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SYSTEMS-LEVEL QUALITY IMPROVEMENT

Based Real Time Remote Health Monitoring Systems: A Review on Patients Prioritization and Related "Big Data" Using Body Sensors information and Communication Technology

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Abstract
The growing worldwide population has increased the need for technologies, computerised software algorithms and smart devices that can monitor and assist patients anytime and anywhere and thus enable them to lead independent lives. The real-time remote monitoring of patients is an important issue in telemedicine. In the provision of healthcare services, patient prioritisation poses a significant challenge because of the complex decision-making process it involves when patients are considered 'big data'. To our knowledge, no study has highlighted the link between 'big data' characteristics and real-time remote healthcare monitoring in the patient prioritisation process, as well as the inherent challenges involved. Thus, we present comprehensive insights into the elements of big data characteristics according to the six 'Vs': volume, velocity, variety, veracity, value and variability. Each of these elements is presented and connected to a related part in the study of the connection between patient prioritisation and real-time remote healthcare monitoring systems. Then, we determine the weak points and recommend solutions as potential future work. This study makes the following contributions. (1) The link between big data characteristics and real-time remote healthcare monitoring in the patient prioritisation process is described. (2) The open issues and challenges for big data used in the patient prioritisation process are emphasised. (3) As a recommended solution, decision making using multiple criteria, such as vital signs and chief complaints, is utilised to prioritise the big data of patients with chronic diseases on the basis of the most urgent cases.

Keywords Real-time remote monitoring · Telemedicine · Patient prioritisation · Big data · Multi-criterion decision making

Introduction

Real-time remote health monitoring systems (RTRHMSs) in telemedicine usually transmit real-time patient data from a remote location to doctors using advanced information and communication technology [29, 91, 135]. Remote monitoring in primary care shows great promise as it is easy to perform, especially for cases involving frail, elderly and housebound patients [81, 144]. Furthermore, remote monitoring systems can be used not only for vital sign monitoring but also for the detection of abnormalities and real-time data transmission to healthcare providers [29]. RTRHMSs are associated with software algorithms, wearable monitoring sensor technologies and communication systems. Telemedicine is a novel way for managing patients with chronic diseases; it ensures the continuity of healthcare in remote areas and improves the integration between patients and hospitals [109, 188]. Remote monitoring is particularly efficient in the management of chronic diseases for the elderly [33, 214, 225]. Furthermore, the remote monitoring of patients with chronic conditions offers numerous clinical benefits [26]. Nevertheless, several issues and challenges confront telemonitoring systems [213]. One of these issues is

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healthcare scalability [148]. Scalability is a challenge in healthcare service provision during disasters and in the context of population aging. In healthcare systems worldwide, the capacity to provide elective health services for all patients immediately is inadequate; one solution is to triage and prioritise patients for access to treatment [101, 225].

Triage nurses and doctors prioritise patients who are physically present at the emergency department (ED). The triage process conventionally depends on the skills of nurses to prioritise patients. Triage and prioritisation become complicated when patients live far from hospitals and telemedicine is used during disasters and peak times; in such cases, triage nurses and doctors are not physically available to help patients, and triage and prioritisation become more complex in telemedicine than in actual ED situations [225]. The triage and prioritisation of patients who require urgent attention in telemedicine have gained considerable prominence [225]. In telemedicine, patients are triaged and prioritised for treatment and transportation to hospitals by evaluating their vital signs [222, 225]. Patient condition should be the primary assessment tool for determining the priority category according to the medical guidelines for assessing priority [96, 222, 225]. Technically, triage and prioritisation processes are complex decision-making procedures [228]. Thus, numerous triage scales have been considered to correspond to decision support systems and provide a guide for making correct decisions [57, 195, 223, 228, 283].

On the one hand, triage and prioritisation processes involve the simultaneous consideration of multiple attributes (vital signs and features) and assignment of proper weight for each feature to score patients according to the urgency of their cases [222, 225]. On the other hand, the increasing number of users of remote monitoring systems per unit area due to population aging and disasters is considered a major problem for providers of healthcare services [72, 213, 225]. Furthermore, big data in the remote servers of telemedicine may lead to critical issues, especially when prioritising remote patients under emergency cases. Thus, triage and prioritisation processes are considered complex decision-making processes when a large number of remote patients are accommodated simultaneously [228]. The prioritisation of a large number of chronic patients presents challenges and gaps in existing literature.

'Big data' as a concept is 'the data that exceeds the processing capacity of conventional database systems' [272]. Data are voluminous, rapidly moving and unable to fit the structure of conventional database architectures [75]. In the health domain, 'big data' refers to 'electronic health data sets so large and complex that it is difficult to manage with traditional or common data management methods and traditional software and/or hardware' [198]. Big data in healthcare systems and medical applications offer many benefits (L. [259]). One such benefit relates to the application of innovative analytics to patient characteristics, profiles and outcomes and cost of care. This application may help in identifying the most cost-effective and clinically suitable treatments, as well as the individuals who may benefit from preventative care or lifestyle changes. Big data in healthcare can be utilised to improve the effectiveness and efficiency of prevention and prediction strategies of health policies, health services and medical interventions [117, 173, 216]. Big data characteristics can be defined by six 'Vs' [37, 73, 78, 164, 168, 208, 217, 259]; [287, 288], namely, volume, value, variety, velocity, variability and veracity.

In real-time remote healthcare monitoring, big data are collected and generated from a large number of users who use telemonitoring systems, such as homecare systems. These systems use heterogeneous sources such as medical sensors and text frames (complaints). Then, advance analytics are applied to take the benefits of big data through the analysis of these data to evaluate patients and further recognise emergency cases. In healthcare, big data refer to the complex and large e-health data sets which are difficult to manage with conventional hardware and software and cannot be simply managed with conventional data management methods and techniques [87, 204, 253, 286]). Large scales of healthcare data are massive not only because of their volume but also because of the speed at which they should be managed and the variety of data types. The entirety of data related to the wellbeing and healthcare of patients result in large scales of data in the healthcare industry [1, 52, 204]. Therefore, large-scale healthcare data applications take advantage of data explosion to improve informed decision making [204]. However, such huge amounts of data which are constantly created by sensing technologies add to the large-scale data problem [162]. Although large scales of data concepts and techniques [132] are involved in areas such as smart cities, they are not extensively involved in the biomedical field and in patient monitoring and telemedicine for the use and integration of data from biosensors [187]. A comprehensive review of literature is essential to determine the requirements for involving big data concepts in patient prioritisation.

This paper presents comprehensive insights into patient prioritisation processes in telemedicine and the related big data characteristics, namely, volume, velocity, variety, veracity, value and variability. Each characteristic is presented and connected to a related part in consideration of the link between the patient prioritisation process and real-time remote healthcare monitoring systems. Then, we determine the weak points and recommend solutions as potential future work, as demonstrated in our study framework in Fig. 1. The remaining sections of this paper are organised as follows. Section 2 presents detailed descriptions of remote health monitoring in telemedicine and the area of chronic diseases. Section 3 discusses the healthcare service challenges in telemedicine. Section 4 presents the details and literature review of patient prioritisation techniques. Section 5 explores big data and related concerns in patient prioritisation. Section 6 identifies the open issues and challenges during triaging and prioritisation.

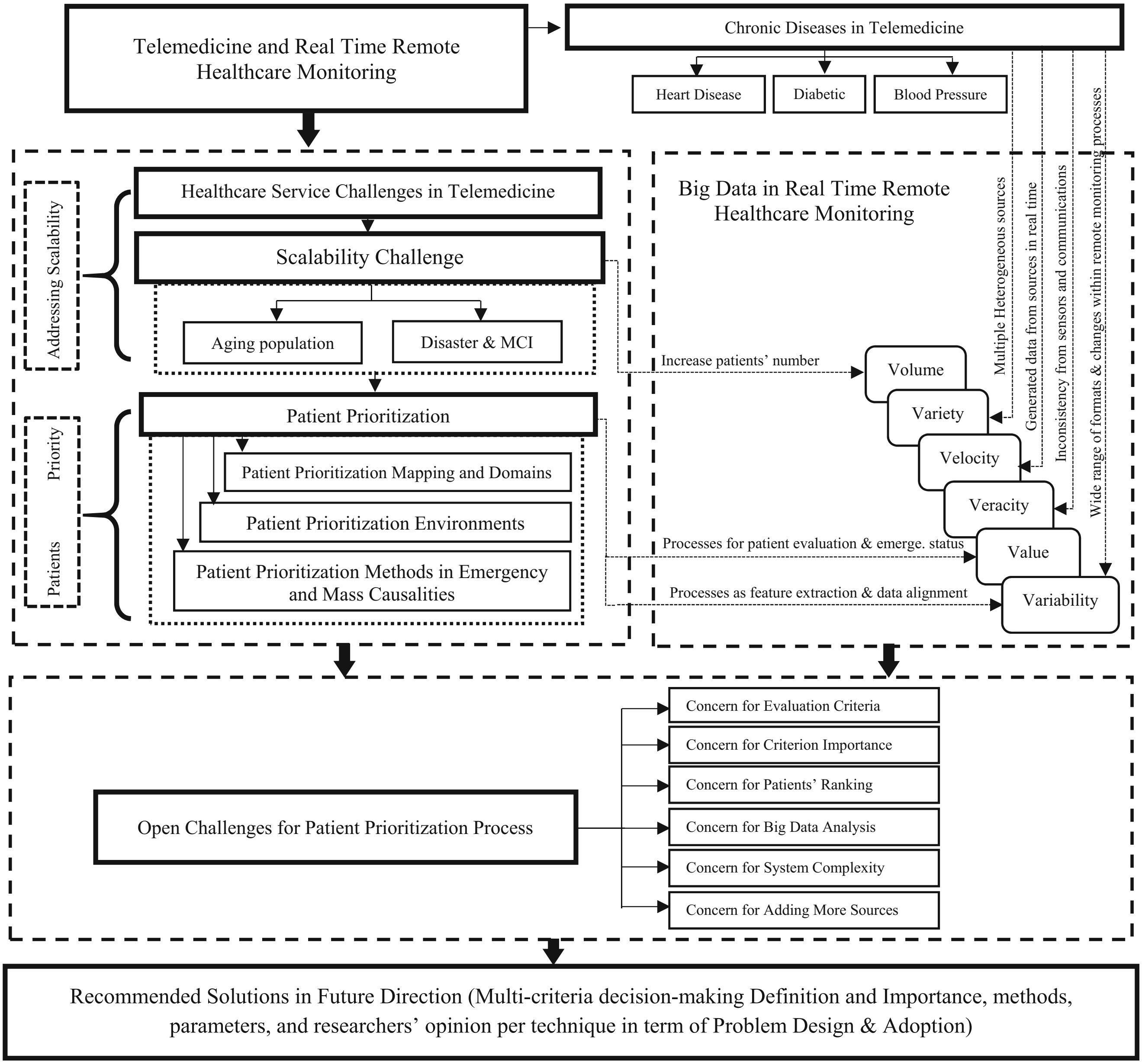


Fig. 1 Review framework

Section 7 discusses the recommended solutions for future directions. Section 8 elaborates the conclusions of the study.

Telemedicine and real-time remote healthcare monitoring

Telemedicine is defined as 'the utilisation of medical information exchanged from one site to another via electronic communications to improve the clinical health status of patients' [23, 48, 192]. Telemedicine offers excessive cost-effective healthcare solutions and services to a wide range of demographics [34, 128, 138, 147, 153, 181]; Penna et al.; [205]. Real-time remote monitoring is one of the main domains of telemedicine implications [46]. Remote monitoring, as defined by the Heart Rhythm Society, is 'the automated transmission of data based on pre-alert related to device functionality, clinical events and clinical condition of patients' [233]. Real-time remote monitoring transmits vital patient data to clinicians in real time using advanced technology [44]. Remote monitoring in healthcare brings great promise because it is easy to perform for the elderly, frail patients and those who are housebound [144]. Several real-time remote monitoring strategies, such as telephone interviews or other sophisticated systems, have been suggested. For example, vital signs can be electronically transferred through remote access control via implantable, wearable or external hemodynamic monitors and devices [188]. Personal health monitoring devices introduced by the 'Telemedicine 2.0' era are now part of the 'disease management system'. A common disease management system augments the functions of data collection and sensing of previous-generation devices with an array of online services. Data visualisation and aggregation, as well as functions such as analysis and alerts for patients' personal physicians, can inform caregivers of urgent conditions, as noted in patients' telemetry. This architecture of the 'Telemedicine 2.0' system is embodied in three tiers [56, 225], as illustrated in Fig. 2.

In telemedicine architecture, Tier 1 involves gathering individual vital signs. This tier comprises interoperable medical devices, each of which is intended to measure a particular type of physiological indicator, such as SpO_2 or ECG. Each sensor is attached to components that filter and amplify the collected data and then sends the resulting measurements to Tier 2. Tier 2 then aggregates the data collected from all monitoring devices that constitute Tier 1. Tier 2 is also responsible for periodically transmitting data to the remote server through an external gateway that provides long-range communication. The server (Tier 3) is a remote computer for real-time data monitoring by clinicians or a database for post-processing. Remote health monitoring in telemedicine is considered an important, attractive and rich research area because it relates to human healthcare. Improvements in this system can be made through different scopes, such as introducing new hardware (sensor devices) and designing new software and algorithms. These modifications can enhance the monitoring process and the efficiency of data handling to improve medical decisions and services. Telemedicine can ensure the continuity of care in chronic diseases [43, 81]. Real-time remote monitoring, in particular, is effective for managing chronic diseases of the elderly, in addition to reducing mortality rates and hospitalisation [33, 214, 225]. Furthermore, the remote monitoring of chronic patients is related to several clinical benefits [26].

Chronic diseases in the telemedicine environment

Chronic diseases have become an increasingly important issue in e-healthcare systems all over the world (M. [50]). For example, clinical expenses for chronic diseases in the US are projected to reach 80% of the overall healthcare expenses, and more than 150 million will experience chronic conditions by 2020 [29]. Chronic diseases also impose a significant burden on individuals and health systems because of frequent unscheduled visits to the ED and lengthy hospital admissions [56, 254]. In the absence of efficient and cost-effective interventions, the rates for chronic diseases will continue to increase in developing countries [40, 124]. Currently, the surge in the number of elderly and chronically ill people in today's society requires continuous health monitoring [152]. The increasing burden and crisis in medical costs influence healthcare service providers, researchers and policy makers to provide remote healthcare services to individuals suffering from diseases [152, 250].

Healthcare researchers and developers have focused on out-of-hospital health monitoring, specifically in home settings where telemedicine is utilised and the continuous and daily monitoring of physiological data (e.g. BP or ECG signals) is important in managing chronic diseases [190]. However, physiological data monitoring alone achieves little [139]. It is subject to proper intervention because the person doing the monitoring should keep observing changes in several vital signs and other measurements for many patients. Thus, the monitoring process should operate around the clock (24/7) to provide sufficient emergency support [267]. In addition, reduction in

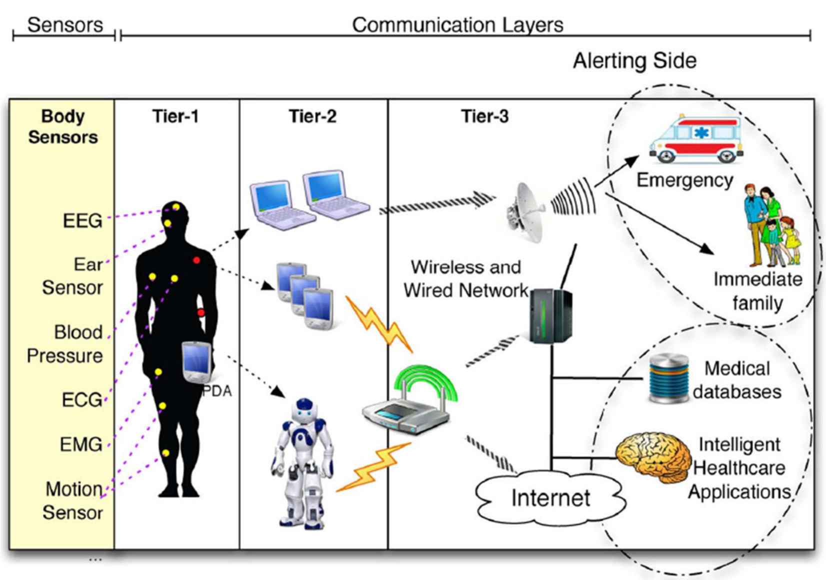


Fig. 2 Three-tiered architecture of telemedicine system for real-time healthcare monitoring [1]

hospitalisation and mortality rates has been reported for home telemonitoring with devices [133, 267, 285].

Home care is a vital and efficient way to manage chronic illnesses [235]. Patients using telemedicine have an increasing need for home management [77]. Telemedicine is a common and efficacious approach that ensures continuous care, especially in cases involving chronic diseases [43]. New technologies have improved the abilities of home care providers as numerous chronic diseases that were previously treated in hospitals can now be managed safely in the home [282].

Wearable devices are one of the technological advancements for the elderly. Researchers have discussed user response to healthcare wearable devices. Steele et al. [237] and Fraile et al. [89] showed the positive attitudes of workers towards the application of wearable devices in healthcare. Hensel et al. [107] found that the perceived ease of use plays a significant role in the adoption of healthcare wearable devices. Claes et al. [62] demonstrated that the elderly should adopt wearable devices because such devices allow them to live independently and safely at home for long periods. The benefits of wearable devices in healthcare are widely studied. Berger et al. [41] showed that 'real-world' healthcare data generated from healthcare wearable devices hold great promise in improving healthcare efficiency and our abilities to develop new cures and treatments. By conducting a discrete event simulation, Radhakrishnan et al. [203] indicated that healthcare wearable devices yield beneficial results in reducing patient denials and serving a large number of patients. In addition, healthcare wearable devices provide doctors with improved abilities to monitor and supervise their patients' wellness [221]. Remote patients, or those who live far from hospitals and use telemedicine, may suffer from different chronic conditions, such as chronic heart disease, diabetes and chronic BP [29, 182]. Thus, we set up a scope for three common chronic diseases from the medical and chronic disease perspective, as shown in the subsections below.

Heart disease The World Health Organization reported that 12 million deaths occur worldwide every year because of heart disease [178]. Chronic heart disease includes several types of diseases, the symptoms of which can be manifested in patients. For example, cardiac arrhythmia is a life-threatening medical emergency that can lead to cardiac arrest and sudden death. According to [29] the American Heart Association (2010), approximately 55% of patients with heart disease die due to arrhythmia [29]. Severe cases of arrhythmia, such as fibrillation or ventricular tachycardia, commonly result in vortex-like re-entrant electric waves in the cardiac tissue. The automatic diagnosis of heart disease is a vital, real-life medical concern because heart disease affects the health and working performance of patients, particularly the elderly [178]. Telemedicine is part of the strategy to efficiently deliver patient healthcare services involving numerous branches of cardiology disease [48, 242].

Many studies have explored the application of real-time remote monitoring in managing cardiac diseases and cardiac home cures, and these works have demonstrated the suitability of this process to reduce costs for the same health outcomes [188]. Telemedicine methods exert valuable effects in chronic heart failure care as well [267]. In home telemonitoring, reductions in mortality and hospitalisation have been reported [133, 267, 285]. Moreover, vital signs such as ECG and SpO_2 are crucial in triage because they provide an objective complement to the triage decision and optimise inter-rater consistency [263].

ECG is the electrical representation of the heart contractile activity over time. It is used for the short-time assessment of cardiovascular diseases, particularly for patients with chronic heart issues. The ECG signal presents data on the regularity and rate of heartbeats. These signals are used to diagnose cardiac diseases [175]. Users can employ either a 3-lead or 12-lead system. The 3-lead ECG system is suitable for patients in nursing homes because of its wearability. Nevertheless, delivering telecardiology services to expert cardiologists to achieve effective and timely interpretation is a challenge. Many EDs do not acquire ECG at triage. Notably, even without the interpretation of the ECG before the assessment of triage nurses, the decision of the triage nurse does not change [94]. ECG analysis is widely studied and used because it is an important indicator for diagnosing many cardiac diseases [199].

Blood pressure In 2008, nearly 40% of people aged 25 years and above suffered from hypertension worldwide; the population with the disease rose from 600 million in 1980 to 1 billion in 2008 [11]. In general, countries with low income present a lower prevalence of hypertension (35%) than other groups (40%) [11, 265]. Moreover, the number of individuals with hypertension who are undiagnosed, untreated and uncontrolled is higher in low-income countries than in high-income countries because of weak health systems. This increase in the prevalence of hypertension is due to ageing, population growth and behavioural risk factors [266]. In summary, deaths due to hypertension conditions will probably rise further if no proper action is taken. Important health and economic advantages are related to quick detection, sufficient treatment and effective management of hypertension. Malhotra et al. [150] explored the correlation of hypertension in 4494 elderly persons living in Singapore. In their study, the group living alone is found to have a higher rate of untreated hypertension (37.3%) than the group living with a spouse or other people. A study by Redondo-Sendino et al. [211] revealed that the risk of hypertension for elderly persons living alone is higher than that for people who are married or living with others.

One progressively common approach in hypertension management is for home patients to measure their own BP and to send this information to their healthcare providers in real time. Studies have shown that home BP monitoring is as reliable as ambulatory BP monitoring [69]. They have also suggested telehealth systems that transmit BP data to servers and provide messaging functions that send daily reminders to users. Users have reported a positive perception about the usefulness and usability of telehealth systems. Many studies have proposed algorithms for health monitoring with the use of BP sensors [3, 50, 92, 225]. Table 1 shows the classification of emergency BP levels according to the American Heart Association [22, 24]. In the table, BP levels are represented by systolic and diastolic levels under related BP categories.

Diabetes Diabetes is a serious chronic disease described by the derangement of carbohydrate metabolism and abnormal levels of glucose in blood and urine [97]. The severity of the disease increases in the absence of proper care and leads to retinal, renal and cardiovascular complications [97]. The American Heart Association classifies emergency blood sugar levels in seven scales, as shown in Table 2 [24].

Recently, a survey has estimated that hospital admission of diabetic patients contributes to 22% of daily inpatient admissions. Half of the overall medical expenses in the US is allocated for this disease (A. D. [21]). Nearly 1.6 million new diabetes cases are reported annually in the US alone, with an overall prevalence of 7.8% and around one-fourth of cases remaining undiagnosed. The costs of illness-related stress hyperglycaemia are not precisely determined, but they should probably be considered in light of the poor prognosis of such cases [30]. Diabetes is spreading rapidly, and the number of diabetic patients worldwide will reach 553 million by 2030 [257].

The influence of telemedicine on diabetes management is remarkably attracting many growing studies and reviews [238]. Telemedicine enhances the cooperation between doctors and patients, and it is achieved by improving the transmission of computerised blood glucose profiles using telephone modem-based home glucose monitoring equipment [97]. By contrast, the focus on chronic conditions, such as diabetes, has dimmed due to the insignificant number of articles available [10]. One of the reported applications of mobile phones in diabetes management is remote monitoring [7, 112, 210]. An assessment of a telemedical support program was carried out by Rami et al. [210] to study its feasibility and to investigate its impact on glycaemic control in adolescents with type 1 diabetes mellitus. A central server was used to receive patients' daily data (time, date, blood glucose and insulin dosage) through mobile phones; the patients were then provided with advice week via text messages sent by diabetologists [137]. Telemonitoring in diabetes offers a number of important advantages involving the control of adverse metabolic events, such as severe hypoglycaemia, and the capability to alert care teams whenever the need arises. Furthermore, telemonitoring permits immediate medical interventions [196]. In current practice, only the data on severe or repeated hypoglycaemia are delivered to diabetologists, and such transmission occurs only after several weeks. According to participants, the applications of telemonitoring involve collecting data regarding glucose and insulin delivery (88%) and technical device information (94%) [196].

Table 1 Classification of emergency blood pressure levels

Blood Pressure Category	Systolic (mmHg)		Diastolic (mmHg)
Emergency care needed	<180	or	<110
Hypotension Stage 2	160-180	or	100-110
Hypotension Stage 1	140-159	or	91-99
Prehypotension	131-139	or	86-90
Normal	110-130	and	75-85
Prehypertension	109-90	or	76-60
Hypertension Stage 1	89-60	or	59-40
Hypertension Stage 2	59-50	or	39-33
Emergency care needed	> 50	or	> 33

Table 2 Classification of emergency blood sugar levels

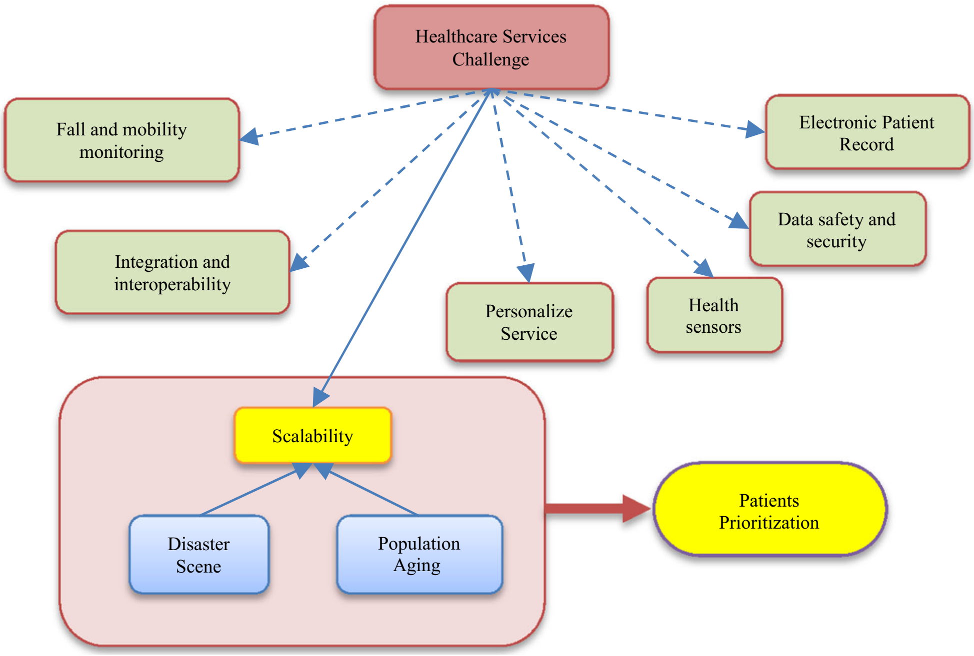
Blood Sugar Category	Scales
Severe Hyperglycemia	< 400
Moderate Hyperglycemia	301 – 400
Mild Hyperglycemia	121 – 300
Normal	80 – 120
Mild Hypoglycemia	60 – 79
Moderate Hypoglycemia	50 – 59
Severe Hypoglycemia	> 50

Healthcare service challenges in telemedicine

The number of healthcare services, especially those provided outside of hospitals, is projected to increase [249]. Chronic diseases (e.g. diabetes, cancer and cardiovascular diseases), in particular, are critical matters for healthcare services because they embody one of the first causes of mortality, morbidity and disability [184]. Many challenges exist in the application of telemonitoring systems in healthcare service provision [213, 225]. However, the current work only focuses on the challenges related to scalability. The taxonomy of the challenges in healthcare services and the scalability problem module are shown in Fig. 3.

Many issues confront telemonitoring systems, and one such issue is healthcare scalability [148, 225]. Increasing healthcare service demands have led to the urgent need for scalable healthcare services [119, 254].

Fig. 3 Taxonomy of healthcare challenges and scalability problem module



Healthcare scalability challenge

Scalability is a challenge in healthcare service provision within patient prioritisation processes [225]. Increases in the number of patients lead to an increased demand for healthcare services. An important problem in healthcare services is the priority given to users according to their emergency status. It also identifies how research can respond innovatively and contribute towards efficient and effective healthcare service provision systems [8, 9, 157–161, 176, 275, 276, 279]. Additional healthcare services, especially those provided outside of hospitals, are clearly needed [249]. Studies have been conducted to improve patient prioritisation for healthcare services in telemedicine and solve the scalability problem [225]. This section introduces the related literature that explores the dilemma of the growing number of elderly patients who need timely and effective telemedicine services. The increase in the number of users is expected to occur in the context of population ageing [50, 85, 142, 146, 225, 261, 262] and disasters [68], as shown in Fig. 4.

Population ageing Population ageing is considered a major problem in healthcare services [163, 228, 261, 262] because the number of patients continues to increase. Current demographic changes are the main reasons that lead to the gradual and persistent growth of older generation groups [134]. This increase causes permanent and serious problems, such as rising incidence of ageing-associated diseases and economic and social burdens [58, 134, 240]. Globally, the society and healthcare systems are loaded with burdens resulting from the ongoing population ageing problems [58, 134, 240]. By 2030, 13% of the total world population, or an estimated 1 billion people, are predicted to be aged 65 years or older [189].

Many age-related chronic diseases have emerged from the momentary increase in the aging phenomenon, and these diseases directly affect and define the determination of medical care expenses [188, 236, 250]. Chronic diseases arising with the surge of the aging population (e.g. diabetes, hypertension and heart failure) make healthcare management a highly relevant issue for health systems all over the world [188]. An ageing population suffering from long-term adverse conditions is a challenge to global healthcare systems in terms of the quality of care delivery [88, 250]. An increase in healthcare users coincides with an increase in user expenditure for healthcare services [88]. Therefore, any accretion in the number of ageing patients is considered a challenge in telemedicine systems [225]. The Center for Medicare and Medicaid Services (CMS) [88] revealed that US expenditure

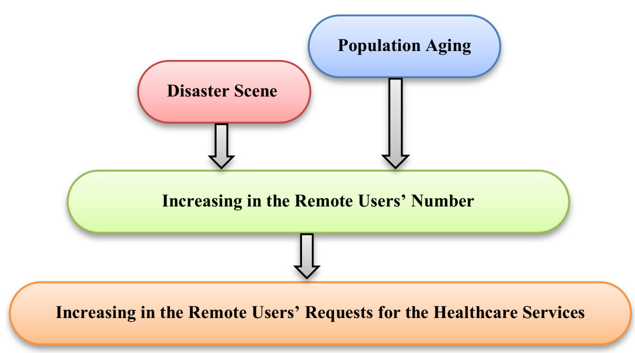


Fig. 4 Problems causing the increase in user requests in remote healthcare monitoring systems

in 1970 was approximately $75 billion, which constituted 7.2% of the gross domestic product (GDP). CMS studies also show that healthcare expenses will reach more than $4.3 trillion by 2018 and will account for 20.3% of the GDP, as shown in Fig 5.

Rapid population ageing raises the number and severity of chronic diseases and requires healthcare researchers to reconsider existing healthcare models [229]. Therefore, researchers have examined how to improve healthcare service provision systems in response to the population-ageing problem. In the work of D.-H. Shih et al. [230], a system was designed to monitor elderly patients using a proposed method that could accurately recognise heartbeat. This system could also be used to continuously monitor elderly patients even in the absence of a healthcare worker. However, this framework should incorporate different classification methods to circumvent drawbacks.

Disasters A disaster is defined as a 'sudden calamitous event that seriously disrupts the functioning of a society or community and causes human, economic and material or environmental losses that override the society's or community's capability to cope utilising available resources, happens when a hazard effects vulnerable individuals' (Societies) Healthcare service delivery in the context [234]. Healthcare service delivery in the context of disasters is more difficult than routine healthcare delivery in many ways. For example, patients are triaged according to severity and probability of survival [66, 140, 284]. When critically ill patients are numerous, those who are dead or expected to die should not be offered attempted resuscitation. Moreover, disasters extensively require quality communication between healthcare providers and receiving facilities, such as surge-capacity care venues, operating rooms and EDs [123, 130, 177]. In addition, disasters lead to an increase in the number of victims without or with minor injuries.

The occasional occurrence of disasters raises the need for pre-hospital care providers to possess triage and treatment skills not utilised in routine practices [60]. Scholars have attempted to compare triage strategies and apply technologies to track patients during disasters [59, 258]. The remote monitoring of patients has been recommended to improve the decision making of clinicians in disasters [60, 270], but the effects of remote monitoring on the triage process in disasters have not been established [60]. In terms of the high rates of chronic diseases, old adults are further subjected to the negative effects of physical and psychological stresses, such as serious disasters [90, 224]. Although a range of functional needs and abilities exist in this population, the prevalence of chronic diseases associated with normal physical, cognitive and sensory changes places homebound patients at critical risk of harm during disasters [268]. For mass casualties in disasters, employing triage to sort casualties in accordance with the priorities of medical care is necessary [209].

Shnayder et al. [231] proposed a system that can be used to monitor the SpO_2 and pulse rates of victims. Another system by Ahn et al. [6] can be used to monitor the pulse rate and ECG of casualties. Both systems can then be used to transmit patient data to a server. With these systems, rescue commanders can monitor casualties in real time, but casualties are not prioritised accordingly. Martí N-Campillo et al. [156] explained the effects of different properties of emergency scenarios on the behaviour of the most noteworthy opportunistic routing protocols and compared the sufficiency of these protocols in realistic disaster scenarios using simulations. Xiang and Zhuang [269] proposed a novel queuing network that models the health conditions of casualties in disasters.

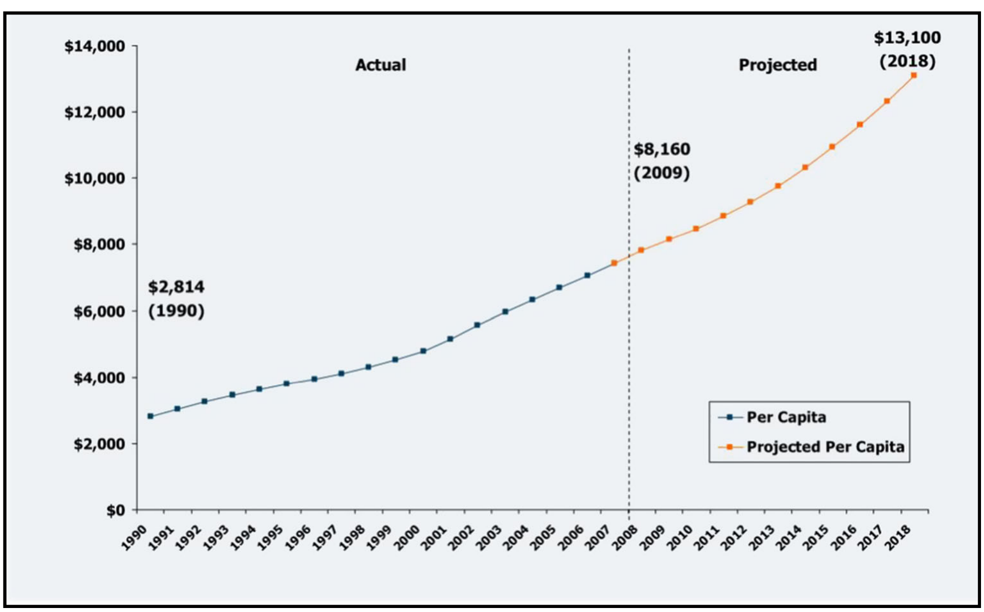


Fig. 5 National healthcare expenditures per capita in the US [88]

Moreover, the study focused on developing rather than solving the problem. The authors used a unimodal sampling algorithm to find applicable optimal solutions for small-scale problems. The design of heuristic algorithms with enhanced efficiency is valuable in solving large-scale problems.

Sakanushi et al. [223] proposed an e-triage system composed of an e-triage server and tags. Electronic triage tags are attached to casualties for continuous monitoring of vital signs. This triage system responds rapidly such that triage officers can immediately identify any abnormal physiological conditions of the casualties. Casualties are prioritised by triage officers, and different colour lights are used to show priority. However, a detailed triage mode is insufficient in mass casualties or in cases in which a triage officer is late. The identification of new risk evaluation and classification systems will support interventions and assist patients, their caregivers and healthcare providers in disaster preparation [268]. In Zane and Biddinger [282] remotely monitored patients may encounter disruption in the support services required. Such disruptions may lead to the decompensation of patients and their increasing dependence on acute care services comprising emergency medical systems and hospital EDs already stretched thin by disasters [282].

As the number of patients continuously increases because of population ageing and disasters, the finite set of healthcare professionals should effectively use any developed system to accommodate the growing demand [213]. In healthcare systems, the capacity to immediately provide elective health services for all casualties is insufficient. One approach to solving this problem is prioritising patients for access to treatment [101, 225].

Patient prioritisation

Patient prioritisation is a complex decision-making process [19, 63, 98]. It is one of the common approaches to tackle the scalability challenge regarding functional capacity, clinical necessity or other social influential factors [246]. Therefore, patients must be prioritised for access to treatment [101]. Prioritisation also improves fairness, decreases the waiting times of urgent patients and affects the differences between areas because it efficiently assigns available resources within each region [215, 246]. In a mass casualty situation, several manual and electronic triage (e-triage) systems are involved in civil and military environments to conduct the prioritisation and order of patients' emergency treatment, transportation and services [67]. Their condition should be the primary assessment tool in determining priority according to medical guidelines [197]. Several studies have investigated patient prioritisation to determine the potential drawbacks of priority assignment in the conventional triage process [165]. In addition, the issue of patient prioritisation is a highly ethical one [53].

Patient prioritisation mapping and domains

The literature on patient prioritisation shows four main categories. The first category concerns general rules and principles that influence the decisions related to priority setting made at different levels [125]. General policy decisions, which are made at the national and regional levels, are comprehensive decisions based on resource allocation, systems for financing providers and national guidelines, including priority setting for the management of common diseases. The second category consists of the dilemmas and opportunities related to priority setting. In this category, analyses are provided for instances such as those in which general practitioners and nurses perceive the application of priority setting in their clinical practice with regard to priority setting criteria, including the severity of health conditions, patient benefit and cost effectiveness of medical interventions [15]. The mapping and domains of patient prioritisation are illustrated in Fig. 6.

The third category is composed of the ethics and attitudes related to priority settings that act as a significant barrier to the effective provision of patient-centred care [99]. For example, the issues related to the time given for each patient during visits and, for complex patients, the prioritisation of issues to address during a given visit must precede discrete decisions about disease-specific treatment preferences and goals [99]. Other aspects in this category are related to prioritisation and patient rights [20] and how patients' ethnicity affects the process [255]. The fourth category details the processes related to patient prioritisation. This category is related to developments in the field of patient prioritisation. It also serves as the focus of the current study. Further exploration of the patient prioritisation process is presented in the following section.

Patient prioritisation processes

Healthcare managers who constantly make difficult resource decisions seek means to improve their priority setting processes [232]. In literature, patient prioritisation processes have been studied in different domains, such as waiting lists, appointments, clinical pharmacist interventions, community rehabilitation and emergency services.

Many studies have addressed patient prioritisation in waiting lists in three main areas, namely, surgery and operating rooms, transplantation and sleep disorders. The first area, surgery and operating rooms, is one of the strategies proposed to tackle the problem of waiting lists for surgery, in which patients are prioritised according to clinical necessity, functional capacity or other social determining factors [246]. Different studies have shown the benefits of prioritising patients on waiting lists for surgical interventions with respect to

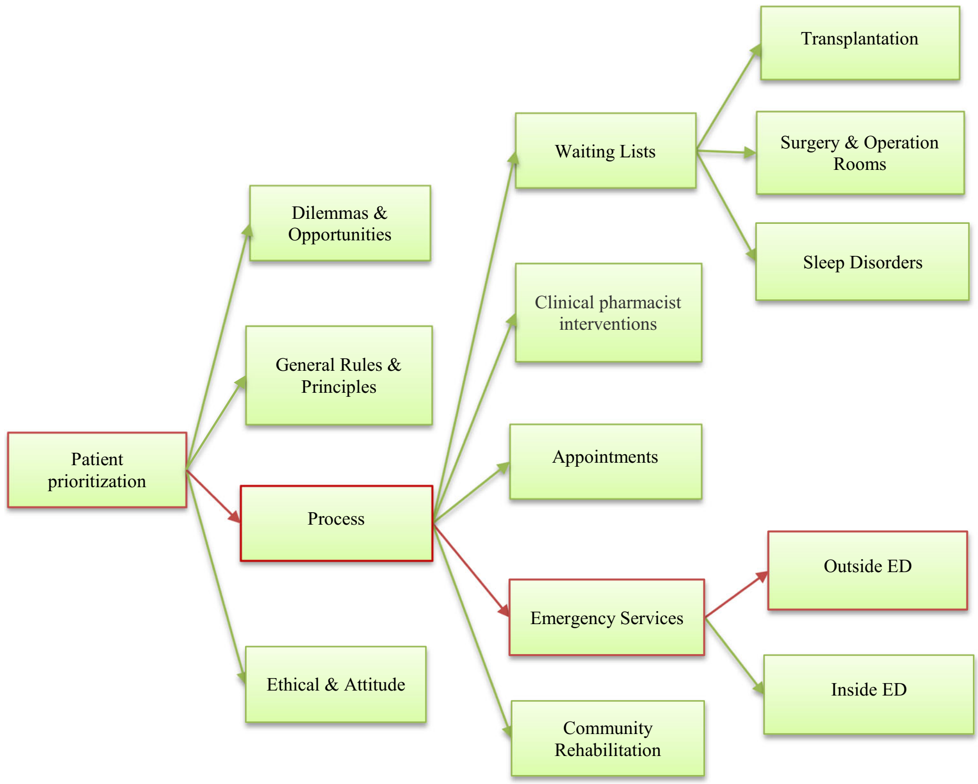


Fig. 6 Taxonomy of the literature on patient prioritisation

a system based exclusively on waiting time [76, 167, 207, 246]. The second area is transplantation, which includes the prioritisation of patients in waiting lists for organ transplant and allocation and the related criteria for prioritisation [42, 61, 116, 206, 239]. The third area is sleep disorders, which relate to identifying system constraints that lead to long waiting times at multidisciplinary sleep centres and utilising patient prioritisation to test solutions that can improve access [191].

The second domain also addresses patient prioritisation in appointments [5, 70, 136, 256]. Studies in this domain have considered patient prioritisation in the appointment systems in healthcare [5]. Several studies have designed appointment systems for outpatient clinics and diagnostic facilities that offer walk-in and scheduled services [136]. Other studies have developed frameworks for strategic, tactical and operational decision making related to outpatient prioritisation in appointments [5].

A few studies have described patient prioritisation in the community rehabilitation domain [103–105]. Within this domain, some studies have aimed to evaluate the agreement between independent clinician raters by using a triage protocol to prioritise referrals for occupational therapy and physiotherapy within a community rehabilitation program [103]. In the fourth domain, some studies have attempted to address patient prioritisation in the context of emergency services. Such topic is the focus of the current study; other domains are beyond the scope of this work. The following sections present further investigations on patient prioritisation in emergency services and related issues.

Patient prioritisation in emergency services

Prioritisation systems are a type of triage that aims to sort patients in order of priority for treatment [104]. Patient prioritisation is a complex decision-making process (O. M. [19, 63, 98]). It is one of the common approaches to tackle the scalability challenge according to functional capacity, clinical necessity or other social influential factors [246]. Therefore, patients must be prioritised for access to treatment [101]. Prioritisation also improves fairness, decreases the waiting times of urgent patients and affects the differences between areas because it efficiently assigns available resources within each region [215, 246]. In a mass casualty situation, several manual and electronic triage (e-triage) systems are involved in civil and military environments to conduct the prioritisation and order of patients' emergency treatment, transportation and services [67]. Their condition should be the primary assessment tool in determining priority according to medical guidelines [197]. Several studies have investigated patient prioritisation to determine the potential drawbacks of priority assignment in the conventional triage process [165]. In addition, the issue of patient prioritisation is a highly ethical one [53].

According to research analyses, the effort to improve prioritisation processing in emergency services is exerted on the basis of two perspectives. The first perspective is that within EDs, which refers to improving the performance of patient prioritisation in cases of overcrowding inside EDs. In

EDs, predictability is noted in terms of the type and number of victims that will present daily. Moreover, EDs have a slight control over the current rate of patients and their total number. Large-scale events that require emergency services may cause rapid, unexpected and overwhelming demand for EDs along with a reduction in capacity [86].

As the population has grown faster than the development of facilities or budgets in recent years, overcrowding in EDs has become a serious issue in healthcare systems globally [17, 19, 80]. Overcrowding exerts adverse effects on the quality of medical care and on hospital profits [131]. Therefore, most EDs use triage systems to sort patients by acuity of injury or illness [64, 94].

Triage is the problem of prioritising and sorting patients in EDs [18]. It is derived from the French word 'trier', which means 'to sort'; hence, triage is a prioritisation process [45]. It is defined as 'the preliminary clinical assessment process that sorts patients before full ED diagnosis and treatment …, patients with the highest acuity are treated first'. In fact, triage is used to identify the level of urgency for care and patient treatment according to their triage level [82]. Furthermore, it is a system used to sort patients by order of necessity of treatment in large-scale emergencies [118]. It is also the process of assessing and prioritising care for all patients present in EDs [111]. Triage protocols are used to decide patient prioritisation for treatments according to the severity of patients' conditions [180] and identify those who can safely wait and those who cannot [47]. A qualified triage nurse assists patients with their conditions, notes any changes and decides patients' priority for ED admission and necessary treatment [228].

For example, most US hospitals use a three-level triage evaluation (emergent–urgent–non-urgent) that sorts patients according to the question, 'How long can this patient wait to be seen?' [12]. A five-level triage evaluation (e.g. ESI, Canadian triage and acuity scale and Australian triage scale) has been developed and validated according to 'Who should be seen first?' and 'What will this patient need?' [79].

The second perspective is that outside of EDs, in which patients are physically far from hospitals and EDs. This perspective is the focus of the present study. From this perspective, the improvement of the prioritisation process entails cooperation between computer engineering and medical guidelines. This prioritisation process involves implementing certain computing algorithms in portable devices on the basis of medical guidelines. The following section presents further investigation regarding the perspective from outside of EDs.

Patient prioritisation outside EDs

In this section, an overview of patient prioritisation outside EDs is presented. As previously mentioned, patients outside EDs are those far from hospitals and those who are home patients. This overview contains three main sections: patient prioritisation in the presence of challenges in healthcare service scalability, environment outside EDs and methods and related studies about the environment outside EDs. The following subsections present the descriptions of the three sections.

Patient prioritisation environment In the outside ED perspective, two main environments exist: on scene or in site environment and remote environment. Both environments are presented in the following subsections.

Patient prioritisation on scene In many mass casualty (MCIs) triage is executed at the incident site to improve the transportation of casualties to the hospitals participating in the response initiative. Ambulances are typical resources for this effort [165, 166]. Decisions made by responders include the order of transportation of casualties [165]. On the bases of current practice, decisions regarding resource allocation at MCI sites are made in a simple manner: prioritisation is automatically determined by the triage class of patients [166]. Triage is also defined as a process of prioritising patients on the basis of their vital signs in disasters and MCIs [127] and as an essential tool in MCI management [121]. Several triage methods can be applied during MCIs: simple triage and rapid treatment (START); Sacco triage method (STM); Homebush triage; triage sieve; and Coscienza, Emorragie, Shock, Insufficienza respiratoria, Rotture, Altro or CESIRA [140]. START, for example, is a common method in the US [65, 140]. It has four color-coded categories: immediate (red) for the most critical casualties that need attention within an hour, delayed (yellow) for patients with serious injuries but are not expected to deteriorate for several hours, minor (green) for victims with relatively minor injuries and expectant (black) for victims unlikely to survive [39]. START has an implied service order from the most critical to the least critical (i.e. red, yellow and green) regardless of the situation.

Remote patient prioritisation Remote prioritisation means triaging patients for treatment and transportation to hospitals by evaluating their vital signs [223]. Continuous monitoring of patients from remote hospitals is highly desirable in taking care of patients and providing suitable guidelines with proper medicine [169]. The remote care of patients is now becoming a major concern in healthcare services [227]. Prioritising remote patients refers to improving the patient prioritisation process for telemedicine patients [225]. Furthermore, prioritisation is required for emergency operations in remote healthcare services and disaster systems. Remote home patients, especially the elderly, are at critical risk of harm during disasters [268]. Thus, prioritisation processes are important to support the continuous care of remote patients in pervasive environments [227]. For remote patients, the overwhelming heterogeneous data cause difficulty in deciding which patient out of many should be provided with care first [227]. Thus, decision-based methods for prioritising patients in this environment are of urgent concern [227]. Table 3 provides a summary of patient prioritisation environments.

Table 3 presents two main patient prioritisation environments outside EDs: on scene and remote. The descriptions, scalability and related references are also presented. Traditionally, triage providers prefer using simple triage methods with a small number of patient classes for ease of implementation. However, recent research recommends that emergency planners may want to evaluate the involvement of additional triage classes or sophisticated prioritisation policies owing to the increase in the expected number of survivors [165]. The next section describes the investigations on patient prioritisation methods and related studies on environments outside EDs.

Patient prioritisation methods and related studies

Several methods have been applied in patient prioritisation. Prior work on patient prioritisation in emergencies and mass casualties have explored three main methodologies [165]. Qualitative fixed-priority methods have largely emerged from the medical community and mainly emphasise patient classification rather than optimal prioritisation for transportation and treatment. Operations and medical literature presents the mathematical programming models used to determine the optimal prioritisation of patients' schedules. Finally, triage rules based on quantitative methods provide an alternative to fixed-priority methods without solving full-fledged optimisation problems. The following subsections present a review of each method with its drawbacks and benefits.

Qualitative fixed-priority methods One of the most common qualitative fixed-priority methods, START, stands for 'simple triage and rapid treatment'. In the US, the START method has been used for mass casualty triages since the 1980s. This method uses strict medical criteria to evaluate each casualty and assign one of four triages: expectant or 'black tag' for casualties who are expected to die regardless of resources provided, immediate or 'red tag' for casualties who require urgent treatment, delayed or 'yellow tag' for casualties in critical condition but can wait and minor or 'green tag' for casualties with no critical conditions and are therefore expected to survive [140]. After the patients are sorted, a simple fixed-priority policy is used. Top priority is allotted for immediate patients, followed by delayed, minor and expectant patients. The latest work conducted to standardise and update triage in mass casualties resulted in the SALT method, which stands for 'sort, assess, lifesaving intervention and treatment/transport'. SALT emphasises the four steps to indicate that mass casualty triage is used for more than just evaluating the condition of casualties. Unlike that of START, the qualitative consideration of SALT in determining whether to tag a casualty as immediate or expectant includes the probability that the patient will survive and the availability of resources. In other words, SALT necessitates operational considerations in a qualitative manner. Similar to START, SALT also prioritises patients in a fixed-priority manner once the evaluation process is over regardless of the number of casualties or the availability of resources.

Quantitative methods for formulating mathematical programs Methods that formulate mathematical programs provide a high level of precision and involve a variety of operational constraints. They also pose extreme challenges to implementation. The STM approach proposed by Sacco et al. [220] combines patient assessment by using a 'Respiration–Pulse–Motor (RPM)' score and prioritisation via linear programming. An RPM score is obtained by rating the casualties on a zero-to-four scale on three dimensions and adding the three numbers, thereby resulting in 13 possible triage classes that match the integers 0 to 12. In the linear program, time is discretised. Each ambulance is assumed to be able to take one patient to the hospital, but treatment time is ignored. Dean and Nair [71] proposed another method, named 'Severity-Adjusted Victim Evacuation (SAVE)'. This method includes more than one hospital and different treatment times based on the triage classes of patients. In this realistic scenario, SAVE

Table 3 Environment for patient prioritisation

Environment	Description	Scalability Concerns	Ref	
Outside ED Perspective	On site	Patients or causalities in disasters and MCIs need to been prioritized in the scene/cite of the incidence in order to improve the transportation process for hospital or other evacuation camps and provide services for them.	Disasters and mass causalities incidence	[55]; [165]
	Remotely	Patients who are remotely monitored and home patients with long-term conditions such as chronic diseases are prioritized according to urgency status. Sensors and other techniques (e.g., wearable devices) are used to transfer patients' vital signs and chief complains to the servers in the healthcare providers' side for prioritization.	Aging population, disasters, and mass causalities incidences	[28]; [151]; [225]; [227]

outperforms STM and other fixed-priority methods [71]. SAVE and STM share the mass casualty triage goal (i.e. to do 'the greatest good for the greatest number') in terms of the expected number of survivors by modelling patient criticality over declining expected survival probability functions.

Dean and Nair [71] provided a general specification that can be adapted to various situations; with sufficient data, such functions can be empirically estimated. Nevertheless, such an optimisation-based approach presents shortcomings. In MCIs, triage often starts (and sometimes ends) before a full incident command can be established [165]. In the absence of a managerial structure, responders can apply simple decision rules, such as those that can be presented on a chart or determined with a simple calculation. However, they will not have the organisational capability or required supported software for solving the mathematical program. Even in a well-organised incident, variations in technology adoption may require the use of triage priorities that can be obtained offline. In the US, mass casualty triage is commonly achieved by first responders in a local emergency medical services (EMS) system. As EMS systems are accomplished in local jurisdictions, a large regional variability in the type and amount of available technological resources to EMS providers exist, and they range from simple pen-and-paper recording to multifaceted electronic systems. Thus, not all EMS systems can realistically provide solutions on the basis of solving optimisation problems in real time. Dean and Nair [71] also emphasised the critical time period immediately after the onset of an MCI and showed how to efficiently evacuate casualties to different hospitals to provide the 'greatest good to the greatest number of patients' without overwhelming any single hospital.

This resource-constrained triage problem is formulated as a mixed-integer program called the SAVE model. I. Sung and Lee [241] modelled the problem as an ambulance routing problem and obtained the order and destination hospitals for evacuated patients. This issue is formulated as a set partitioning problem, to which a column generation approach is applied to effectively handle a large number of feasible ambulance schedules. Mizumoto et al. [170] utilised e-triage and medical treatment statistics to formulate a solution to issues in the order of patient transportation. This solution increases the life-saving ratio, given the latest vital signs and variations in each patient's survival probability. Mizumoto et al. [171] proposed a system that uses the e-triage tag to enable emergency medical providers to identify the conditions and locations of patients.

Triage rules based on quantitative methods These methods are considered the major stream concerned with patient prioritisation in emergency services. Prioritising patients in MCIs can be modelled from a queuing perspective as a multi-class clearing system. In such systems, each casualty is available at time zero and attached to a class. In turn, each class has different rewards, lifetimes and service times. Several studies have emphasised patient prioritisation from a resource-based perspective. For example, several authors [13, 113] have modelled the lifetime of each patient as a random variable distributed according to the patient's class. Patients in critical situations will have short lifetimes in a stochastic sense. If a patient will not be served before the lifetime, then he or she will die. If the patient is served, then he or she will either survive with a class-dependent probability [113] or definitely survive [13]. Argon et al. [13] stated that, if the optimal policy is an index policy, then it must agree with the '$r\mu$' rule; however, the optimal policy is more complicated than an index policy. Jacobson et al. [113] created a threshold policy depending on the total number of patients that recovers well in the two classes. However, the above-mentioned studies are only concerned with impatiens and abandonments.

Other studies, such as that of Mills et al. [166], have involved a fluid model by reducing survival probability functions to design the ReSTART rule. ReSTART consists of available resources to determine the priority of immediate and delayed patients who were evaluated using SALT, START or other 'colour tag' systems. This system conducts an index on the basis of the number of patients in each class, survival probability functions, rate of service and amount of resources. ReSTART offers an intuitive and simple prioritisation policy, but the main specification of which is concerned with the variance between two survival probability functions. Furthermore, it does not provide a natural extension to more than two classes of patients. In their other study, C. W. Chan et al. [51] presented a patient prioritisation system for transferring patients to burn beds and showed its applicability compared with other triage methods that use simple heuristic parameterisations. Mills [165] also proposed a simple yet effective decision support policy called survival look ahead, in which prioritisation is given to the class with the most reduced survival probability over a class-specific period of time.

In the current work, we demonstrate that this type of policy is nearly as efficient as other sophisticated optimisation models but is far more practical from an implementation perspective. Kamali et al. [121] designed a mathematical model that considers available resources to transport patients and disaster scale in the prioritisation process. This model assumes a disaster location with a set of casualties categorised by severity that need to be transported to hospitals using a fleet of available ambulances. The main contribution of the study is developing a tractable model that determines the optimal service order by considering the casualty type's dependent service time, multiple servers and more than two causality types.

A. K. Childers et al. [55] focused on patient prioritisation during evacuation. The authors intended to offer insights into the patient prioritisation problem during complete evacuations in healthcare facilities. They proposed a dynamic programming model for emergency patient evacuation and identified the need for continued discussion amongst healthcare workers in terms of the ethical dilemmas associated with making evacuation decisions. A. Childers et al. [54] also proposed a two-phase modelling approach. They developed a decision framework that prioritises patient evacuation, in which factors such as patient health classification, survivability and evacuation rates affect decision making. Certain studies have addressed the prioritisation of patients for services and treatments from the triage perspective. For example, Kashiyama et al. [126] attempted to increase the number of expected saved patients in disaster scenes with restricted medical resources. They proposed a heuristic algorithm that is based on a depth-limited search. The main advantage of this study is the increase in the average of saved patients by 10% compared with other greedy methods. However, the algorithm does not calculate patient priority; patients are assumed to have already been triaged, and the priority level is only assumed in the simulation. The authors also assumed that the server knows the number of patients that each area can transport or treat on the basis of information from medical resources (i.e. numbers of physicians, nurses and ambulance units).

Regarding the environment of patient prioritisation, all the aforementioned studies have targeted patients at the scene of disasters or MCIs. On the contrary, some studies [223, 225, 227] have used a remote method for prioritising patients. For example, Sarkar and Sinha [227] designed a pervasive system to continuously help patients at remote places from connected hospitals on the basis of a priority-based classification and nurse assignments for urgent patients. The study focused on caregiver allotment to remote patients according to patients' conditions. The proposed system develops fuzzy rules to make decisions on the basis of priority amongst specific groups in a dynamic environment. This proposed model formulates an indexed hash key for urgent patients and proper nurse relatively. Patients in this model are categorised into five groups, namely, 'urgent', 'high', 'medium', 'low' and 'very low', according to the severity of the context data acquired from smartphones. However, the rank and order of the patients are not provided. Hence, this study is not validated.

Studies such as those by Bagula et al. [28] and Mandava et al. [151] have utilised machine learning techniques to improve the accuracy of the triage scale by learning from data sets. In these studies, prioritisation is based on four triage system scales that classify patients into four categories. However, prioritisation, such as patient rank and order, is not provided. Furthermore, studies targeting the general situation of patients have used only four features. Specifically, only vital signs are used to determine a patient's condition without consideration of the patient's complaints. Large numbers of patients are not considered as well. Instead, they have targeted patients in general without considering a specific disease.

Sakanushi et al. [223] used the term 'e-triage' to refer to electronic triage for remote users. The e-triage tag determines the priority (level of triage classification) on the basis of the START method. Capillary refill time (CRT) is assessed in the START method. The START method involves CRT, which is a simple index obtained without medical equipment and used as a circulation index. It uses the pulse and breath rates in place of the CRT to assess the circulatory system. Only two sensors are used with one feature from each, and such step affects the accuracy of patient evaluation. Patients are prioritised by classifying or sorting them into categories. However, the order of patients within each category is not shown. Furthermore, this study is inefficient to achieve rapid prioritisation of patients in the context of mass casualties or cases in which the triage officer has not arrived yet and the large scale of patients has not been considered.

Salman et al. [225] covered the shortcomings of Sakanushi et al. [223] by addressing the issue of scalability and prioritising patients through order assignment and patient ranking. In their study, they applied prioritisation for a specific group of diseases, namely, chronic heart diseases, by identifying vital signs and related complaints. It involved three sensors and four text features to indicate complaints that merit prioritisation for patients with chronic heart diseases. This study proposed a multi-source healthcare architecture (MSHA) to increase healthcare scalability effectiveness by improving the prioritisation process in the telemedicine environment. The mathematical model of MSHA is a data fusion method used to prioritise patients. However, this study exhibits several shortcomings. (1) The priority process is performed in Tier 2 (base station) and provides a priority code (PC) value without comparing it with other patients in the server. (2) The technique used for feature weighting utilises the set and test method that is also applicable to five other diseases according to the data set of patients. Whether the overall data set is used in the set and test method only or as part of it is not specified. However, a data set of 120 patients may not reflect all the cases that show the exact weights for each feature. (3) Patients are prioritised using a PC ranging from 0 to 100. Patients within this range are prioritised, whereas those with the same PC value in the server are sorted in descending order on an FCFS basis. However, FCFS cannot be used in reality because some patients may have cases that are more urgent than those of others who came before them [63, 243]. (4) This study considers the scalability challenge but ignores large number of patients and the amount of data from the features. Hence, this study needs a robust method that can accommodate the increasing number of patients and consequently handle the increasing data size.

In conclusion, the patient prioritisation methodologies and the studies reviewed indicate three main streams, namely, qualitative fixed-priority methods, quantitative methods that formulate mathematical programs and triage rules based on quantitative methods. However, major and recent works in this field have been performed only in the third stream, and they have recognised several perspectives, such as resource-based [51, 165, 166], evacuation [54, 55], abandonments and impatiens [13, 95, 113] and services and treatments [126, 223, 225, 227]. Table 4 summarises the three main methodologies and perspectives of the focus stream with their descriptions.

Table 4 summarises the patient prioritisation methodologies by providing descriptions of their advantages, disadvantages and references. Furthermore, it highlights the triage rules on the basis of the stream of quantitative methods and related perspectives. Table 5 presents state-of-the-art patient prioritisation in emergency services in the focus stream. It addresses specific issues, such as the methods used for each study and its target or environment. Furthermore, the prioritisation perspective and concerns related to scalability are listed as well as whether the prioritisation supports chronic diseases and healthcare providers.

As shown in the review and analysis presented in Table 5, most studies on the environment outside EDs target patients on disaster or incidence sites. Only a number of studies [28, 151, 225, 227] target patients in remote sites. From these studies on patients in remote sites, only Salman et al. [225] explored prioritisation in terms of patient rank and order; others prioritised patients as categories and groups. Furthermore, most of these studies do not address scalability as a challenge, except for Jacobson et al. [113] and Salman et al. [225]. Only Salman et al. [225] targeted chronic diseases as long-term conditions associated with remote patients; others targeted injury or illness in general within disasters and MCIs. In conclusion, studies that address remote prioritisation as the capability to rank and order a large scale of patients for services and treatments according to emergency status are lacking. The review shows that different methods have been applied to prioritise patients from the methodological perspective. However, in general, healthcare decisions are complex and involve trade-offs between multiple, often conflicting, objectives [247]. Specifically, patient prioritisation based on medical condition and chance of survival is a complex decision-making problem [19, 63, 98] because the decision is made on the basis of a set of attributes [83].

Big data for real-time remote healthcare monitoring

Big data in real-time remote healthcare monitoring include high volume, clinical, lifestyle, high diversity, biological and environmental information gathered from single individuals and large committees in relation to their wellness and health status at one time point or another [25]. Some data related to healthcare are characterised by the need for timeliness; for example, data from implantable or wearable biometric sensors (e.g. heart rate or BP) are commonly needed to be gathered and analysed in real time [106]. Data analytics is one of the main parts of the big data environment that involves simplifying data complexity and calculation for accomplishing expected patterns of data sets and outcomes [208]. Sufficient large-scale analyses usually require data to be gathered from multiple sources (heterogeneous data) [259]. For example,

Table 4 Patient prioritisation methodologies

Main Strems	Perspective	Description	Concerns	References
Qualitative,Fixed-Priority Methods		The common traditional qualitative, fixed-priority methods, such as START.	Used specific classes for categorizing causalities and patients in the disasters and mass causalities incidences	[140]
Quantitative Methods that Formulate a Mathematical Program		Methods that formulate a mathematical program	Provide a high level of precision and can involve a variety of operational constraints, but they also pose the greatest challenges to implementation.	[71]; [170]; [220]; [241]
Triage Rules Based on Quantitative Methods	Resource-based	Patient prioritization from resource-based perspective such as allocating the needed ambulances and doctors as well as the patients distribution to one or more hospital	Considers the major stream and contain the latest improvements in this research area that concerning patient prioritization in emergency services.	[13]; [51]; [113]; [121]; [165]; [166]
	Evacuation	Patients' prioritizing as a problem during complete evacuations in healthcare facilities such as patients transportation and ethical dilemmas associated with making evacuation decisions		[54]; [55]
	Services and treatments	Prioritization of patients for services and treatments from triage perspective		[28]; [127]; [151]; [223]; [225]; [227]

Table 5 State-of-the-art of patient prioritisation studies from emergency service perspective

Ref/Year	Method	Target/ Environment	Prioritization Perspective	Scalability Concerns	Support Scalability	Support Chronic Disease	Support Healthcare Providers
Kamali et al. [121]	developing a tractable model that determines the optimal service order	On scene	Resources based	Disaster & MCI	Not Addressed	No	Yes
Mandava et al. [151]	Propose a cyber-healthcare system using a micro cloud server be equipped with an intelligent data analysis algorithm and machine learning	Remotely	Service & treatment	No specification	No Addressed	No	Yes
Bagula et al. [28]	Propose a deployment model for the proposed Cyber-healthcare system, and describe a patient prioritization process as part of its situation awareness component using supervised machine learning	Remotely	Service & treatment	No specification	No Addressed	No	Yes
Mills [165]	Proposing a general decision support rules that used to take over the functions of survival probability and the numbers of classified patients.	Incidence Site	Resource based	Mass-Casualty	No Addressed	No	Yes
Salman et al. [225]	Multi Sources Data Fusion. Combined method: Evidence Theory and Fuzzy C mean rules.	Remotely	Service & treatment	Disaster And Aging population	Yes	Yes	Yes
Sarkar and Sinha [227]	Develop fuzzy rules to make decision based on priority among specific groups in a dynamic environment	Remotely	Service & treatment	No specification	No Addressed	No	Yes
A. K. Childers et al. [55]	Using a dynamic programming model for the evacuation of urgent causalities and illustrated that a greedy policy "all or nothing" is not always optimal.	On scene	Evacuations	Not considered	No addressed	No	Yes
Mills et al. [166]	Propose a fluid model of causality triage in a MCI	On scene	Resource Based	Mass Casualty Incidents	No	No	Yes
Sakanushi et al. [223]	Proposed an electronic triage system. The electronic triage tag continuously monitors patients' vital signs and send them to the electronic triage server. The electronic triage system presents the existing priorities.	Remotely	Service & treatment	Disaster	No	No	Yes
C. W. Chan et al. [51]	Develop a new patients prioritizing system for transfer to burn beds and shows its applicability rather than numerous other triage methods using simple heuristic parameterizations	On scene	Resource Based	Disaster	No	No	Yes
Jacobson et al. [113]	Proposed sample-path methods and stochastic dynamic programming	On scene	Resource Based	mass-casualty events	Yes	No	Yes
Kashiyama et al. [127]	Proposed a heuristic algorithm on the bases of depth-limited search	On scene	Service & treatment	Disaster	No	No	Yes
A. Childers et al. [54]	Decision framework for prioritizing patient evacuations	On scene	Evacuation	Mass Patients	No	No	Yes
Argon et al. [13]	Stochastic dynamic programming	On scene	Resource Based	Mass Casualty Incidents	No	No	Yes

obtaining a 360-degree health view of a patient (or a population) is realised through the integration and analysis of medical health records with available internet environmental data and readings from various types of metres (e.g. accelerometres, heart metres and glucose metres) [115].

For real-time remote healthcare monitoring, the six 'Vs' of big data can be described as follows. (1) Volume is related to the amount of data that is generated and grows rapidly on a daily basis [208]. In certain systems [56, 225], the telemedicine architecture consists of three tiers, namely, Tier 1 (user), Tier 2 (base station) and Tier 3 (server). The data sent from Tier 2 to Tier 3 include the user's vital signs which are further used in Tier 3 by doctors to provide the user with personalised healthcare services. The improvement in remote triage, prioritisation and healthcare services using this data has been demonstrated previously. This section aims to show how adding such data affects the total message size and how these data are considered big data in the server (Tier 3). The size of a user's message can reach the big data challenge by considering many stages (number of users, number of requests for one user per day, telemedicine users and in-hospital users for many departments inside the hospital such as EDs), as illustrated in Fig. 7. In remote monitoring, many sensors can be used, such as ECG, SpO2 and glucose sensor. These sensors may contain signal and image forms that may increase the data size. The increasing data size of users or patients is related to those inside the hospital and those who are outside the hospital and using the telemedicine system.

(2) Velocity is increasingly considered due to the rising volume of data that are provided instantly whenever the need for real-time processing arises [208]. It also indicates the frequency of data that are produced, processed and analysed [84]. In the current study, the velocity of big data is marked as the following sequence. (1) Data are produced from wearable medical sensors in the form of signals. The signals are produced as continuous real-time signals in Tier 1 and then sent to Tier 3 using a Tier 2 device. (2) In Tier 3, the signals are processed as records (each signal is converted to a record). Each record typically contains vital signs sampled (i.e. data) per one second of the signal. In Tier 3, (3) the records are analysed, and the big data are converted to information and then to knowledge on the basis of decision-making matrix.

(3) Variety refers to the data collected from a variety of sources [25]. Effective large-scale analysis commonly needs the collection of heterogeneous data from multiple sources [259]. The heterogeneity of sources in remote monitoring is represented by sensory (e.g. ECG, Spo2 and BP) and non-sensory measurements (chief complaint). The variation in the format of the collected data for one user per time slot offers benefits that can be summarised as follows. (1) Variation improves the outcomes of healthcare using precise and accurate diagnoses, customises care at the individual patient level (personalised medicine) and identifies patients who are at risk of poor outcomes. (2) Variation reduces cost via early disease detection. (3) Variation helps manage and predict health risks and detect healthcare fraud efficiently and quickly.

(4) Value is defined by 'the added-value that the collected data can bring' [259]. Many types of values are provided by remote monitoring. They include knowledge about patients, evaluation of patients and recognition of emergency cases.

(5) Variability is reflected in the wide range of format of big data and the changes during processes [25, 259]. In remote monitoring, various types of data are used, such as signals, images and text. Furthermore, the processes involved in changing data include feature extraction and data alignment.

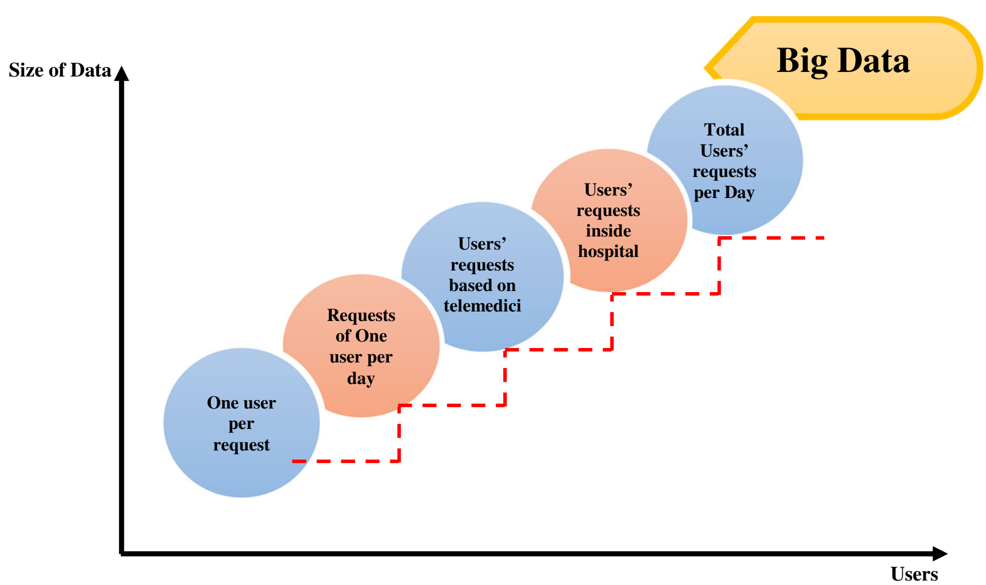


Fig. 7 Increasing measured data size in the healthcare server (Tier 3) for many users per day

In feature extraction, many real-time data processing algorithms have been designed to extract features and values from raw data. In data alignment, features of various sources have different values. Thus, evaluating the values of patient features requires standardisation and structuralisation. Increasing variability and variety also increases the capability to provide valuable, hidden and unexpected information and attractive data [259].

(6) Veracity comprises two aspects: data consistency (or certainty) and data trustworthiness [259]. It assumes the concurrent scaling up of the performance and granularity of the architectures, platforms, algorithms, methodologies and tools to cover big data requirements [204]. In such healthcare systems, various types of sensors can be involved, and they may differ in terms of accuracy and trustworthiness. However, connections between telemedicine tiers utilising Bluetooth, infrared and the Internet may raise the issue of inconsistency. Furthermore, in telemedicine, big data analytics will be executed in the server (Tier 3). Many tools and algorithms may be utilised for data analysis and processing, and they include data mining algorithms and decision-making techniques that are integrated with medical guidelines that may raise the veracity issue. Veracity in healthcare data faces many common concerns, such as 'Is this the correct patient/hospital?' Other veracity concerns are unique to healthcare, such as 'Are diagnoses/treatments/prescriptions/procedures/outcomes captured correctly?' [204].

Open challenges for real-time remote big data in patient prioritisation process

According to the aforementioned description of prioritisation processes, remote prioritisation of patients with big data analysis in medical systems faces many issues and challenges. The open research issues in the remote prioritisation study area are demonstrated in Fig. 8 and briefly explained in the subsections below.

Concern for evaluation criteria In general, various evaluation criteria have been used to triage and prioritise patients in EDs [225]. The majority of these criteria target injuries and illness in general [80]. Specifying a set of evaluation criteria for specific cases or diseases may increase the applicability and efficiency of the evaluation process. For remote patients, a set of evaluation criteria may be applicable because they are monitored on the basis of specified diseases or long-term conditions, such as chronic diseases. Literature demonstrates differences in vital signs and chief complaints used in triage scales [82]. An urgent need for the utilisation and integration of heterogeneous biomedical information to improve medical research, point of care and clinical practice is also noted [27]. Different sources (heterogeneous) that need to be

Fig. 8 Open research issues in remote prioritisation system

involved in the evaluation criteria for triaging and prioritising patients comprise sensory (vital signs and signals) and non-sensory (chief complaint) sources [225]. Each source is composed of subsets of features which involve a range of data used in various emergency cases and is important in generating compatible healthcare services to users. In conclusion, the demand for multiple heterogeneous sources in triaging and prioritising patients is increasing in ED and telemedicine environments.

Concern for criterion importance As mentioned in the previous section, different sources (heterogeneous) need to be considered in the evaluation criteria for triaging and prioritising patients. Each source (vital sign and/or chief complaint) comprises one or more features. However, the relation between vital signs and chief complaints are operationalised as the changing relative importance of vital signs [19]. Nurses or doctors may interpret vital signs differently in a case of two patients, in which one has a headache and the other one has chest pain (i.e. the relative importance of vital signs may change depending on the patient complaint) [19]. In addition, some sources are more important than others, and the features of each source may differ in importance. Doctors may assign great weight or importance to a specific source or feature. Thus, a server aimed at providing a score for a patient may give greater weight to a vital feature than to other features that attract little interest on the basis of medical guidelines. By contrast, developers who aim to design software for solving this problem will probably target different attributes as the most important attribute.

Concern for patient prioritisation Most studies have used the term ‘prioritisation’ to categorise patients into priority groups according to the triage level. The ranking within a priority group is obtained using the FCFS principle [64, 244]. However, FCFS cannot be used in reality because some patients may face more urgent emergency cases than others who have come before them and because of the continuous changes in patients’ vitals that require timely, well-informed and quick decisions in patient prioritisation [63, 243]. Patient condition should be the primary assessment tool for determining the prioritisation of patients according to the medical guidelines for assessing priority. This process involves simultaneous consideration of multiple attributes (vital signs and complaints) to score patients according to level of urgency. Patients with the most urgent cases should receive the highest priority levels, whereas the patients facing non-urgent cases should receive the lowest priority levels in the telemedicine environment. In general, healthcare decisions are complex and involve confronting trade-offs between conflicting and multiple objectives [247]. Specifically, patient prioritisation based on medical condition and chance of survival is a complex decision-making problem because decisions are made according to a set of attributes [16]. Therefore, structured and explicit decision-making methods that use multiple attributes can improve the quality of decision making and techniques [247].

Concern for big data analysis In general, the massive amounts of data gathered in healthcare practices are too voluminous and complex to handle and analyse using conventional methods [178]. Data analytics is one of the main parts of the big data environment. It is responsible for simplifying data complexity and calculation for accomplishing expected patterns of data sets and outcomes [208]. In remote healthcare monitoring, data are continuously generated from monitoring sensors. Consequently, for such systems, increasing the number of users per unit area due to population ageing and disasters is considered a main problem for providers of healthcare services. In prioritising patients in the telemedicine environment, several sources and features need to be evaluated for a large scale of patients. The big data from sources of large-scale patients do not fit the structures of traditional database architectures, they move too fast, and they require robust methods to facilitate the prioritisation process [75].

Concern for adding sources Continuous health monitoring needs the system of sensors to be active around the clock [213]. According to literature, patients may use different types of sensors [212, 250]. In general, vital signs and chief complaints involved in triage scales vary [82]. Further developments of remote triage and prioritisation methods are being planned and carried out to add other heterogeneous or homogenous medical sources, such as wireless body area network medical sensors, localisation sensors and environment sensors [225]. Adding sensory and non-sensory sources, such as image, video and text representations that reflect patients’ complaints, is necessary. Employing decision-making theories to raw data for heterogeneous sources is not mathematically applicable because of the following: (1) the raw data have inconsistent format (e.g. the signals from sensors are represented by numbers, and the complaints are represented by texts) and (2) the numbers are differently interpreted in medical diagnostics (e.g. ‘99’ in SpO2 means ‘normal triage level’ whereas ‘50 mm Hg’ in systolic BP means ‘risk triage level’).

Concern for system complexity The trade-off between adding and integrating medical sources and the increasing complexity of telemonitoring systems is a challenge, and it should be verified and evaluated for any proposed remote triage and prioritisation method [225]. In remote monitoring, huge volumes of data from heterogeneous sources are generated frequently [225]. For triaging and prioritising patients in a scalable environment, servers need to accommodate the number of patients and the large amount of data from sensing devices and other sources. However, this accommodation may raise the issue of complexity. Furthermore, the decision-making techniques and mathematical analyses for improving the process of triaging and prioritisation for patients may give rise to time and other complexity issues.

Recommended solutions for future directions

The scalability problem mainly occurs because of population aging, disasters, and mass causalities in the ambient environment. Emergency healthcare for mass casualties is a sophisticated process with multi-participants [248]. Transporting patients to hospitals is a possible solution, but it causes other problems related to triaging time and triaging accuracy of triage nurses in the ED. To solve those problems, remote triage using the paper triage method was presented as a solution. The paper triage method has many problems and weaknesses related to the accuracy of triaging and the prioritization process. Electronic triage was developed as a solution to the problems in paper triaging accuracy. However, triaging the remote patients into three classes using START guidelines is not the optimal solution [225]. Triaging the remote patients into 5 classes and the usage of heterogeneous sources can improve the accuracy of the extracted triage level. The rank of patients within the priority groups is usually obtained using a FCFS method [64, 244]. However, FCFS cannot be used in reality since some patients may have more emergency case than the others come before and because of the frequent change in patients’ vitals, a timely, quick, and well-informed decision in prioritizing the patients is required. Another problem appears which relates to the increasing in the size of the received data from a large scale of users in the server side of the telemedicine architecture. Besides, in order to implement a method to tackle all the issues above, a cases study need to been adopted (for instance; chronic heart disease, diabetic, or hypertension). Narrowing down the scope of the targeting patients by specifying a case study (disease) help in determining particular sources (sensors and chief complaints) that are directly related to the case study.

The process of prioritization involve simultaneous consideration of multiple attributes (vital signs and complaints) to score big data of patients based on the most urgent case. Therefore, adapting explicit and structured methods to decisions using multiple attributes may increase the decision-making quality and a set of methods, known under the collective heading multiple criteria decision analysis (MCDA), are applicable in such cases. In the real world, useful methods that deal with MCDM challenges are introduced as the recommended solutions that collectively assist decision makers organize the problems to be solved and conduct analyses, assessments, and ranking [114].

Multi-criteria decision making (mcdm): definition and importance Keeney and Raiffa [129] define MCDM as "an extension of decision theory that covers any decision with multiple objectives. A methodology for assessing alternatives on individual, often conflicting criteria, and combining them into one overall appraisal…" In addition, Belton and Stewart [38] define MCDM as "an umbrella term to describe a collection of formal approaches, which seek to take explicit account of multiple criteria in helping individuals or groups explore decisions that matter." MCDM is the most well-known decision-making technique, and it is a branch of operations research (OR) that deals with decision problems regarding decision criteria [149, 193]. MCDM is involved with structuring, planning, and solving decision problems using multiple criteria [149]. The goal is to help decision makers resolve such problems [289]. MCDM is often expressed as a process that uses a set of quantitative and qualitative methods to explicitly and simultaneously consider multiple and often conflicting factors [31, 247]. The use of MCDM is rapidly increasing owing to its capability to improve the decision quality by making the process decision more efficient, rational, and explicit than that by conventional processes [183]. The aims of MCDM are as follows: (1) help data miners select the best alternative, (2) rank the alternatives in decreasing order of performance, and (3) categorize the viable alternatives among a set of available alternatives [36, 114, 120]. Accordingly, the suitable alternative(s) will be scored. The fundamental terms in any MCDM ranking should be defined, containing the decision matrix (DM) or the evaluation matrix (EM), as well as its criteria [264]. An evaluation matrix consists of n criteria and m alternatives that required to be created. The intersection of each criteria and alternative is specified as x_ij. Therefore, we have a matrix (x_ij) _ (m*n) expressed as follows:

$$\boldsymbol{D} = \begin{array}{c} \\ \boldsymbol{A}_1 \\ A_2 \\ \vdots \\ \boldsymbol{A}_m \end{array} \begin{array}{c} \begin{array}{cccc} \boldsymbol{C}_1 & \boldsymbol{C}_2 & \ldots & \boldsymbol{C}_n \end{array} \\ \begin{bmatrix} \boldsymbol{x}_{11} & \boldsymbol{x}_{12} & \ldots & \boldsymbol{x}_{1n} \\ \boldsymbol{x}_{21} & \boldsymbol{x}_{22} & \ldots & \boldsymbol{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{x}_{m1} & \boldsymbol{x}_{m2} & \ldots & \boldsymbol{x}_{mn} \end{bmatrix} \end{array}, \tag{1}$$

Where A_1, A_2, …. , A_m are probable alternatives, which decision makers need to rank (i.e., patients). C_1, C_2, …, C_n are the criteria against which the performance of each alternative is evaluated (i.e., vital signs and/or complaints). Lastly, x_{ij} is the rating of alternative A_i with respect to criterion C_j, and W_j is the weight of criterion C_j. Certain processes must be achieved to score the alternatives, for example normalization, maximization indicator, adding weights, and other processes depending on the method. For instance, suppose that D is the decision matrix used to score the performance of the alternative Ai, where based on C_j Table 6 is an example of multi-criteria problem described by [110].

The data in the chart is not easy to been evaluated due to the large numbers of c2 and c3 (Fig. 9)

The process of decision-making can be enhanced by involving stakeholders and decision makers and provide the process with structure and support. Using explicit, structured methods to decisions concerning multiple criteria can increase the decision making quality and a set of techniques. This set of techniques offers clarity on which criteria are relevant, the importance attached to each, and how to involve this information in a framework for evaluating the existing alternatives. By doing so, they can help increase the transparency, consistency, and validity of the decision. MCDM has the potentiality to contribute to a fair, transparent and rational priority-setting process.

Multi-criteria decision making (MCDM) applications MCDM methods are largely practical for various applications through ranking and finding the best solution to select the best alternative [14]. Furthermore, MCDM applications are effectively involved to solve decision-making problems in various fields, such as sustainable energy management [260], energy

Table 6 Example of multi-criteria problem

Ai Cj	C1	C2	C3	C4	C5	C6
A1	2	1500	20000	5.5	5	9
A2	2.5	2700	18000	6.5	3	5
A3	1.8	2000	21000	4.5	7	7
A4	2.2	1800	20000	5	5	5

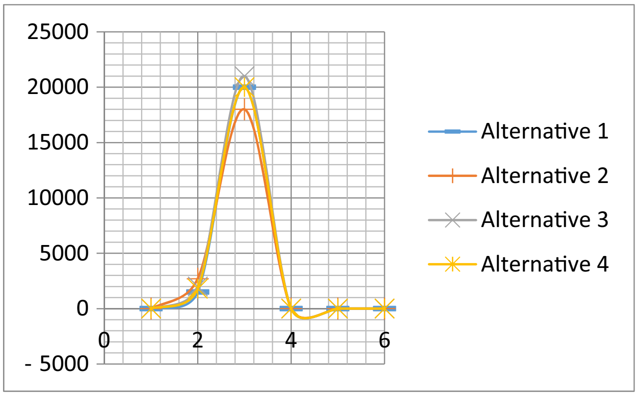


Fig. 9 Graphical presentation of the example in Table 4

planning [102], transportation [202], geographical information systems [93, 145], and resource and budgeting allocation [194]. The use of MCDM in healthcare applications has increased recently [247]. An overview of using MCDM in the healthcare domain will be clarified in the next section.

Multi-criteria decision making (MCDM) in healthcare domain The use of MCDM in healthcare is now familiar practice [2, 74, 247]. With the various MCDM methods, healthcare decision makers can improve their decision making by systematically obtaining the best solution [174]. The importance of healthcare decision making cannot be emphasized enough, as many of these decisions are complex, involving uncertainties and the elicitation of stakeholders' values and preferences [2]. MCDM improves consistency and transparency in the process of decision making and the accountability of decision makers in healthcare. It does not mimic or replace medical judgments but is relatively used to identify, collect, and structure the required information by those judgment makers to improve the decision-making process [247]. With MCDM, the preferences, value judgments, and priorities of patients, experts, and insurers can be integrated transparently and systematically into the decision-making process [174]. The main future challenges regarding the use of MCDM are the lack of familiarity with the variety of MCDM methods and the absence of instructions on which MCDM process is most applicable in a particular healthcare situation [174]. No crucial solution is available for improving the process of decision making in healthcare; nonetheless, tools such as MCDM will be a step further [2].

MCDM is becoming a common methodology to help and support decision making in healthcare [154]. The literature comprises a number of reviews regarding MCDM applications in healthcare. Ho [108] conducts a survey for the applications of the integrated analytic hierarchy process (AHP) using a literature review and classification of the international journal publications from 1997 to 2006. Furthermore, Liberatore and Nydick [143] provide a literature review of the AHP application regarding important problems in healthcare and medical decision making. Guindo et al. [100] also recognized the criteria of decision making and its frequency in healthcare literature. Diaby et al. [74] documented healthcare MCDM applications and identified publication patterns, along with the kind of issues encountered by MCDM. In addition, Kevin Marsh et al. [155] provide a review of the literature to evaluate healthcare value interventions using MCDM. By contrast, a systematic review provided by Adunlin et al. [2] identified MCDM applications of healthcare areas and recognized the trends of MCDM publication in healthcare on the bases of recognized bibliographical records. Thus, recently, MCDM has been applied in different healthcare domains in the literature and is considered a new trend.

Multi-criteria decision making (MCDM) methods Several MCDM theories are explored [271]. The most common MCDM methods that employ various concepts include weighted product method (WPM), weighted sum model (WSM), multiplicative exponential weighting (MEW), simple additive weighting (SAW), hierarchical adaptive weighting (HAW), analytic network process (ANP), AHP, and technique for order performance by similarity to ideal solution (TOPSIS) ([200, 201, 226, 280, 281, 274]). The advantages, shortcomings, and recommendations for popular MCDM methods are presented as follows on the basis of the literature [14, 186, 251, 252, 273].

HAW and WSM are easy to understand and use. However, the attribute weights are assigned arbitrarily, and both methods are difficult to adopt in case of numerous criteria. An additional drawback of these methods is that common numerical scaling is used to calculate the final score. The advantages of WPM and MEW are their capability to eliminate any item to be measured and the use of relative values rather than actual ones. On the contrary, these two methods do not offer any solution with equal decision matrix (DM) weight. SAW considers all criteria, provides simple calculation, and makes decisions intuitively. Nevertheless, all criteria values must be positive and maximum. In addition, SAW does not usually reveal the real situation. AHP allows DMs to structure the decision-making problem into a hierarchy that simplifies and facilitates understanding of the problem. However, this method is time-consuming because of the number of pairwise comparisons and required mathematical calculations, which increase as the number of criteria and alternatives increase or change. Scoring in AHP relies on the alternatives considered for evaluation. The deletion and addition of alternatives may alter the final ranking (rank reversal problem). The TOPSIS method is connected to discrete alternative issues and is one of the most effective approaches to solve real-world problems. The important merit of TOPSIS is its capability to immediately recognize the most suitable alternative. The major drawbacks of TOPSIS include the lack of provision to weigh elicitation and check the consistency of judgments [230]. The use of AHP is significantly restrained by the human capacity for information processing; thus, 7±2 is regarded as the ceiling for comparison [219] [4].

By contrast, the ANP method provides a complete understanding of the significance level that a criterion can take regarding its correlation with other criteria. The advantage of this method is that it allows for measurement of the judgments' consistency, which is impossible to evaluate in the method that assigns weights by compromise. An additional advantage of the ANP model is that it helps assign weights by breaking up the problem into smaller parts so that a group of experts can have a manageable discussion because only two criteria are compared in assigning judgments. Conversely, ANP has two disadvantages. First, providing a correct network structure among criteria is difficult even for experts, and different structures lead to different results. Second, the formation of a super matrix requires pairwise comparison of all criteria with all other criteria, a step that is both difficult and unnatural [141, 218]. Based on this perspective, TOPSIS decreases the pairwise comparisons required, and the capacity limitation may not significantly dominate the process. Consequently, TOPSIS is applicable for cases with numerous alternatives and criteria; it is also specifically convenient to use when quantitative or objective data are provided.

To our knowledge, none of the discussed methods has been used to rank a large scale of patients in a telemedicine environment. However, these methods lack indicators of how well this healthcare service can satisfy the needs of patients. An additional issue with these methods is the non-adoption of a requirement-driven approach that makes them insufficient for priority scoring based on decision making [277, 278]. However, TOPSIS is functionally related with discrete alternative problems. This technique is one of the most practical ways to solve real-world problems. The benefit of TOPSIS is its capability to rapidly find the best alternative. Thus, it is appropriate for situations with numerous alternatives and attributes [179]. The chief shortcoming of TOPSIS is the lack of provision for weight elicitation and the checking of judgment consistency [230]. Accordingly, TOPSIS requires an effective technique to obtain the relative importance of various criteria with respect to the objective; AHP provides such a procedure. AHP is used to establish weights for objectives based on the preferences of stakeholders [179]. However, as it is significantly restricted by the human capacity for processing information, 7±2 is regarded as the comparison ceiling [219]. From this viewpoint, TOPSIS alleviates the requirement of paired comparisons, and the capacity limitation might not significantly dominate the process [122].

Recently, the newest trend regarding the use of MCDM techniques is to integrate two or more techniques to compensate for weaknesses in a single technique [32, 49, 185]. AHP and TOPSIS have become a commonly accepted integrated MCDM method for the following reasons: the use of weights and objective data to obtain relative distances, the capability to offer complete ranking results, the smoothing of trade-offs by dealing with nonlinear relationships, the ease at which it can be converted into a programmable procedure, and the suitability to be combined with stochastic analysis [179, 185]. A number of integrated approaches are involved in alternative prioritization and ranking issues in the literature. An example of an application is provided by Nilsson et al. [179], who successfully combine AHP and TOPSIS to rank a large number of strategic plans for managing the forest in cases with several stakeholders and multiple objectives. Beikkhakhian et al. [35] propose an evaluating model for agile supplier criteria selection and supplier ranking by using fuzzy AHP–TOPSIS methods. Certainly, AHP–TOPSIS has applications in several fields [172], but patient prioritization in healthcare applications is not addressed. Taylan et al. [245] use fuzzy AHP to conduct suitable weights for five main criteria, namely, quality, safety, cost, time, and environmental sustainability. They then applied fuzzy TOPSIS to score 30 construction projects based on seven decision makers in various sectors in Saudi Arabia. Thus, a methodological approach is recommended to cover this gap. As a conclusion, to prioritize a big data of patients in the telemedicine environment, an integration of the AHP is recommended to establish weights for evaluation criteria based on the experts' judgments, and TOPSIS is recommended to provide an overall ranking of patients.

Conclusion

This study presented a review on triage and prioritization of large scale telemedicine patients with big data analysis. Several techniques for triaging and prioritizing patients have been presented and evaluated. The weakness points were also determined, and possible solutions were discussed and recommended. The findings emphasized open issues and challenges for triaging and prioritizing patient's process. Moreover, the MCDM in the framework of the triaging and prioritizing patients were discussed. Several decision-making techniques showed different configurations and contexts (e.g., individual decision making and group decision making. Thus, we recommend the selection of the appropriate technique, method, and context experimentally as methodological approach to cover this gap. In future direction, to prioritize a big data of patients in the telemedicine environment, an integration of the AHP is recommended to establish weights for evaluation criteria based on the experts' judgments, and TOPSIS is recommended to provide an overall ranking of patients for different chronic diseases (heart, diabetes, and BP) requires further investigation in the future. Moreover, increasing the sources (such as, video, audio, image, medical sensors, and

GPS) for triage for the prioritization and designation of appropriate emergency levels to patients remains an issue.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study.

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