] Vaccines are currently licensed and distributed in the United States to prevent the spread of COVID-19. Although individual immune responses to vaccines vary widely, the CDC's V-safe program found that most people reported systemic side effects after the second dose. A recent study found a relationship between reactogenicity symptoms after vaccination

and a humoral immune response. In the study conducted by Quern et al. (2022) [39] collected daily wearable sensor data from 7298 volunteers who received at least one dose of the COVID-19 vaccine. They hypothesized that there are digital, objective biomarkers of reactogenicity that could be identified by detecting subtle deviations from an individual's normal resting heart rate. In the DETECT study, 7,298 participants received at least one mRNA vaccination. Of these, 5674 (78%) participants contributed adequate data to evaluate changes in activity and sleep, respectively. They observed that the average RHR increased the day following vaccination, reaching a peak on day 2 and not returning to baseline until day 4 and 6, respectively. The majority of participants experienced an increase from their normal RHR. They explored several participant and vaccine characteristics that could impact immune response, and found that women experienced higher RHR changes with respect to baseline in the 5 days following vaccination after the first dose only. In contrast, RHR responses vary by age, with individuals age 40 having the greatest increase in RHR. Although a direct comparison is not possible, changes comparable to the ones observed after the second dose of the Johnson and Johnson vaccine were detected in their cohort. After adjusting for potential confounding factors, prior COVID-19 infection was independently associated with a higher RHR increase after the first dose, and female sex was independently associated with a higher RHR increase after the first dose. After adjusting for age, device, vaccine type, and prior COVID-19 infection, they observed higher RHR increases from Apple devices on average, but not after the first dose. The first dose of the vaccine had minimal effect on activity and sleep, but the second dose caused a significant decrease in activity and an increase in sleep, which returned to baseline by day 2. They demonstrated that it is possible to detect physiologic manifestations of reactogenicity to COVID19 vaccination through individual changes in RHR. This provides a potential new mechanism for identifying individuals with either a suboptimal or an exaggerated immune response to a vaccine. Similarly, a study using Garmin Vivo smartwatches 4 to measure heart rate and heart rate variability showed that smartwatches more accurately predicted post-vaccination physiological states than patient self-report [40]

DISCUSSION

The rapid development of technology has created a new group of patients called e-patients. These individuals use various technological tools to track and monitor the progression of their diseases [4]. Scientific works such as Assad et al. (2019) [41], Masters et al. (2017) [4], Charge et al. (2019) [42] and Herrmann-Werner et al. (2019) [43] highlights the need to integrate medical curricula that improve communication skills and address the challenges of e-patient engagement. Research suggests training medical students to use electronic medical records in health care, advising patients about reliable online sources, evaluating website credibility strategies, and using blended learning methods to improve student competency with this unique patient population. Therefore, it is critical that clinical students have the skills to effectively interact with these technologically savvy individuals. This can only be achieved through comprehensive education provided by educational institutions. Wearable technologies, such as smart watches, are increasingly popular in healthcare because they can optimize

practices and promote healthier habits [44]. However, the integration of these devices presents challenges, such as seamless integration into clinical workflows and efficient data management [45, 46]. Medical students using smart watches are role models for patients, so it is important for future healthcare professionals to have technical skills and a thorough knowledge of these technologies. Technological advances, smart watches and wearable technologies are increasing in diagnosis and symptom reporting, Feld [47, 48]. Researchers have conducted studies to evaluate the effectiveness of these techniques with encouraging results. A study showed that smart watches and mobile devices can accurately detect the first signs of health problems, such as irregular heartbeats [64]. Additionally, users can receive valuable feedback through this technology. In addition, researchers have found that such devices play an important role in identifying potential health risks at an early stage before they become critical conditions [49]. Another study looked at how wearable devices can monitor patients with chronic diseases. A study found that these devices can detect changes in vital signs such as heart rate and blood pressure and alert medical personnel to potential problems [50]. This can be especially helpful for people who cannot communicate effectively with their health care providers or are prone to sudden changes in health care.

CONCLUSION

Advances in technology have led to the number of e-patients who rely on technology to track and monitor their illnesses. Integrating medical curricula is critical to improving communication skills and addressing e-patient engagement issues. Wearable technologies such as smart watches are increasingly popular in healthcare, but their integration presents challenges. The review highlights the link between smartwatches and their effectiveness in healthcare systems. Smart watches can be effective in diagnosing and reporting symptoms, early detection of potential health risks and monitoring patients with chronic diseases. However, security considerations must be taken into account, as most smartwatches are designed for ease of use rather than for medical diagnosis. The reliability of smart watches in healthcare is also a concern due to the lack of transparency of their algorithms and variable results in diagnosing clinical symptoms. Instead, the healthcare network is increasingly in demand for clinical assistants powered by AI. These types of assistants could provide more accurate and reliable information, being better equipped to handle the complexities of healthcare. Given these findings, further research is needed to understand and exploit the potential of smart watches in healthcare and to develop more advanced and effective clinical assistants that use artificial intelligence technology.

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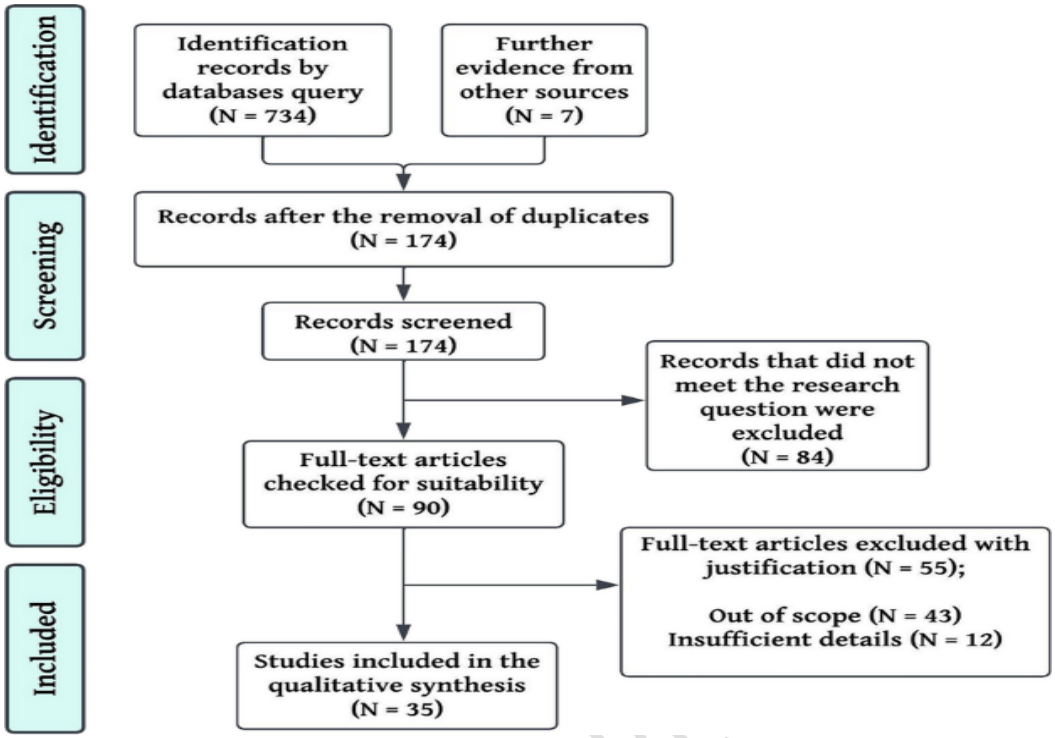

Fig. 1 An overview of the article selection process according to ScR-PRISMA

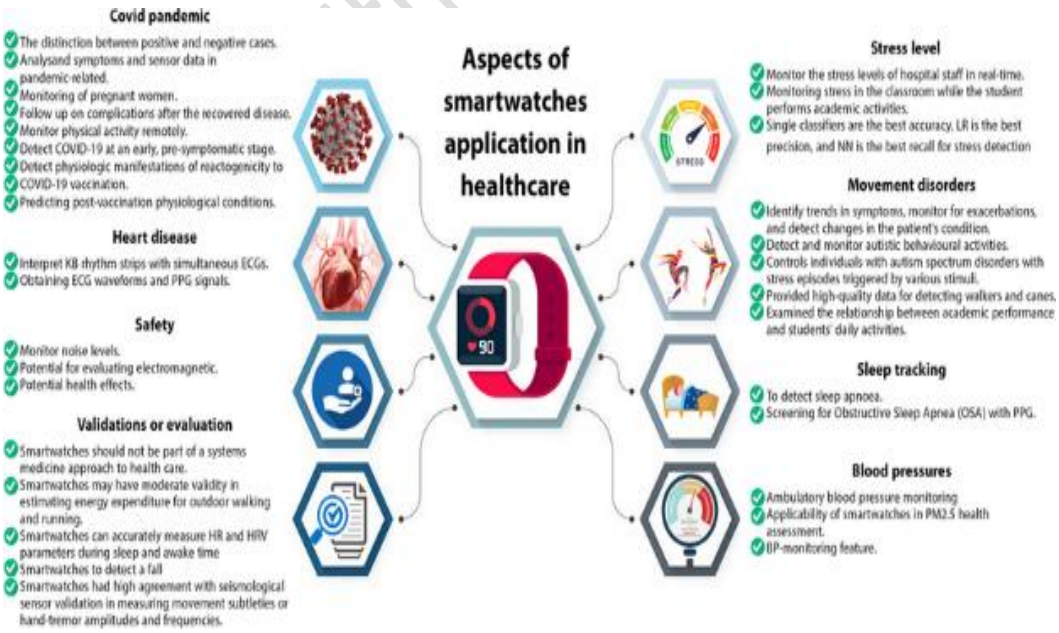

Fig. 2 A graphical representation of the distribution and classification of studies based on the use of smartwatches

Fig. 3 Keyword analysis of studies