STUDIES IN HEALTH TECHNOLOGY AND INFORMATICS 291

Accident and Emergency Informatics

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Time is short in emergency situations; the need for action becomes imperative. Biomedical Informatics can be invaluable in supporting the management of emergency medicine, and the need for the creation of Accident and Emergency Informatics (A&EI) as a novel subfield became obvious. As in all areas of Biomedical Informatics, A&EI must deal with issues such as relevant data collection, the management of data extracted from accident sites, health records or sensors, wearables and apps, and appropriate data processing, with the dual purpose of preventing harm and decision support.

This book is an introduction to the research and application domain of A&EI, and is the product of three years' work by the Working Group in A&EI of the International Medical Informatics Association (IMIA). The book presents ten chapters organized in four sections. The first section explores the framework for achieving an emergency-informatics health information infrastructure; the second focuses on the gathering of critical clinical data related to the building up of a smart environment for A&EI; the third introduces state-of-the-art technologies for integration into virtual emergency registries; and the final part considers the delicate issues of patient safety raised by the introduction of surveillance technologies into clinical care, along with other issues presenting challenges to the domain of A&EI for the future.

The book is an important contribution to the field of A&EI, and will be of interest to healthcare professionals, informaticians, and all those who want a better understanding of the domain of Accident and Emergency Informatics.

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ACCIDENT AND EMERGENCY INFORMATICS

Studies in Health Technology and Informatics

International health informatics is driven by developments in biomedical technologies and medical informatics research that are advancing in parallel and form one integrated world of information and communication media and result in massive amounts of health data. These components include genomics and precision medicine, machine learning, translational informatics, intelligent systems for clinicians and patients, mobile health applications, data-driven telecommunication and rehabilitative technology, sensors, intelligent home technology, EHR and patient-controlled data, and Internet of Things.

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Foreword

Accident & Emergency Informatics: Proposals for Enhancing Emergency Medical Services

Until the 19th century, the term urgent was limited to the technical and didactic lexicon of medicine to denote "what must be taken care of without delay" because the vital prognosis was engaged. If 'urgent' is deeply correlated with 'vital' in the case of a sick or injured individual, this is also the case for phenomena with a more collective dimension, such as large fires, pandemics, wars, and natural disasters. This extension of the range of emergency situations has been accompanied by the exaltation of the person who faces them. The value of the emergency physician lies in their capacity to collect, store, treat, and manage data to preserve the vital under time pressure. As such, they are commonly considered to be magicians of decision.

In 1944, Paul Valéry wrote [1]: "All this requires such a rich collection of abilities, such a rapid and thorough memory, such a reliable science, such a sustained character, such a lively presence of mind, such a physical resistance, such a sensorial acuity, such an uncommon precision of gestures […]."

Thus, the mythical figure of the emergency physician embodies the ideal of human perfection, combining all the aptitudes of the body (physical resistance, precision of gesture, awakening of senses) and all the skills of the mind (knowledge, memory, assertiveness). Besides, since the various faculties necessary to the decision are not chronologically presented, celerity and vivacity are also mandatory to guarantee the safety of this decisional instantaneity.

Given all the qualities of the emergency physician, the role of Biomedical Informatics to support the management of the urgent and the vital became obvious, as did the creation of Accident and Emergency Informatics as a novel subfield. As in all areas of Biomedical Informatics, Accident and Emergency Informatics must provide solutions to relevant data collection, management of heterogeneous data (extracted from accident sites, health records of subjects involved in such accidents, sensors, wearables, apps, etc.), and appropriate data processing, with the dual purpose of serving prevention and patient-care decision support. However, time is short in emergency situations, the need for action becomes insistent; it requires attention, imposes speed, demands rapid action and care while limiting thought, all of which makes time pressure management the specificity and the challenge of this new subfield.

Brigitte Seroussi

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[1] Paul Valery, « Discours aux chirurgiens » in *Variété V*, Paris, Gallimard, 1944, p. 48.

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Preface

Preparing and publishing a first book on Accident and Emergency Informatics (A&EI) is not only an important task, but also an enormous accomplishment with a profound impact for the scientific and healthcare community. The International Medical Informatics Association, with its Working Group in A&EI, has worked in a productive and innovative way in this field for the last three years to introduce this research and application domain as a field of great interest; the Informatics in Emergency Medicine and Clinical Care.

This book is the outcome of many discussions, meetings, workshops, and scientific exchanges in the domain, as viewed and experienced by the distinguished editorial team and the expert and renowned authors. The ten chapters in the book are organised in four sections.

The first section is mostly dedicated to the framework for achieving an emergency-informatics health information infrastructure. The second part is focused on the sensory information gathering of critical clinical data related to the building up of a smart environment for A&EI. The third part introduces the state-of-the-art technologies of Virtual technology and the Internet-of-Things for integration into Virtual Emergency Registries. The final part considers the delicate issues of patient safety raised by the introduction of surveillance technologies into clinical care, along with other issues being tackled by the domain of A&EI in facing the challenges of the future. In addition, the final part discusses the principles and methods for evaluating A&EI applications; a critical challenge for gaining the acceptance of healthcare professionals.

It is clear that such a book, prepared as a concise edited volume and introducing a new domain such as A&EI for the first time faces a unique challenge to be up to date and to the point, to define principles, to formalise specific methodologies, to describe applications, to provide methods for evaluation and to see and foresee future challenges and suggest solutions. All these aspects have been considered and tackled in an excellent and masterful way in this book, which is an important contribution to the field of A&EI, making it very appropriate and suitable for recommendation to Healthcare Professionals and Informaticians wishing to understand and fathom the domain of Accident and Emergency Informatics.

John Mantas
Athens, 25 Jan 2022

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Introduction: Accident and Emergency Informatics Book

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In Germany alone, more than two million traffic accidents are reported annually. Although the number of injuries, including fatal injuries, is decreasing steadily, a quarter of a million people were hurt in Germany in 2021, and the number of deaths was 2,148 [1]. According to the World Health Organization (WHO), the number of fatalities is approximately 1.3 million worldwide [2].

While death is a clearly defined endpoint, minor or severe injury is rather vague, in particular if compared on an international level. A similar ambiguity holds true for damage to the vehicle, which is often measured in terms of monetary cost rather than mechanical impact, although such data is available from the event-data recorder (EDR) of modern vehicles [3].

But what if data from the EDR were linked to the occupant's electronic health records (EHR)? And what if such linked data were recorded for every traffic accident worldwide? Then, any car involved in an accident could browse this database, find similar events in the past, access the corresponding health impact, and provide prognoses of possible harm individually for each occupant depending on their seat, size, weight, and seat belt status. Using information and communication technologies (ICT), the car could instantaneously request the appropriate rescue services [4,5], which would save time for the injured occupants and costs for the healthcare system [6].

It is not only vehicles that are equipped with sensing devices, computational power and communication abilities in the era of the Internet of things (IoT). Smart phones and other wearables, smart homes, and smart cities not only report the accidents and medical. emergencies of a given individual, but also environmental hazards, disasters, and pandemics [7,8].

More generally, Accident & Emergency Informatics (A&EI) is the trans-disciplinary science of systematically collecting and managing medical data (e.g., electronic health records) as well as sensor data from the human environment (e.g., event-data recorders such as acceleration sensors in the vehicle), their syntactic and semantic integration, and their analytics, in order to forecast, prevent, or lower the impact of such events on the subject [9].

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The core mission of A&EI is saving lives – on the one hand by combining and jointly analysing medical and non-medical data, and on the other hand, by involving decision-makers, actors, and stakeholders from politics, infrastructure, health management, and industry.

In 2017, the Peter L. Reichertz Institute for Medical Informatics (PLRI) of TU Braunschweig and Hannover Medical School, one of the largest and most famous academic centres for electronic health in Germany, filled a new professorship (Prof. Thomas M. Deserno) to combine accident research with medical informatics, and in 2018, the Metropolitan Region Hannover Braunschweig Göttingen Wolfsburg selected the Center for Accident & Emergency Informatics of PLRI as a lighthouse project of the Metropolitan Region, Germany[9]. The German state of Lower Saxony then provided essential funding to foster research aimed at creating an International Standard Accident Number (ISAN) [9].

In 2018, the International Medical Informatics Association (IMIA)'s General Assembly confirmed the IMIA Working Group on A&EI. The founding members of this working group are drawn from the Asia Pacific Association for Medical Informatics (APAMI), the European Federation for Medical Informatics (EFMI), the Regional Federation of Health Informatics for Latin America and the Caribbean (IMIA LAC), the IMIA North America, and the Middle East and North Africa Health Informatics Association (MENAHIA) [10].

(source: https://aei.plri.de/de/network/imiawgonaei)

According to the IMIA working group, A&EI research is focused on the conception (syntactic and semantic interoperability), implementation (at least on the prototype level), and operation (at least as a field experiment) of sensor-enriched medical information systems. Their research is addressing the following tasks:

- *Data collection*: Collecting sensor-based event data related to accidents and medical emergencies must happen in real-time. Relevant data is recorded with fixed sensors in a living space, in a vehicle, or with sensors worn on or even inside the human body. Today's vehicles are already equipped with a variety of sensors (e.g., temperature, rain, global position, seat belt status, airbags, brakes, surroundings, voice and image recognition, and other assistance systems) but other living spaces (e.g., homes) will need to be enriched with recording sensors.

- *Data management*: A&EI data must be stored in appropriate registries. The design and implementation of such data repositories that are interoperable and meet data privacy and security requirements is important. In the near future, decentralised or virtual registries will play an important role in A&EI data management.

- *Data integration*: Linking event-related data to medical data will yield increased knowledge of accidents, emergencies, and disasters. Location and time-based identifiers are needed to bridge the different registries. Such automatically generated identifiers (e.g., the ISAN [5,6,11]) need appropriate integration in existing data systems.

- *Data analytics*: In order to predict adverse health events, to take a specific action for prevention, or to lower their impact on humans, the merged data have to be analysed. Therefore, A&EI involves state-of-the-art methods of data science and analytics targeting at automatic alarming systems that actually save lives.

Therefore, IMIA WG A&EI supports the United Nations' 2030 Agenda for Sustainable Development [12], where the Sustainable Development Goal (SDG) goal 3 on health and well-being is to ensure healthy lives and to promote well-being for all people of all ages; as well as the WHO 13th General Programme of Work [13], which has three interconnected strategic priorities to ensure healthy lives and well-being for all: (i) achieving universal health coverage, (ii) addressing health emergencies, and (iii) promoting healthier populations.

In 2019, the IMIA WG A&EI had its first in person meeting at MedInfo world congress in Lyon, France. The members decided to focus on four subjects, which have guided the structure of this book:

1. Frameworks for Record Linkage in Emergency (Chapters 1–3),
2. Smart Environments for A&EI (Chapters 4–6),
3. Physical and Virtual Emergency Registries (Chapters 7 & 8), and
4. Future Challenges and Opportunities in A&EI (Chapters 9 & 10).

Reports on international efforts were collected for this book. Within two years, 18 chapters had been proposed, and ten have been selected for publication. Twenty eight authors have followed the entire early-rescue chain: from the sensor-based systems alerting emergencies and disasters through response to curing systems, together with their interconnections.

Part 1 of the book elaborates the type of data and components required in an emergency, irrespective of its location. It addresses the technical barriers and technological restrictions associated with the practical use and exchange of data to shape a network of rescue components in an emergency. This part also considers event triggering, where machine learning (ML) contributes to automatic event detection at the point of care. The authors of this section describe how ML applications are spread over various stages of a rescue operation.

Part 2 focuses mainly on the technologies applied to the point of perception of emergencies, disasters, and other events. The general aim is to develop a smart environment for the continuous and unobtrusive monitoring of individuals. This section highlights the importance of health monitoring in private spaces (e.g. smart home, smart car) and emphasises "health for everyone in any occupation". It discusses the pros and cons of mobile health monitoring and other options for continuous health monitoring anywhere, at any time and for anyone.

The Covid-19 pandemic has highlighted the necessity for virtual emergency and disaster alerts. Maintaining distance between people for protection, the overwhelming of emergency and triage sections of the hospitals by unnecessary visitors, shortage of facilities and time for the examination and curing of patients with a higher priority; all of these represented a serious alert for the healthcare system to be prepared in order to overcome the next potential disaster. Thus, part 3 of this book takes advantage of the available paradigms, trends and technologies such as ICT, IoT, mobile health (mHealth) and network security to:

i) analyse the virtual emergency requirements in a disaster
ii) propose a pipeline
iii) give examples of applications
iv) outline current limitation
and
v) suggest solutions for the bottlenecks.

Part 4 raises and evaluates the fundamental questions of A&EI applicability. The authors, after outlining the requirements of current healthcare systems, elaborate on data linkage and the benefits of such approaches. This section precisely formulates an event, accident or emergency and distinguishes the type of data and its contribution within the early rescue chain. Challenges and opportunities in the automatic reporting of events are discussed from point of view of both the medical professional and the patient.

A&EI is growing fast and finding its role in public-health services. Its aim is to serve public health by contributing to the health of individuals from the perspectives of long-term monitoring and instant-event detection. The field increases the correspondence knowledge of on-site accident data by automatic data linkage from distributed sources.

This book is aimed at inspiring the most important aspects and dimensions in the field of A&EI. It collects the views of the individual authors, which may not necessarily be those of all the authors or editors of the book. These differing opinions may well serve to foster a scientific discussion. We hope that you will enjoy reading the book and actively contribute and further the development of accident & emergency informatics.

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Contents

Part 4. Future Challenges and Opportunities in A&EI

Part 1

Frameworks for Record Linkage in Emergency

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Towards the Application of Machine Learning in Emergency Informatics

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Abstract. Emergency care is one of the cornerstone parts of the world health organization's action plan. Rapid response and immediate care are considered in agile emergency care. Artificial intelligence (AI) and informatics have been applied to fulfill these requirements through automated emergency technology. Machine learning (ML) is one of the main parts of some of these proposed technologies. There are various ML algorithms and techniques which are potentially applicable for different purposes of emergency care. AI-based approaches using classification and clustering algorithms, natural language processing, and text mining are some of the possible techniques that could prove useful for investigating models of emergency prevention and management and proposing improved procedures for handling such critical situations. ML is known as a field of AI which attempts to automatically learn from data and applies that learning to make better decisions. Decision-support tools can apply the results of either supervised or various semi-supervised or unsupervised learning methods to tackle the how decisions about emergency situations are typically handled by the best professionals at the scene of an emergency, in the pre-hospital, and in healthcare facility settings. Enhanced and rapid communication at the moment of emergency, with the most effective decision making for triaging to estimate the acute nature of injuries and possible complications, how to keep a patient stable on the way to the care facility, and also avoiding adverse drug reactions, are some of the possible directions for exploring how ML can help to gather the data and to make emergency management more efficient and effective. The wide range of scenarios present in emergency situations and the complexity of different legal and ethical constraints on what responding personnel are allowed to perform on an injured subject before reaching a hospital makes for a most challenging set of problems for investigating the components of "intelligent" decision support that could help in these highly interactive and humanly tragic situations.

Keywords. Machine Learning, Emergency Care, Artificial Intelligence, Informatics

1. Introduction

Emergencies may occur at any time, often without warning, and even though the latest technologies are used. Even in a perfect world, it's crucial to be prepared for handling emergencies. Accident and emergency management is a synchronized activity involving

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numerous agents [1]. According to the 2019 report from the United Nations (UN) office for disaster risk reduction (UNDRR), there were 7,348 cases of major recorded disaster events affecting 4 billion people in the last 20 years [2]. To tackle these situations, at the societal level, risk reduction approaches are required. We propose a multisector professional approach aiming at avoiding emerging risk types and circumstances, addressing pre-existing types of emergencies, sharing information between those that are involved, and proposing good alternatives to tackle a particular type of situation, as already considered in [1, 2]. According to the definition provided by the American College of Emergency Physicians, emergency care is a medical field focusing on the diagnosis and treatment of acute and severe illnesses or injuries. It has a fundamental role in providing care to patients seeking urgent medical care [3]. Emergency informatics emphasizes the application of informatics for managing accidents and emergencies. Informatics has the potential to improve effectiveness of emergency responses and theircompetent and ethical handling with rapid information updates, providing prompter reactions from possible preplanning by using simulators, and estimating possible possible outcomes in accidents and emergencies

Informatics has been defined as the interdisciplinary study of the design, development, adoption, and application of information technology-based innovations in healthcare services delivery, management, and planning [4]. It is closely related and sometimes taken as synonymous with computer science but mainly known as the application of computing technologies as a profession, according to Association of Computing Machniery (ACM) Europe and the Informatics Council [5]. It is applied to various real-life problems providing novel and effective solutions. Computer systems and computational processes technologies have various subfields in which artificial intelligence (AI) is an emerging one composed of computer science methods and reliable datasets [6]. Machine learning (ML) is a major subfield that is frequently mentioned in conjunction with AI. This discipline is comprised of algorithms seeking expert systems creation for predicting or classifying available data to develop models for decision-making support. There are various applications of ML in everyday life. The popularity of the implementation of these systems is dramatically growing due to the increase in the availability of data in our society[6]. Recently, ML techniques have become popular in various fields to define algorithms based on the use cases for patterns extraction in big data [7].

The clinical practice of emergency informatics encompasses the initial assessment, diagnosis, treatment, coordination of care among different physicians, and stabilization of cases such as injuries and infections, heart attacks and strokes, asthma, and acute complications of pregnancy. The care may vary based on the degrees of acuity for any given patient [8]. An integrated view of emergencies from early recognition to rapid management of cases can save lives. This view has been addressed by the World Health Organization (WHO) and the output is a visual summary drawing the essential functions of an agile and responsive emergency care system (Fig. 1). The key human resources, equipment, and information technologies are considered in three main sections [9]. In an emergency, necessary activities in the scene, prehospital, and in hospital setting must be conducted, as precisely and quickly as possible. Proper technologies such as AI might be a good support to achieve this crucial aim.

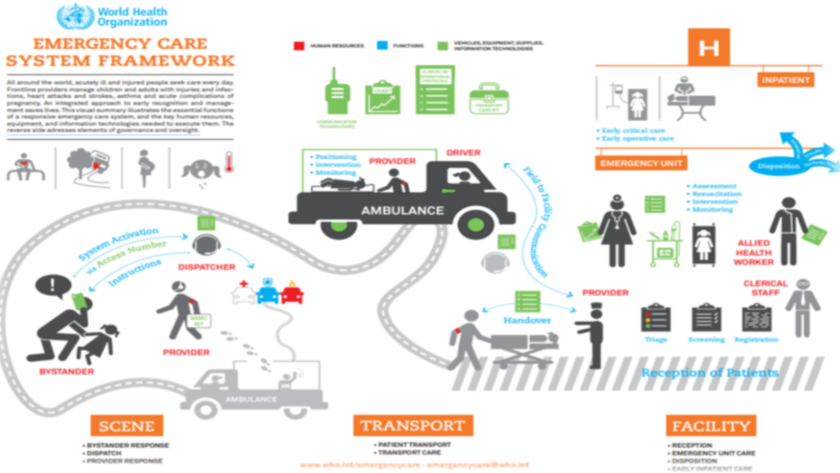

Figure 1. The WHO framework for emergency care [9].

2. Intelligent Emergency Informatics

Intelligent emergency informatics implies the usage of AI in technology-based emergency care and support. This application has been in various usages, such as automated triage and dispatching system using intelligent resources to detect medical emergencies, optimize planning, and improve prioritization [5, 10]. To understand the use-cases of AI for emergency care in detail, the survival chain may work well, as the staging of emergency care addressed in Fig. 1 by WHO is general. The chain encompasses triaging of emergency calls, provision of emergency medical services, treatment in the emergency department, inpatient and intensive care treatment (if needed), and the discharge of patients or transfer to long-term care. Technology has been applied to each component (Fig. 2). Provided technology may improve the speed and quality of care for each emergency-based solution on the given step.

As an example, intelligent triage centers detect cardiac arrests and help dispatchers to detect out-of-hospital cardiac arrests with an average of 30 seconds faster than human operators [11]. At the emergency department, AI has been applied for predictive modeling, patient monitoring, and day-to-day running of emergency departments. These intelligent tools may support health care providers in reducing waiting times in the emergency department, decreasing errors, and increasing the efficiency of care [12]. The impressive progress of AI to support emergency care has been enhanced by applying improved computing methods, integrated databases, and algorithm development. AI composed of the theory and computer systems development can perform tasks that normally require human intelligence such as visual perception, speech recognition, decision-making, and translation between languages [13]. ML is a key component of AI enabling emerging technologies to provide services in practice. It is well known as a field of AI with the ability to automatically learn from the data and applies that to make better decisions. Fig. 3 presents the applications and use-cases of AI as an emerging technology for intelligent emergency care [10]. They are mainly conducted by applying ML algorithms.

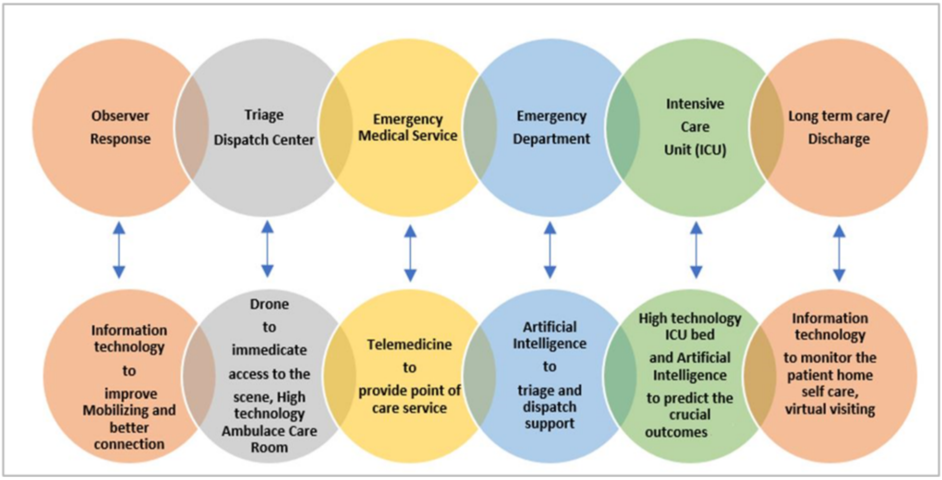

Figure 2. Available emergency technologies for each step of the survival chain in emergency care.

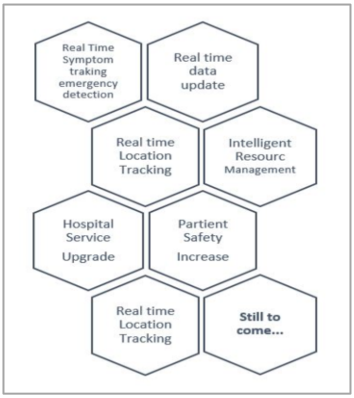

Figure 3. The artificial intelligence applications in emergency care.

3. Machine Learning for Emergency Informatics

With the rise of Al and ML, monitoring of information during emergent situations and decision-making under time-sensitive conditions have significantly enhanced. This achievement has created the potential for the spread of disease prediction, more efficient evacuation plans development, and effective distribution of resources to areas in need [5]. ML models are typically trained on large quantities of representative data for the target task and subsequently applied to unseen test data without a requirement for explicit programming and handcrafted decision boundaries. During the training process, these algorithms normally perform iterative updates to parameters of the model, which is then used to make predictions and improve at achieving the desired task over time. Comparatively, ML is similar to statistics as both fields can be used, in principle, to make inferences or predictions [14].

The utilization of computer science and statistics concerned with automatic improvement over time, leads ML to support the user including the clinicians in decision-making under uncertainty [6]. ML is an inductive process that automatically creates a classifier tool. It is conducted via learning the characteristics of classification categories from a set of pre-classified documents. The major ML approaches fall under the category of supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning algorithms build a mathematical model by using a set of historically labeled data known as the training data; however, in unsupervised learning, no label is available for each record of the dataset. Using the training data and supervised learning algorithms, a model is developed; it is then tested on test data with the goal of output prediction based on input. Supervised learning algorithms include classification and regression [7, 12]. Some of the most important algorithms in this field are logistic regression, support vector machines (SVM), naive Bayes algorithm, decision trees, random forest, gradient boosting, and deep learning.

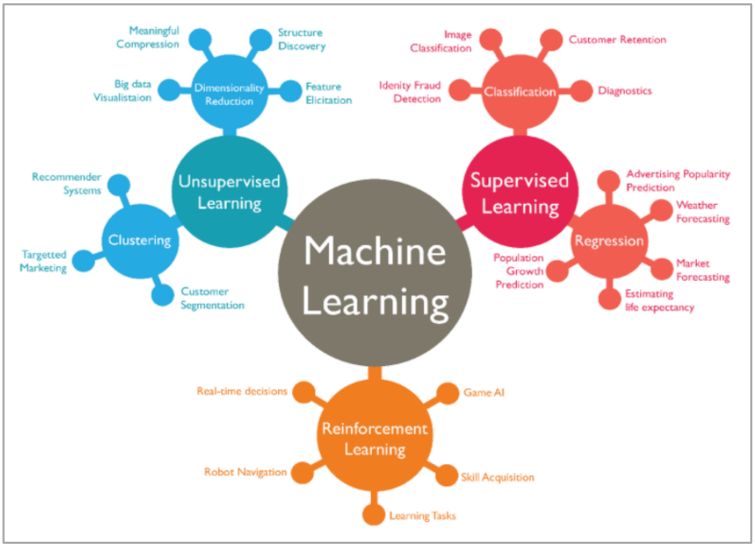

Figure 4. Machine learning area of application for data analysis and model development comprising three main categories [6, 7].

Logistic regression is a ML algorithm, which discovers a linear model of the relations between variables by fitting a line on the curve of the given data. It can also be applied for classification. One of the frequently used algorithms for data classification is SVM; it is an algorithm to discriminate the best data classifier for the data. SVM can achieve a very good generalization performance. A decision tree is another algorithm for mapping data using tree-like structures, classifying the decisions to output as classes or boundaries. Ensemble learning method applied if several decision trees are deployed, producing random forest. Moreover, the gradient boosting method is also widely used in some ML problems, producing an ensemble model of the data by employing some weak models [7]. The primary advantage of this method is its ability to reduce bias and the variance level in the model. Deep learning is a more recently introduced algorithm that is successfully applied to some complex tasks. It is a part of another class of ML methods named artificial neural network (ANN) in which a network of cells is produced and the connections between the cells, adjusted in a way that the resulting network can learn the structure of the training data. Usually, the number of layers in the network in the deep learning method is much higher than in an ordinary ANN. Thus, in deep learning, there are higher-level extracted features from the input data [15].

ML algorithm usage may allow assessing the collected historical data and provide the required information to improve emergency medical processes [12]. Through the available sophisticated algorithms, the analysis process may lead to useful knowledge for reducing the workload of medical staff, avoiding possible human fatigue, leading to fewer errors in healthcare.

Table 1. The most applied ML methods definition for emergency-related outcome prediction [16]

ML Method	Definition
Random Forest	An ensemble ML algorithm combining multiple learners in the form of nodes and predictors.
Deep learning	A method of ML that makes use of large neural networks. The adjective "deep" comes from the use of multiple layers in a network.
Ant colony optimization (ACO)	A population-based optimization algorithm where artificial agents work to solve problems as efficiently as possible by mimicking the behavior of real ants.
Reinforcement learning	A learning paradigm that is concerned with how intelligent agents ought to take actions in an environment to maximize the notion of cumulative reward.
Adaptive boosting	A ML meta-algorithm that combines other learning algorithms into a weighted sum that represents the final output of a boosted classifier.
Gradient boosting	A ML technique for regression and classification problems. Produces a prediction model in the form of an ensemble of decision trees.
Ensemble learning	Multiple learning algorithms were used to obtain a better predictive performance than could be obtained from a single constituent learning algorithm.
Constraint programming model	A paradigm is used to solve combinatorial search problems in which the user establishes constraints and the constraint solver finds a solution to them.
Hierarchical task network planning	An Al approach to automated planning in which a hierarchically structured network can give actions to solve a series of tasks.
Active learning	An approach to ML in which the learning algorithm can interactively query a user to label new data points with desired outputs.
Semi-supervised learning	An approach to ML that combines labeled data with unlabeled data during training.
Binary decision tree	A structure that serves as a compressed representation of sets or relations. It is often associated with 'Boolean functions' in computer science, or a graph with several nodes.
Supervised learning	An approach to ML that uses labeled data.

4. The Use-Cases of Intelligent Emergency Informatics

The framework of WHO presented in Fig. 1 encompasses three main sections of an emergency: the scene, prehospital and EMS, and hospital and care facility. In this section, the use cases of emergency management using machine learning methods based on these three sections are demonstrated.

4.1. Emergency Informatics Applications in the Scene

In the scene of an emergency, rapid response for quick and optimum decision-making is essential and requires efficient communication of information between governmental agencies, corresponding organizations, and healthcare facilities.

During natural disasters, emergency evacuations are very important. Machine learning-based modeling is often used to predict the best evacuation routes and provide useful insights to develop more effective evacuation plans. Ant colony optimization (ACO) algorithm has been a common algorithm used for evacuation route computation. The best route for an evacuation in a crisis is the output of the model after validation [16]. ACO algorithm has also been used for emergency management to distribute resources in disaster situations to overcome the vehicle routing problem. There is a mathematical optimization model which incorporated the idea of a virtual central "depot" or resource distribution center for distributing emergency resources from a stock center during an emergency. The proposed algorithm performed more efficiently than previous vehicle routing problem optimization models, calculating the best routes without traffic blockages or other disruptions considerations that could affect the results of the model [17]. Furthermore, a decision support system (DSS) was developed to allocate the resource and human force in case of emergencies with the highest level of efficiency [18].

ML algorithms have been useful in establishing DSSs aiding the response plans and embedded into an emergency. Hierarchical task network planning is a technique to train a model to search for a solution to obtain an initial task network in the early state. This tool coordinates the agencies involved in disaster scenarios and prepares standard operating procedures. This decision-making model was dynamic and able of dealing with temporal uncertainty in emergency response situations. Another agent-based decision-making system, working without the staff presence, is under progress. It will work based on reinforcement learning, a method in ML that enables an agent to learn from experimenting [18, 19] shown in Fig. 4.

Using ML, a classification model for survival prediction was built to quickly and precisely triage victims by wearable devices application in the emergency scene with the absence of medical personnel. Logistic regression, random forest, and neural network algorithms were all found to outperform using the datasets collected from patients sustaining accidents in daily life rather than in a disaster context. The deficiency of samples collected from the patients in a disaster is a key limitation of this study[20]. Furthermore, a game module has been developed to directly train on how to supervise the students during an active shooter scenario on commands. The model applied for the game was trained by the data of real-world scenarios that have already occurred. The game is used for training real related experiences to users and put them in the roles such as teachers, staff and administrators, law enforcement officers, school resource officers, and the suspect role [12].

With the crisis, reports of casualties might be limited due to infrastructure damage. The urgent use of social networks such as Twitter and Facebook can provide important information in the first few hours of an event, helping significantly to reduce both human loss and economic damage. An ML approach was used to tag and label data derived from tweets that were shared during emergency scenarios. Using this system, they were able to identify tweets that were relevant to disaster response efforts [16]. Furthermore, ML algorithms such as Adaptive Boosting, Gradient Boosting, and Random Forest were used to analyze heterogeneous social media data, including various types of emergencies and disasters[15]. Also, a project named Evolution of Emergency Copernicus services (E2mC) addressed that satellite imagery can be enhanced by social media data. The ML component can preprocess the social media posts to decipher slang and predict the relevancy of the post generating a damage assessment that may not be available from the satellite. Using ML techniques for analyzing the data obtained from temporal and spatial information derived from social media using digital volunteers and local eyewitness reporters has created a witness system to depict the emergency scenario at hand with as few gaps in information as possible [21].

Moreover, social media data have been applied for text and images analysis driven from social media posts in crisis and emergencies. The developed classifier was applied to detect notifying words in messages written in the tweets to identify the informative tweets using a supervised ML classifier such as SVM. There is also a keyword-based data-retrieval method and modeled the data during the training stage using SVM with an AUC of 0.937. This model to detect alarming posts of social media such as Twitter has been improved using deep learning methods such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN)[22-24].

Furthermore, machine learning-based matching models support effective communication between the disaster victims and the emergency teams immediately following a disaster event. These models help in clearly identifying the useful availability of resources and aid for those who need support stated in a post. Automated matching of resource requests and offers for emergency relief coordination has been explored [23, 24]. Furthermore, the problem-solution approach was developed by Varga et al. [25] to enhance emergency coordination via discovering the match between two sides: victim who requests support and aid provider.

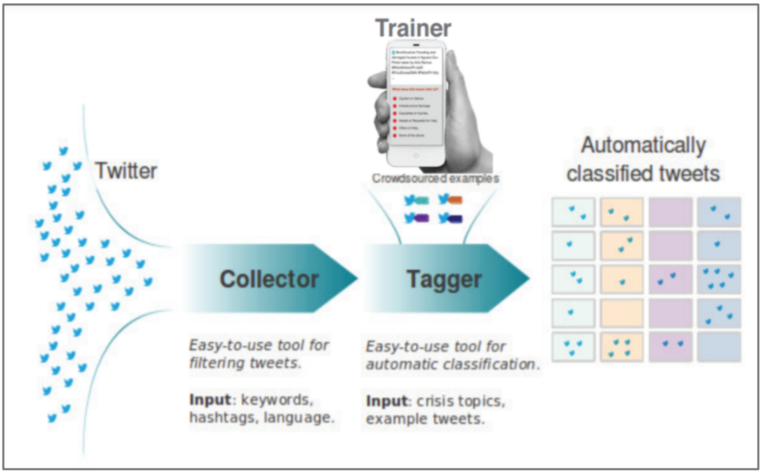

Figure 5. The diagram of social media (Twitter posts) classification using ML methods [26].

Deep learning also has been used for images classification taken from social media posts. the domain adaptation approach called Domain Adversarial Neural Network (DANN) was used to classify the images of a disaster event in a real-time setting[27]. Further work is required for this purpose to improve the model for analyzing the picture when it composes some other features which make it vogue or not clear enough to be processed.

4.2. Emergency Informatics Applications in Pre-Hospital Setting

In prehospital settings and emergency medical service (EMS), the need or not for critical care has been the focus of researches. Classification models using learning methods have been developed. This early identification may save patients' lives by helping clinicians to make quicker and more accurate decisions regarding the patients' transfer. ML algorithm and deep learning algorithms are applied for training and validated [14]. If the patient is expected to require critical care, the EMS technician must pass through the nearest low-level ED to a high-level ED. Accurate tools for predicting prognosis play an important role in communication between the prehospital EMS technician and hospital medical staff through providing online medical directions and preparing in-hospital management [28].

Furthermore, for deterioration prediction in the prehospital setting and need for critical care, different tools such as emergency severity index (ESI), Korean Triage and Acuity System (KTAS), Modified Early Warning Score (MEWS), and National Early Warning Score (NEWS) were compared. These tools became more improved through intelligent model development [19]. As can be seen in Fig. 6, ensemble methods of a convenient scoring system and ML algorithms outperformed the convenient scoring system with a higher level of the area under the receiver operating characteristics curve and the proposed method can more accurately predict the need for critical care in a prehospital EMS situation[14].

Moreover, patient prioritization and categorization in prehospital settings were conducted. That is, a triage decision for traffic road injured patients at three main levels using ANN and adaptive neuro-fuzzy inference system (ANFIS) was made. This was a requirement due to the excessive road traffic accidents in many countries and several referrals of injured people to ED. The system may support caregivers to focus on life-threatening conditions as they cannot provide emergency service to several cases simultaneously; that is, the shortage of resources does not allow caring for all of them at the same time. Therefore, injured individuals should be prioritized at triage by EMS. The models were built with a data set of 3015 data designed by Iranian medical experts and were based on patients` general status, vital signs, and chief complaints. Results showed less triage time and a shorter queue of patients, and the out-performance of the overall ANFIS model [29].

4.3. Emergency Informatics Applications in Hospital and Care Facility

4.3.1. Triage Improvement

Applying ML for emergency care of a case in hospital-based setting in various studies has been considered [14, 30]. Optimal emergency department (ED) for patient care depends on quick and accurate clinical decisions based on limited information. The number of emergency visits in ED is increasing over the past 20 years [31]. The increased level of ED crowding raised costs, and delays in care may result in more adverse consequences such as elevated morbidity and mortality for patients.

There are different clinical prediction tools, such as the Canadian CT Head Rule and Quick Sequential Organ Function Assessment score which have been developed to support decision-making under these demanding circumstances. However, these tools are limited to specific clinical scenarios. Their development requires substantial time and resource investment [10, 14, 15]. ML-based tools and models have emerged to support ED decision-makers in the triage the emergency cases, prognosis analysis, emergency detection, and early management and adverse drug event prediction [10].

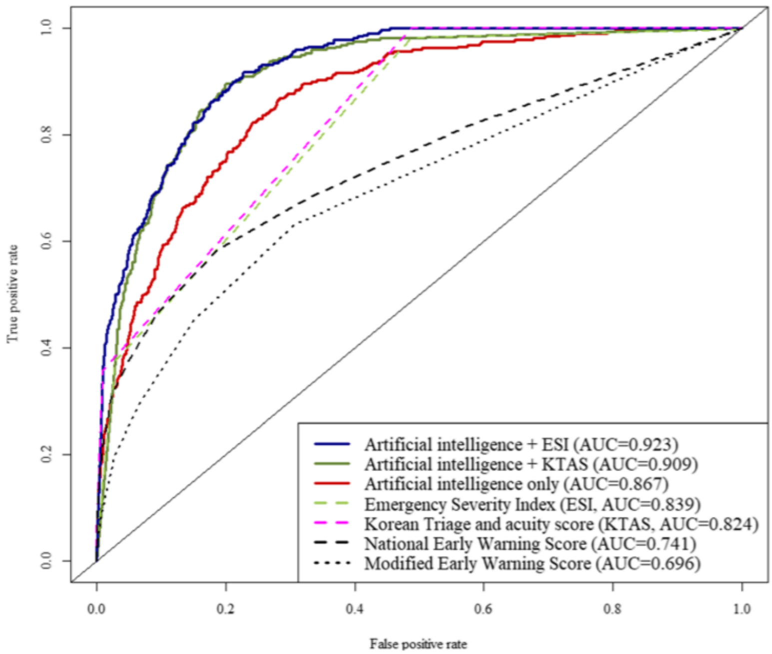

Figure 6. The receiver operating characteristics curve for predicting critical care needs to be enhanced with AI methods [14].

4.3.2. Probable Outcome Prediction

A study addressed the application of ML algorithms to develop a predictive model for clinical deterioration in hospitals. The tool, which is called Mayo Clinic Early Warning Score (MC-EWS) was developed using 2-year data of tertiary care of hospitals trained by gradient boosting and feature engineering. The occurrence of inpatient deterioration, including resuscitation call, intensive care unit (ICU) transfer, or rapid response team call during the next 24 hours was considered. The model demonstrated excellent discrimination in both the internal and external validation datasets with a high level of sensitivity analysis. The developed model had lower alert rates but was more accurate in discrimination cases. This might be due to applying more MC-EWS as it includes both nursing assessments and extensive feature engineering. The superior performance of MC-EWS to predict general care inpatient deterioration using more nursing-related variables and sophisticated models using ML algorithms, resulting in a reduced rate of alert and higher efficiency [32].

An emergency chest pain has always been significantly considered an alarming symptom. However, the level and quality of this symptom are challenging. ML methods were used to predict the critical care requirement in patients with chest pain, and simultaneously compare its performance with available scoring tools such as HEART, GRACE, and TIMI. Having considered different possible outcomes after chest pain, including cardiac arrest, transfer to ICU, and death during treatment in ED, the predictive model developed. LASSO regression model significantly outperformed the available tools regarding the metrics of accuracy, sensitivity, and specificity presenting an accurate model providing substantial support to clinicians' decision-making at ED [33]. Besides, ML outperformed the convenient statistical method to assist emergency physicians to classify the undifferentiated chest pains and promptly diagnose the life-threatening causes such as acute myocardial infarction (AMI) and prognosis of a major adverse cardiovascular event (MACE) with a higher level of accuracy. ANN, random forest, SVM, and gradient boosting studies have been the most common applied algorithms outperforming the existing risk stratification scores [34].

Due to uncertain decisions regarding the medical intervention related to a drug, an adverse drug event (ADE) may occur. It includes adverse consequences such as medication errors due to inappropriate use of drugs or adverse drug reactions (ADR) due to harm caused by drugs at normal doses, allergic reactions, and overdoses [35]. Predicting and preventing ADRs in the early stage of the drug development pipeline enhances drug safety and decreases financial costs. To prevent ADEs in an emergency department, informatics-based technologies such as CDSS and CPOE have been applied [36]. ML also has been used to automate the systems and give the ability of detection and prediction to these systems. As drug prescription is an important task of daily work of doctors to be done for each patient, it needs more attention and accuracy. The drug prescription must be done considering all potential drug sides. Deep learning methods were utilized to accurately detect and professionally identify unreported drug side effects using widely available public data. The dataset of 10,000 reviews was gathered from WebMD and www.drugs.com. It was manually labeled by utilizing a hybrid transfer learning from pre-trained BERT representations and sentence embeddings. The proposed model achieved a highly satisfying AUC score of 0.94 for ADE detection and an F1 score of 0.97 for ADE extraction. This approach can be applied to multiple healthcare and information extraction tasks and to be used for solving the problem that doctors may face over medication prescribing. Overall, this research introduces a novel dataset using social media health forum data demonstrating the viability and capability of using deep learning techniques in ADE detection and extraction. The model may be applied to other multiple healthcare and information extraction tasks, including medical entity extraction and entity recognition [37]. Also, a deep learning algorithm was used to early predict adverse drug reactions (ADRs) which are unintended and harmful reactions caused by normal uses of drugs. The applied algorithm was convolutional deep learning to simultaneously construct chemical fingerprint features and assess their associations with ADRs [38]. The AwareDX algorithm has been created to use ML to predict sex risks for ADRs. The algorithm mitigates the biases and minimizes adverse events by modifying drug prescription and dosage to gender [39].

5. Emergency Informatics Challenges and Solutions

There are various challenges in using ML algorithms for emergency care. The main challenges are dataset access, data integration, information delivery, and network connectivity [17]. To overcome current limitations, a systematic method with defined regulations is required to share the available datasets. To develop an experimental model leading to higher performance, free access to available data to all interested researchers should be supported, equally. Furthermore, the possibility of sharing the information among emergency related systems through applying interoperability standards may lead to enhanced operational processes. It is achieved provided that access and use of automated data be guaranteed for both humans and machines. Data combination from various sources such as electronic medical records (EMRs), social media data, data collected by sensors, or even satellites may lead to synergy and consequently more accurate solutions. This creates a synergy to benefit from different sources of data, collected by various platforms resulting in quicker and more accurate decision making and service in emergencies; the E2mC project by the usage of satellite imagery and social media data is an example [21].

Besides, the restrictions of ML methods corresponding to the large-scale distributed data sources should be addressed. Some algorithms are limited in terms of speed, tackling with the high dimensional big data, and susceptibility to bias [40]. The uncertainty associated with many of these algorithms besides other pitfalls has prevented them from being widely used in medical applications and health care [41]. Applying the ML models may encounter some limitations such as overfitting. It occurs when the learning algorithm performs well the training and testing data of the same dataset and delivers poor performance on a new dataset upon external dataset validation. A statistical method such as the goodness of fit test can measure how closely the model's predicted values match the observed (true) values. Cross-validation and partitioning the example randomly into training and validation sets are useful techniques to tackle the overfitting and prove the internal validation. Employing a simpler algorithm with less complexity may be a solution to deal with overfitting provided that the desired result might be achieved [7].

There are researches regarding the application of ML in public health-related emergency care and the ED at the hospital [5, 15, 17]. Although the applied ML algorithms outperformed the current approaches, there is still a need for a standardized method of ML application in terms of minimum data requirement, feature analysis, learning process, and reporting guidelines. Further progress is required to improve the reliability and accuracy of ML and AI applications in the management of critical care in an emergency through the development of clinical decision-making support, focusing on patient-orientated outcomes, and patient and physician acceptability improvement.

6. Conclusion

Emergency medicine has been a major focus for study and solution development with the advent of artificial intelligence. Technological advances have brought various tools that have great potential to improve processes and will improve the operational efficiency and quality of healthcare service delivery. ML and deep learning encompass different algorithms used for predictive and regression models developed for emergency-related outcomes including public health and the prehospital scene or in the emergency department. The validated outcome may support decision-makers to be much quicker and more efficient. The available data for training the algorithms differ from image, satellite, social media, individual data, or historical data of casualties or former emergencies. The approach of combining the available data to overcome the knowledge deficiency has also been applied and needs to be more considered.

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Improving Emergency Medical Services Information Exchange: Methods for Automating Entity Resolution

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Abstract. The 21st century has seen an enormous growth in emergency medical services (EMS) information technology systems, with corresponding accumulation of large volumes of data. Despite this growth, integration efforts between EMS-based systems and electronic health records, and public-sector databases have been limited due to inconsistent data structure, data missingness, and policy and regulatory obstacles. Efforts to integrate EMS systems have benefited from the evolving science of entity resolution and record linkage. In this chapter, we present the history and fundamentals of record linkage techniques, an overview of past uses of this technology in EMS, and a look into the future of record linkage techniques for integrating EMS data systems including the use of machine learning-based techniques.

Keywords. emergency medical services, emergency department, entity resolution, health information exchange, record linkage

1. Introduction

High-quality prehospital care relies on the ability to quickly and accurately retrieve and document data into a patient's medical record. Emergency medical services (EMS) often interface with multiple hospital systems and individual EMS agencies. The challenge of obtaining and synthesizing multiple sources of medical information for patients is heightened by the unpredictable, emergent nature of EMS care. These challenges are exacerbated further by the need to utilize accurate, standardized, and complete data in

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broader systems-of-care. Overcoming these obstacles requires rigorous entity resolution methods.

During pre-hospital care, patients and their data first encounter EMS clinical information systems, which record and document the patient's history, condition, vital signs, presumptive diagnoses, treatments received, and their disposition. Subsequently, downstream clinical systems involved in real-time clinical care, quality assurance, public health, disaster planning and response, and/or research perform better when EMS clinical systems communicate with electronic health records (EHRs), clinical registries, and public databases. Bidirectional data exchange allows downstream systems to be primed with important patient information, improving accuracy and reducing duplicate therapies and documentation, and can provide valuable outcome data to EMS information systems. However, to date, information exchange of health information technology systems with EMS systems remains woefully underutilized.

Patient handoffs between EMS and emergency department (ED) teams stand to benefit from better interoperability between EMS and hospital-based information systems [1]. In an ideal environment, EMS information systems would be prospectively interoperable with one another and with hospital systems. This would include end-to-end integration of emergency-call management, computer-aided dispatch systems, EMS patient care records, and hospital charting to facilitate improved real-time handoff of information as proposed by Schooley and Hikmet in Santa Clara County, California [2] or as proposed by Park *et al.* after a formal needs assessment [3]. The ability to uniquely identify a patient is a requisite first step in this process which utilizes record linkage methods, defined by Shah *et al.* as "the ability to compare and match data records from multiple sources in order to determine which sets of records belong to the same person, object or event" [4]. However, given the chaotic nature of pre-hospital care and the challenges of achieving agreement across systems and organizations, data in EMS systems and other relevant data repositories suffer from missingness, inaccuracy, and inconsistency in representation, thus creating challenges in record linkage.

An exponentially increasing number of publications on record linkage since the early 2000s demonstrates the importance of the field [5]. In this chapter, we introduce fundamental concepts in record linkage, provide examples of record linkage involving EMS systems, and summarize the current and future state of the field. We do not explore EMS integration with health information exchanges. The current state of EMS health information exchange was recently reviewed by Martin *et al* [6] and current barriers to implementation were articulated by the National EMS Management Association [7]. We similarly do not discuss hardware, network, or EMS vehicle related architectural concerns. These challenges were well summarized by Landman and colleagues [8].

2. Fundamental Concepts in Record Linkage

The literature describing probabilistic algorithm development for linking records with imperfect identifiers or keys dates back to the 1950s [4]. Shah and colleagues provided an excellent review of the basics of record linkage techniques [4]. There are three overarching classes of techniques used in record linkage systems: deterministic (direct/exact), probabilistic record linkage, and machine learning (ML)-based linkage.

Because of its accuracy, deterministic or rules-based link linkage is the preferred method when uniquely identifying information is uniformly available, which unfortunately is rarely the case in real-world EMS systems. Deterministic record linkage traditionally requires an exact match for each linked data element. Various methods attempt to improve matching performance by normalizing data elements based on spelling variances or common data entry errors, but these methods ultimately return a dichotomous outcome (matched or not matched) [9]. Most commercial and open-source database applications can perform deterministic linkages between data sets. Semi-deterministic approaches include the use of truth-tables, which create unique identifiers from several variables (name, date of birth, address, etc.) when a truly unique key is unavailable. A "master patient identifier" has been proposed both in the US and the European Union, though has not been universally implemented. Denmark's efforts to unify its EMS systems with other medical systems using a civil registration number provide a representative example of what is possible using deterministic linkage when political and administrative will and privacy concerns align to make such a process feasible [10].

Probabilistic record linkage was introduced by Newcombe *et al.* in 1959 [11]. In their work, which linked birth and marriage records to explore connections between family fertility and the presence or absence of genetically inherited diseases, the authors used an array of error handling methods to account for spelling mistakes. To prepare for linkage, they included phonetic encoding of surnames and the inclusion of maternal and paternal surnames, provinces or countries of birth, and first initials, which were available on all births and most marriage records. Probabilities of appropriate record matching were then calculated using probabilities of matching in a target population either via previously published statistics or based on the characteristics of the population itself. The probabilities by different predictors were then logged and combined to generate the odds of a match. Fellegi and Sunter built on this work in 1969 to establish the mathematical theory behind modern probabilistic record linkage, which remains foundational in the field [12]. Their paper first established that an empiric approach using likelihood ratios was in accordance with classical inferential hypothesis testing. Later work showed that this technique could be derived using Bayes theorem [13]. For these techniques and those that followed, probabilistic linkage techniques required manual calibration of parameters, match thresholds, and linkage weights. These techniques typically require human adjudication when the probabilistic linkage system fails to classify with adequate confidence.

Several studies have compared deterministic and probabilistic approaches. Gomatam *et al.* explicitly compared deterministic and probabilistic approaches in linking records between a Florida intensive care registry with educational records from the Florida Department of Education database, using social security numbers (present in both databases) as the gold standard [14]. Specifically, they compared a stepwise deterministic method with the AUTOMATCH algorithm previously described by Jaro [15] and determined that the probabilistic method had a far greater match rate and sensitivity at the expense of a slightly lower positive predictive value, since deterministic methods are less susceptible to false positives given their more exact nature. Jamieson and colleagues compared a deterministic strategy, a probabilistic strategy, and a mixed strategy for linking Public Health Nursing Services with income assistance and found the mixed approach most effective with specificity of 0.98 and sensitivity of 0.94 [16]. Roos *et al.* linked 96.6% of records between Manitoba hospital encounters and physician claims using a staged approach with a deterministic stage followed by multiple probabilistic stages on several identifiers [17]. Many open source and commercially available software packages implement these record linkage techniques for commonly used statistical and analytics packages [4,18].

The third category of record linkage systems uses machine learning. The parallels between the Fellegri-Sunder probabilistic approach and ML-based classifiers such as naïve Bayes alongside the increasing availability of adequate computing power for handling large data sets have contributed to a rapid expansion of these alternate techniques for record linkage [5]. Supervised classification approaches, including decision trees, support vector machines, ensemble methods (*e.g.* random forests), or conditional random fields; and unsupervised methods, including *k*-means clustering, have been applied [4,5]. The literature is still emerging on the optimal approach for healthcare-based record linkage systems using machine learning [19].

Machine learning based approaches, which historically were only available to expert statisticians and data scientists, are becoming more approachable with the use of freely available packages such as *RecordLinkage,* an open source R package, which allows users to choose between traditional Fellegri-Sunder typed probabilistic, supervised ML-based, and unsupervised ML-based approaches [20]. Future techniques seeking to handle language translation, sound or video-based information, visual representations, and multiple-dimensional surfaces might also prove useful someday to projects integrating audio or video footage from EMS providers or surveillance cameras.

In practical use, many projects combine manual, deterministic, and probabilistic approaches, especially in stratified probabilistic approaches, where a deterministic match facilitates stratification or blocking to split a large population into smaller subgroups for probabilistic assessment [13]. Often, non-technical practical challenges represent the greatest barriers to successful record linkage, including the need for extensive data cleaning and standardization, imputation for data missingness, and ethical/privacy concerns [5].

2.1. Examples of Record Linkage Projects Involving EMS Information Systems

One of the earliest examples linking EMS data to hospital outcomes using modern probabilistic methods was presented by Dean *et al.*, who used probabilistic linking methods in Utah between EMS and hospital discharge records [21]. Since, there have been a wide array of specific uses of record linkage involving EMS data that we will discuss here.

2.1.1. Cardiac Arrest and Acute Coronary Syndrome

An early applied example of probabilistic record linkage techniques for EMS usage was conducted by investigators in Toronto, who were able to compare rates and survival outcomes of cardiac arrest survivors from different area hospitals by linking three databases: the Metro Toronto Ambulance database, the Canadian Institute of Health database, and the provincial Vital Statistics Information System database [22]. Their manuscript provides an excellent account of how to handle many of the data cleaning tasks that arise during record linkage. Another team working with the California EMS Information Systems database attempted to link EMS data to California's Office of Statewide Health Planning and Development Inpatient and Emergency Outcomes database using probabilistic linkage. This attempt demonstrated the challenges with very high degrees of missingness often found in EMS data sets [23]. A United Kingdom-based study used deterministic record linkages between EMS, ED, intensive care, and administrative data sets to evaluate the feasibility of registry-based follow-up on cardiac arrest patients, who had been cluster randomized to receive mechanical assisted chest compressions vs. usual therapy [24].

In North Carolina, deterministic matching was used to link a Pre-Hospital Medical Information System with the Acute Coronary Treatment and Intervention Outcomes Network Registry. The goal was to assess if hospitals participating in the Regional Approach to Cardiovascular Emergencies (RACE) quality improvement program achieved an adequate performance in guideline suggested timeliness for percutaneous coronary intervention [25].

A mixed probabilistic and deterministic record linkage study in New Jersey facilitated the joining of patient-level EMS data, hospital utilization, and death information to evaluate outcomes between centers adopting therapeutic hypothermia and those who did not using a wide array of process and clinical outcomes [26].

2.1.2. Trauma and Traffic Safety

Cook et al. in 2000 probabilistically linked Utah hospital discharge databases with Utah Department of Transportation data on reportable motor vehicle crashes to facilitate a logistic regression analysis comparing outcomes by age adjusted for alcohol or drug involvement and features related to the crash itself, yielding valuable insight into accident patterns and predictors of morbidity and mortality [27]. Subsequently, the same team, working with the US National Highway Traffic Safety Administration (NHTSA) between 1993 and 2013, created the Crash Outcomes Data Evaluation System (CODES), which linked crash, vehicle, and behavior characteristics to medical and financial outcomes by collaborating with States to develop data linkage programs, with systems becoming autonomous in 2013 [28]. This system used an augmented probabilistic approach that included multiple imputation steps for missing data with a Markov Chain Monte Carlo step to ensure sample independence [29]. Ultimately, they used this system with data from 11 States to evaluate medical outcomes based on motor vehicle collision circumstances, including the impact of age on clinical outcomes, the impact of safety restraints on children, the impact of helmets on motorcycle head injuries, and the impact of differences in driver's education program rating on teen injuries. This project also yielded new techniques for generating test data for assessing record linkage algorithms and for Bayesian record linkage approaches for multiple imputation of missing links [30,31].

A Massachusetts team used rule-based deterministic linking to match the Massachusetts Crash Data System (CDS) and Massachusetts Ambulance Trip Record Information System (MATRIS), facilitating evaluation of the relationships between crash characteristics and injury patterns [32].

Bianchi Santiago *et al.* compared deterministic to probabilistic matching algorithms when working to link the Puerto Rican CRASH database to data from a state-run personal injury insurance company [33]. They found a 20% improvement using probabilistic matching and used the linked records to develop a crash-cost estimation model for traffic-related personal injuries.

A study in Alabama, USA, demonstrated that deterministic linkage can facilitate the comparison of Glasgow coma scale (GCS) scores between EMS and trauma center clinicians [34]. Differences between EMS and hospital staff assigned GCS scores were seen in the patient population with moderate to severe head injury, suggesting some improvement in the patient's condition during transport.

Newgard combined deterministic matching of a unique identifier with probabilistic matching of secondary data to link a community EMS service database with a state trauma registry with high accuracy [35]. He concluded that matching ambulance records to a trauma registry without the use of patient identifiers is possible using probabilistic linkage. However, sensitivity of identifying true matches depends on the number and type of common variables (e.g., age, gender, race, county, hospital, date, rural setting, call and arrival times, mechanism, penetrating injury, vital signs, intubation, and intoxication) included in the analysis. Subsequently his team expanded these efforts to include multiple imputation, ultimately generalizing the process across 11 trauma registries and 94 EMS agency databases [36].

2.1.3. Mental Health and Substance Abuse

A team in Melbourne, Australia used deterministic linking techniques to match records from the Melbourne Metropolitan Ambulance Service with National Death Index data, yielding actionable knowledge about the association between non-fatal opioid overdoses attended by EMS teams and subsequent fatal overdose, providing an opportunity for outreach and prevention [37]. More recently, an iterative deterministic approach with substantial clerical review facilitated improved linkage of EMS runs with emergency department data in patients receiving naloxone for presumed opioid overdose over prior efforts, facilitating outcome studies [38].

In Scotland, researchers used the National Health Service Information Systems Division Unscheduled Care Data Mart, which is created via a mixed probabilistic and deterministic approach to integrate Scottish EMS data, EDs, inpatient and psychiatric admission data, and death records – providing insight into the frequency of patient medical contact prior to a self-harm event or a suicide attempt [39].

2.1.4. Stroke Care

A team striving to build a better registry for evaluating stroke care quality compared deterministic and probabilistic matching when linking Michigan's EMS Information System with the Michigan Coverdell Acute Stroke Registry – matching 46% of records using deterministic matches and 68% using probabilistic matches [40]. Another effort in North Carolina using deterministic linkage to match the North Carolina Emergency Medical Services Data System to the North Carolina Stroke Care Collaborative database yielded a 63% potential match rate with a positive predictive value of 89% [41].

2.1.5. EMS Protocol Safety and Quality Improvement

A Western Australian team used probabilistic matching techniques with multiple passes followed by clerical review of doubtful matches to match EMS data to hospital morbidity, emergency department, and death register data to facilitate a safety evaluation of patients receiving methoxyflurane in the pre-hospital setting [42,43].

The University of Rochester linked EMS dispatch data to hospital records using probabilistic matching, which revealed a small subset of dispatch codes that were highly associated with admission or mortality, facilitating better allocation of resources using dispatch codes [44].

2.1.6. Disease Severity Prediction

In King County, Washington, probabilistic linkage techniques were used to match EMS records to the Washington State Comprehensive Hospital Abstract Reporting System (CHARS), facilitating the derivation of a generalized non-traumatic, non-cardiac arrest disease severity prediction score for deployment by EMS services [45]. A similar illness severity score for the elderly was derived for seven counties in Oregon, Washington, Colorado, California, and Utah using EMS records probabilistically linked to hospital records [46].

2.1.7. Integrated Systems

An Oregon team successfully linked all EMS agencies in the state to state hospitalization and motor vehicle collision registry data using probabilistic matching, which required an immense effort to normalize and link data from 14 distinct electronic patient care record (ePCR) systems [47]. The same team worked in Oregon and Washington States to link nine databases, including EMS ePCR systems, state trauma registries, discharge registries, vital statistics registries, a Medicare claims database, and the Oregon Physician Order for Life-Sustaining Treatment registry [48]. They used probabilistic linkage and multiple imputation to match these data and handle missingness, which allowed for one year follow-up of this large cohort.

2.1.8. Machine Learning for Record Linkage in EMS

Several studies have demonstrated the feasibility of various supervised and unsupervised algorithms for record linking with EMS systems. A team from Beth Israel Deaconess in Boston used logistic regression with 5-fold cross-validation and L2 regularization to link Boston's EMS ePCR with their hospital's electronic health record (EHR) [49]. The coming years will likely reveal expansion in the use of these techniques in novel ways.

2.2. Future Steps

The prior sections demonstrate the myriad record linkage techniques investigators have harnessed to solve a multitude of problems and develop novel knowledge only possible by "marrying" various data sets with EMS data. The biggest challenges with current techniques are the extensive data cleaning and validation efforts required to facilitate entity resolution. As a result, real-time record linkage to date has required pre-defined unique fields that can be deterministically linked (as are used in most health information exchanges). Advances in matching techniques, especially unsupervised classifiers that can be iteratively updated with new data, may reduce the need for data cleaning and supervised turning. However, there remain privacy, information standard, and cultural barriers that make this process challenging. The United States National EMS Information System (NEMSIS) – one of the many projects of the NHTSA (National Highway Traffic Safety Administration) – was designed as "a standardized system for electronic documentation and sharing of EMS data [that] allows local agencies to measure performance and support more effective quality improvement programs. Standardized national data have also facilitated a growth in EMS research, which is essential to ensuring EMS continues to provide the best care to patients across the country" [50]. The development of NEMSIS has provided a road map for the design of ePCR software that specifically accounts for the challenges in data collection during pre-hospital care while integrating nationally and internationally scalable EMS data standards. Many hoped that NEMSIS would facilitate tight integration between EMS and hospital systems. While integration efforts continue, most EMS ePCR systems remain uncoordinated with hospital systems, resulting in data silos that will require joining via the use of record linkage techniques for the foreseeable future.

Ample opportunity awaits to optimize the care and outcomes of patients managed in the pre-hospital arena with improved entity resolution. Incentives must arise to compel system designers to link data, in the interest of assuring quality of care while providing valuable sources of data to public health professions. We want to leave you here with a scenario that demonstrates the potential for the future – a patient with heart failure is managed by a small community health care system and occasionally receives specialty care at an academic medical center. The community paramedics are dispatched to a post-discharge follow-up visit entailing history taking, physical examination, 12-lead electrocardiography, vital sign and weight checks, and a medication reconciliation. While on scene, the paramedics seamlessly connect with both the local community health system and the academic medical center to review the recent clinical course. They document their findings so that the patient's on-campus providers can review the visit. The patient's medications are adjusted in real-time, keeping the patient safely at home.

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Medical Emergency Data and Networks: A German-Canadian Comparison

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Abstract. A significant number of problems in emergency care are caused by a lack of provider access to pre-existing patient information at the point of care. Medical Emergency Datasets (MEDs) are brief summarizations of an individual's medical history, providing vital patient information to emergency medical providers. The German MED was validated by German physicians and – based on an international research project – also by Canadian physicians. Physicians in both countries considered the content very useful. The MED is currently being introduced in Germany as part of the Telematic Infrastructure. At the same time, the COVID pandemic forced healthcare professionals around the work to optimize the digital information exchange among different healthcare providers. While the exchange of data is important, additional personal expert advice is sometimes vital. Real time virtual support systems (RTVS) were introduced in Germany and Canada to support team-based healthcare delivery, independent of the actual location. Such systems have been implemented for intensive care, emergency medicine, primary care and several other medical specialties. These systems serve as a safety net, a funnel (appropriate utilization; linking patients back to primary care networks – thus reducing fragmented or disrupted services) and a medical network by building interprofessional relationships.

Keywords. medical emergency, dataset, telemedicine, virtual care

1. Introduction

The first network for medical emergencies – strokes - in Germany (TEMPiS) was founded in 2003 in Bavaria. Since then, this network has treated over 7000 patients annually. The rate of stroke-related permanent disabilities and the mortality rate of stroke patients could be drastically reduced [1]. This network is an excellent example of how emergency medicine is implemented in Germany and how it can be optimized with modern technology. A stroke is a time-critical emergency, where important decisions regarding treatment must be made quickly. The diagnosis of a stroke is made using medical imaging such as computerized tomography (CT) and possibly magnetic resonance imaging (MRI) and patient examination. There are a number of treatment options available, some of which can only be carried out at specialized treatment facilities. However, there are also treatments options available at less specialized clinics.

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If a patient suffers a stroke in the area covered by the TEMPiS network, an emergency physician will admit them to the nearest in-network clinic. Then, all necessary diagnostics are carried out there, and the nearest specialized treatment centre is contacted, if that clinic is not part of the TEMPiS network. The images are transmitted electronically, so with the help of a video teleconferencing solution, not only the doctor at that clinic, but also a specialist in the stroke centre can examine the patient. The experts can then decide together whether the patient needs to be brought to the specialized stroke centre. This is even enhanced by offering a CT-diagnostic in the ambulance car, transmitting the images to a specialized treatment center and the option for the emergency physician on scene to communicate with other specialists.

Another example of successful hospital networking is the German Society for Trauma Surgery's nationwide Trauma Network initiative. Similar to a stroke, some injuries, such as serious road traffic injuries, require effective treatment [2]. As of February 2021, 700 hospitals have joined to form 53 certified trauma networks. In order to ensure the same standard of care at each clinic, they exchange patient data amongst each-other. X-ray and CT images of critically ill and injured patients are sent to a superordinate hospital. Decisions can be made together on how to proceed and the patient transferred if necessary.

The increasing integration of systems in all sectors, across all boundaries, means change is coming to the medical profession. Increasing specialization means no physician today is capable on their own of offering each patient optimal care for every illness. In emergency medicine, fast decisions are also essential. The Ministry of Health in Northrhine-Westphalia (NRW) has decided that in the near future a network of tele-emergency physicians must be introduced in NRW, so that medical emergency professionals have the opportunity to consult with experts already on scene, thus avoiding unnecessary hospital admissions or inter-hospital transports.

Another special aspect of emergency medicine is the lack of information concerning the patient. Often the patient who presents with an acute medical emergency is not known to the admitting physician and often not able to present important information–such as current medications, allergies, diagnoses, etc. To optimize this, the German Federal Ministry of Health started an initiative to introduce a medical emergency patient summary, which includes all important information about the patient. However, this Medical Emergency Dataset has not yet been implemented completely in Germany as of February 2021.

In Canada, telehealth activities have been initiated for over 50 years [3, 4]. These early exemplars included, but are not limited to telepsychiatry in Alberta [5] and the Tele-health and Educational Technology Resource Agency (TETRA) in Newfoundland (Memorial University of Newfoundland) [6]. Federal policy changes introduced in early 2000's stimulated the development and implementation of provincial and national health information highways and opened up a new level of telehealth adoption. This supported the establishment of large-scale telehealth provincial programs such as the Ontario Telehealth Network [7], and electronic prescribing such as the MOXXI program in Montreal [8]. The establishment of a national agency, Canada Health Infoway, an independent, not-for-profit organization funded by the Canadian government, in 2001 was another important milestone in Canada [9]. Canada Health Infoway's role is to advance national electronic health record (EHR) and telehealth infrastructures [10]. These are important milestones for the advancement of telehealth across Canada that have led to the development and implementation of many additional telehealth and virtual care initiatives across Canada. However, there were and continue to be a number of challenges in implement critical technology. This includes addressing challenges such as health professionals' and patients' digital literacy, comfort with technology, privacy and confidentiality considerations, change and sustainability of technology and new policy focused on health professional remuneration models as well as a lack of motivation for change overall [11, 12]. In 2020, a Canadian Virtual Care Task Force, formed through a tripartite partnership between the Canadian Medical Association, the Royal College of Physicians and Surgeons of Canada, the Canadian Family Physicians of Canada, and the Associations of Faculties of Medicine of Canada, undertook the opportunity to chronicle the fundamental building blocks of virtual care in Canada, and identify the path forward to leverage virtual care to change our health system to improve equity in access and quality of care in Canada (Canadian Medical Association 2020) [10].

The current COVID-pandemic has led to a tremendous increase in the uptake of telemedicine in Germany, Canada, and worldwide. Many patients were not able to safely go to a hospital as a result there was a need to develop other means for connecting patients and physicians. Safe and easy to use online video-conferencing applications, which were developed especially for the healthcare sector, enabled physicians to see and talk to the patient, saving them a personal visit. However, online video consultation cannot be used for all patients, especially not for those who need a physical examination or any other procedure that requires physical attendance.

A study in United States chronicled the rapid increase in adoption of virtual care from 11% in 2019 to 76% in May 2020 [13]. A contemporary Canadian study also found that, by the end of May 2020 since the onset of COVID, almost half of all Canadians accessed virtual care to interact with health professionals and the satisfaction rate reached 91% (Canadian Medical Association 2020)

This chapter will describe the various activities as examples of using modern digital technology in Germany and British Columbia, Canada in emergency medicine. We will also emphasize the importance of usability aspects of these technologies. Finally, when international travel will pick up again with an increase in the vaccination the world's population, the international exchange of medical information will become even more important.

In order improve and support patient-health professional communication and positive health outcomes, the usability of virtual care systems needs to be considered [14]. Usability can be defined as the capacity of a system to allow users to carry out tasks effectively, efficiently, safely, and enjoyably [15]. Many researchers have identified that the usability and usefulness of a system is important to the adoption of a technology, its continued and ongoing use, its correct use, and its effects on health interventions being delivered via the technology [16]. Usability of systems has become a critical attribute of many health technologies. Usability is of particular importance in emergency medicine, where there are time and urgency constraints at play for accessing information in a useful and timely way to support critical decision making.

2. Real Time Virtual Support Systems in Emergency Medicine

In March 2020, in response to the COVID pandemic, in Canada the BC Ministry of Health, Rural Coordination Centre of BC [17], First Nations Health Authority [18], Provincial Health Services Authority, Providence Health Authority, BC Emergency Medicine Network [19] and UBC Digital Emergency Medicine worked together to establish the Real Time Virtual Support Network (RTVS) in BC [17]. It has two key components: (i) the provision of peer-to-peer support between health professionals, and (ii) patients-and-providers support for patients to seek care from health professionals through virtual care. These pathways were formed to ensure that equity of access of care services were made available across the province through the rural collaborative framework (BC framework). The peer-to-peer just-in-time support was exemplified by the Rural Urgent Doctors in-aid (RUDi) that focuses on emergency practices, ROSe on intensive care, CHARLiE on pediatrics, and MaBAL for maternal and newborn care. The patients-to-physicians services included the First Nations Virtual Doctors of the Day [18] to serve the indigenous populations and community members. Besides, HealthlinkBC Emergency iDoctors in-assistance (HEiDi) established for the general population through calling 811 province-wide [17]. As of March 2021, there were over 160 physicians serving in these different virtual services, and over 30,000 cases of patients being served by this provincial network of just-in-time services, connected through Zoom, text messaging, and connected electronic health records.

At the same time, in Germany the Ministry of Health in Northrhine-Westphalia rolled out a tele-emergency physician system in NRW. NRW covers a population of 17.9M people, living in one of 31 communities and 22 cities, each of these offering its own emergency services. 345 hospitals are located in NRW including six university hospitals. Altogether, over 4.6M patients are treated in hospitals in NRW each year. Emergency services were called over 1.4M times in 2020 in NRW, including emergencies which required an emergency physician on-scene. Currently, tele-emergency services have been implemented in only a few regions in NRW. The first tele-emergency service was implemented in Aachen in 2014. In 2021, 75 tele-emergency physicians served over 28,000 emergency calls in Aachen and the neighboring regions [20].

In order to improve the effectiveness of tele-emergency services, not every community or city is required to offer these services. Instead, each of the five so called community regions (“Regierungsbezirk”) may offer a tele-emergency physician service until the end of 2022. Each of these community regions covers a population between 2.6 and 5.2 million. The tele-emergency physician is called whenever the paramedic on scene needs urgent medical advice. The tele-emergency physician can see the patient’s data, including the ECG. Additionally, a video-call is possible so that physicians can also see the patient and, if necessary, talk to the patient. Typically, there are three scenarios in which a tele-emergency is called:

- Affirmation of medication, e.g. pain medication, that is administered by the paramedic
- Support in either choosing the appropriate hospital or affirmation that the patient does not need to be admitted to a hospital
- Support of the paramedic in complex emergency cases until the emergency physician arrives on scene

While there are formal requirements that each physician must fulfill before being eligible as an emergency physician, these requirements are not yet formalized for tele-emergency physicians. Ideally, these physicians must be experienced emergency physicians and have additional expertise in tele-emergency care. Since this type of care has recently been implemented, tele-emergency physicians will be those physicians who have worked for several years as emergency physicians on scene [20]. It is important to identify and train the special skills, which are needed for tele-emergency physicians. The tele-emergency physician does not have the complete set of information the emergency physician on scene would have. The physician needs to communicate with the paramedic on scene and make the right decisions based on the available information. In addition, the physician can only advise the paramedic, but cannot treat the patient directly. Thus, the physician must also be able to take the paramedic through certain procedures, if necessary. This requires not only a deep knowledge of the procedure itself, but also the ability to instruct other people via tele-communication.

Another typical aspect of emergency care is limited access to patient information. Ideally, the emergency patient is already known to the hospital or emergency physician, so that the medication and pre-existing conditions of the patients are also already known. Unfortunately, this is not always the case. Patients presenting with acute medical emergencies are often not known to the paramedics, nurses and physicians and are sometimes also not able to communicate. While some countries, such as Sweden or Denmark, offer electronic patient records which allow for access to all relevant medical information online, Germany currently has no such system implemented. In order to improve the access to emergency medical information, the Federal Ministry of Health of Germany has introduced the so-called Medical Emergency Dataset (MED), which can be stored on the electronic health card. The MED is supposed to be introduced in Germany in 2021 (it was originally intended to be rolled out earlier, but the underlying technical telematics infrastructure was not in place). If implementing the MED is successful, it is a great opportunity to improve timely access to emergency medical information and improving emergency medical care [2].

3. Usability Aspects in Linking Emergency Medicine

In emergency medicine, patients often arrive to a hospital emergency department with varying levels of criticality in their health condition(s). Some patients can describe the events that have led to their emergency department visit (e.g. a car accident) while others cannot because of being unconscious, having varying levels of alertness or some disabling event that many have impaired their ability to communicate (e.g. a stroke) [5]. Even the most knowledgeable and health literate patient may forget to disclose or bring information that is important to a physician's diagnostic reasoning and decision-making processes. This places a great deal of burden on the physician to diagnose and treat a patient given a lack of information. Technologies that address physician-patient information needs and support information gathering are important tools to aid in physician decision-making. However, these tools are only effective if they provide useful information. There are significant time and urgency constraints in emergency medicine. Thus, the systems designed for emergency physicians must be effective and timely.

To address this issue, researchers have examined varying aspects of patient information and usability of systems in the context of emergency department visits. Researchers have studied: (i) the type of information that emergency physicians would like to review during emergency visits, (ii) how the information is structured and (iii) the platforms that best suit a physician's ability to access such information. In emergency medicine this has included work by Shapiro and colleagues [21] that described analytical approaches to eliciting the information requirements of emergency physicians by applying online surveys and designing health information exchange (HIE) based on that requirements gathering [21, 22]. Further work in human factors engineering has resulted in designing systems that support critical health information interchange across disparate healthcare systems. These systems are used in emergency situations and support critical decision-making under time restrictions [22]. We point out the essential need for integration, flagging urgent information from different systems, removal of duplicate information, and improvement in the information structure and display relevant to decisions made in emergency contexts, as the human factors barriers.

From a patient perspective, many researchers have advocated that patient information should be accessible via a mobile device in an emergency (i.e. with health care app containing important information about the patient) or via a patient portal that is accessible over the WWW. With a mobile app, a patient could provide access to the information stored on a mobile device during an emergency room visit and this information could be downloaded to the local emergency department's EHR [23, 24]. Patient portals have also been identified as a key source of information for emergency department physicians. Patients could support physicians by providing access to personal health record portals, and information such as medication lists. Using portals to support emergency physician decision-making has been pioneered since the late 1990s [25]. They have since proven their effectiveness in areas such as accessing information about the patient's current diagnoses and medications. Researchers in Taiwan have also used chipped health identification cards that are read by a card reader in a hospital or physician's office. Such an approach focused on sharing patient information with physicians has also been shown to be effective. However, usability concerns regarding use of such devices by patients and their caregivers exist around system accessibility to a wide range of patients and caregivers. Along these lines consideration of digital and eHealth literacy as well as work towards designing systems, applications and user interfaces that are intuitive and understandable by a wider range of users is critical [11, 26].

In order to establish virtual care that ensures quality and accessibility, future work needs to be anchored on core principles in 4 domains [27]:

- Clinical to ensure quality optimization, communication facilitation, and continuity of care.
- Medicolegal to ensure informed consent, confidentiality and privacy, consistency with the legal and regulatory frameworks, and transparency of virtual care involvement.
- Andragogic to ensure competency based training of health professionals, harmonization with curricular priorities, and life-long learning commitment
- Social to ensure contextual sensitivity, return on investment, social reform and continuous quality improvement.

Furthermore, in order to choose and implement digital technologies, we should consider six dimensions to DECIDE [9]:

- **D**igital mirror to reflect data to provide information and insights for change;
- **E**thics to ensure appropriate use of technologies for service delivery that do not violate ethical principles;
- **C**ompetition between industry vendors and how this can positively or negatively affect quality and access;
- **I**nteroperability of all technologies to facilitate data and semantic information flow;
- **D**iscovery to ensure that research and innovation will always be needed to advance future practice of digital health;

- **E**merging future of digital health that will certainly look different from today through advancement and evolution.

4. Cross-Border Emergency Care

The COVID-pandemic has shown dramatically that medical care is not a question each nation can handle separately. In a connected world, healthcare is an international issue. The first COVID-case in Germany appeared by the end of January 2020, only weeks after the first case was discovered in China. Two months later, public life in Germany was shut down. One reason for the rapid spread of the virus and the difficulties of confining it, is the interdependent nature of the different states. Germany has nine different neighboring countries, with a number of people living, working and shopping cross-border. In 1958, the EUREGIO was founded, an organization that links 129 different German and Dutch cities and communities in order to improve cross border life in all its aspects. Other similar organizations can be found across the country.

One of these aspects is healthcare. A lot of different projects and activities have taken place since the foundation of EUREGIO. A German ambulance helicopter, for example, also operates in regions of the Netherlands. When an emergency occurs near the border, the next ambulance is dispatched regardless of its nationality. Dutch and German Level-1 trauma centres take care of trauma patients from both countries. There is also an App available which helps the paramedic translating typical phrases between German and Dutch.

Unfortunately, the information exchange between different countries in Europe is still very limited, despite of some activities by the EU to implement a European EHR in the future. Some countries already offer EHRs to their citizens, however, these records can only be accessed nationally. When the COVID-pandemic will be over, travel activities will resume quickly. Medical Emergency Information needs to be available to physicians outside of the home country of the patient, should he or she face a medical emergency elsewhere. This implies certain challenges, which need to be addressed:

- Different languages: this refers not only to the different languages spoken by the patients and the emergency physicians, but also to different medication names (e.g. paracetamol vs. acetaminophen) and different terms for medical conditions. This challenge emphasizes the need for an internationally approved standardized medical terminology that is used by all countries.
- Privacy and data protection: emergency data needs to be easily and quickly accessible. However, only medical personal should have access to these data. The identification as a medical professional can be assured in the home country of the patient (eg. national electronic medical profession IDs [16]), but there is no standardized international certificate of medical profession that could be used to limit access to medical information. This challenge emphasizes the need for a standardized international process of certification of medical professionals which allows them to access medical information in case of emergency safe and fast.
- Knowledge and education: even if a national medical emergency dataset exists, the medical personal in a foreign country needs to know where to look for it and how to access the information. This challenge emphasizes the need for an

internationally standardized and established process of storing and accessing medical emergency information.

Most smartphones already offer the possibility to store such information (eg. iOS Health or Android ICE – In Case of Emergency). While this information is entered by the patient and may thus not always be complete and valid, smartphones are common worldwide and can be used in different languages. However, this option does not solve the above mentioned challenges concerning medical language, privacy and data protection.

5. Conclusion

In case of emergency, fast and easily accessible expertise is vital. Several projects in Canada and Germany aim to provide specialized medical expertise for medical emergency professionals, regardless of time and place using modern communication technology. In order to provide such expertise, the access to medical information such as medication and pre-existing conditions is important. A standardized medical emergency dataset is to be introduced in Germany in 2021, providing the emergency professionals the information they need. While such a dataset is beneficial inside one's own country, it is desirable to implement a medical emergency dataset that can be read everywhere in the world.

Implementing tele-emergency services is not only a technical challenge, but also needs education and training. Handling an emergency as a tele-emergency physician differs from handling it on scene. Communication becomes even more important. Besides the mere technical training, communication training must be emphasized, so that tele-emergency physicians will have all the skills they need. Since tele-emergency is a new developing field in healthcare, further research will be necessary to identify the essential skills and knowledge to provide tele-emergency care successfully.

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Part 2

Smart Environments for A&EI

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Integrated Sensing Devices for Disease Prevention and Health Alerts in Smart Homes

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Abstract. The rapid development of elderly population is changing demographics in Europe and North America and imposes barriers to healthcare systems that may reduce the quality of service. Telemedicine is a potential solution supporting the real-time and remote monitoring of subjects as well as bidirectional communication with medical personnel for care delivery at the point of perception. Smart homes are private spaces where young or elderly, healthy or diseased-suffering, or disabled individuals spend the majority of their time. Hence, turning smart homes into diagnostic spaces for continuous, real-time, and unobtrusive health monitoring allows disease prediction and prevention before the subject perceives any symptoms. According to the World Health Organization, health, well-being, and quality of life assessment require the monitoring of interwoven domains such as environmental, behavioral, physiological, and psychological. In this work, we give an overview on sensing devices and technologies utilized in smart homes, which can turn the home into a diagnostic space. We consider the integration of sensing devices from all four WHO domains with respect to raw and processed data, transmission, and synchronization. We apply the bus-based scalable intelligent system to construct a hybrid topology for hierarchical multi-layer data fusion. This enables event detection and alerting for short-time as well as prediction and prevention for long-time monitoring.

Keywords. smart home, health monitoring, unobtrusive monitoring, Internet of medical things, quality of life, International Standard Accident Number

1. Introduction

1.1. Aging Population

The life expectancy in many countries has increased due to several dominant reasons including (i) improved healthcare systems, medical science, and diagnostic technology; (ii) increased individual awareness on personal and environmental hygiene, health, nutrition, and education [1–3]. Demographically, this yields an increasing average age of populations. By 2035, one third of the population in Europe and North America will be older than 65 years [4]. Such a rapid growth of elderly will adversely impact the healthcare systems by increasing the human resources, imposing additional costs, and

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consequently reducing the quality of services [5, 6]. Furthermore, an increased life expectancy is connected with demands of the elderly for independence and higher quality of life (QoL) [7]. Hence, in order to adapt to these developing requirements in elderly healthcare services, it is fundamental to create low-cost, unobtrusive, and simple-to-utilize healthcare solutions [8]. Remote health monitoring allows medical personnel to keep track of environmental, behavioral, physiological, and psychological signs. Such an ambient assisted living (AAL) environment enables elderly to live longer autonomously but safely in their homes, maintaining privacy and independence [9]. Thereby, smart homes can advance autonomy, the feeling of prosperity, and empower the inhabitants to gain personal satisfaction [10].

1.2. Healthcare Systems

In our current healthcare systems, a subject meets a doctor when feeling sick, observing symptoms, or for regular check-ups. This yields treatment after diagnosis: medical professionals are mainly involved in the healthcare process by detecting symptoms, diagnosing, and curing after the outbreak of a disease. Their decisions are based on several physiological examinations (e.g., blood and urine tests, blood pressure, body temperature, and heart rate measurements). However, future visions emphasize the importance of prevention and prediction [11]. Next to regular check-ups of risk groups, this can be accomplished by telemedicine, mobile health (mHealth), electronic health (eHealth), and the Internet of medical things (IoMT) [12–14]. These trends aim at managing and integrating large volumes of heterogeneous (big) data, which is generated by sensing devices and stored in electronic health records (EHR). The automated fusion of data from multiple sensing devices minimizes uncertainty and improves the detection of trends in the individual's health status as well as adverse health events. Modern healthcare systems implement data analytics to find patterns and trends within the data, to detect abnormalities or symptoms at an early stage, and to provide decision making [15].

1.3. The Influencing Domains of Monitoring

The World Health Organization (WHO) refers to six domains on health, well-being, and QoL [16], four of them are measurable technically:

- *Environmental* parameters include hazardous or toxic gases that affect the indoor/outdoor air quality and physical parameters such as sound level, ultraviolet (UV) light index, temperature, or humidity [17];
- *Behavioral* parameters include physical activity of a subject (e.g. walking, body posture changes), gait parameters, activity of daily routine (ADL), habits, and nutrition [18];
- *Physiological* parameters include the vital signs (e.g., body temperature, heart rate, respiratory rate, blood pressure, and oxygen saturation) and non-vital signs (e.g., skin conductance) [19];
- *Psychological* parameters include the mood and emotions of an individual [20].

(Remote) sensing in these four domains requires appropriate technologies to measure the respective parameters. Furthermore, continuous and unobtrusive monitoring yields big data. Since the WHO domains are interwoven, fused data analytics and pattern recognition may significantly contribute to real-time event detection in the short-term, as well as prediction and prevention of adverse health events in the long-term, in particular, for vulnerable groups of the population (e.g., children, elderly) [21, 22].

1.4. Smart Homes

Prolonged life expectancy and reduced birth rates yield a fast-growing rate of the elderly. Furthermore, an increased anticipation of QoL aspects is observed that can be met by new healthcare systems [23, 24], supporting elderly to continue living in their own homes, as long as possible. In this new paradigm, the focus shifts from physician-centric to patient-centric healthcare systems, where AAL technologies will revolutionize the delivery of healthcare [25]. In this context, we define the term “smart home” as a residence equipped with sensors and actuators that are integrated into a platform, leading to the capability of monitoring the residents, improving QoL, and promoting independent living [26–29]. More specifically, the benefits of smart homes include monitoring the health status, detecting changes in health conditions, and predicting emergency events (e.g., fall). Hence, smart homes may help to reduce the costs of healthcare systems.

In summary, we identify three major reasons for health monitoring in smart homes:

- *Medical:* detect health conditions and changes that else might have stayed unnoticed;
- *Personal:* allow elderly to continue living at home and having their privacy and independence [26];
- *Economical:* save costs in comparison with living in a nursing home or hospital [30].

1.5. Transforming Smart Homes into Diagnostic Spaces

We consider the smart home as a private space that can be transformed into a diagnostic space [21]. A diagnostic space should enable simultaneous monitoring of parameters from all the four WHO domains. This concept is inline with the paradigms of shifting the: (i) subject-to-device in a hospital → device-to-subject in a point of perception; and (ii) diagnosis on symptoms → preventive medicine. This supports the idea of "an accurate forecast for a specific individual longest before the predicted event" [21]. Such an approach provides unobtrusive, continuous, and long-term data acquisition for real-time monitoring. Integrating inexpensive medical and non-medical sensing devices in smart homes copes with the requirements. Combining signal and bio-signal processing and reducing the hardware complexity by analytical software via artificial intelligence (AI)-based techniques may contribute to a valid diagnosis. The smart home as a diagnostic space potentially solves problems related to smart wearables and clothes, such as obtrusiveness and lack of power supply.

1.6. Target Groups

Several people benefit from transforming smart homes into diagnostic spaces:

- *Inhabitants*:
    - *Healthy individuals* who are unable to seek help in case of an emergency (e.g., fall, stroke, myocardial infarction) due to falling unconsciousness or living in communities with inadequate provision of health services (e.g., rural areas);

    - *Elderly* who suffer from physical impairment such as lowered auditive, visual, or muscular power and/or cognitive derogation (e.g., Alzheimer's disease, dementia);
    - *Disabled people* who need help in daily life to perform personal care (e.g., eating, toileting, getting dressed, bathing) and instrumental activities (e.g., cooking meals, taking medication, doing laundry).
    - *Patients* who suffer from chronic diseases and who need continuous monitoring [26].

- *Caregivers* including family, friends, and relatives of the inhabitants; and
- *Healthcare professionals* giving care either locally (e.g., nursing service, meal on wheels) or remotely by telemedicine systems [31].

1.7. Motivation

The IoMT paradigm has facilitated the interconnection of diverse devices and electronic sensors in an embedded way. Utilizing IoMT in a smart home enables the collection of heterogeneous data from a broad range of sensors. The chain of data aggregation begins with the perception of data via a sensor network tier, which is then reported to a personalized gateway and transmitted to an application tier (i.e., cloud/server) [32]. This architecture enables the communication between various sensing layers and yields telemedical diagnostics and care delivery at the point of perception [33]. Adequate decision making is supported by:

- *Complete integration* of parameters from all measurable WHO domains enables reliable detection of sudden events, such as accidents and emergencies, as well as long-term tendencies of particular diseases.
- *Continuous monitoring* of the health status of a subject requires real-time data analytics for timely alerts.

In summary, transforming a smart home into a diagnostic space (point of perception) requires medical and non-medical sensing devices, which must be integrated for simultaneous monitoring in all four domains. Due to limitations in infrastructure and adequate data processing, this has not yet been accomplished.

We structure this work as follows: in Section 2, we overview the sensor technologies and data management. Building upon that, in Section 3, we summarize typical smart home applications and current research projects making use of them. In Section 4, we show the limitations of current work and use a bus-based scalable intelligent system (BASIS) to enable the measurement of all four WHO domains and thus, we unfold the potential of smart homes as diagnostic spaces.

2. Methods

2.1. Technologies in Smart Home

As seen from its definition, the technologies involved in the smart home can be very broad. Smart home solutions utilize a wide range of technologies serving different goals.

Sensor technology and signal processing play the key role in (environmental, behavioral, physiological, and psychological) data collection; machine learning is essential in information extraction and knowledge discovery; and to implement proper automatic response functions, human-machine interaction (HMI) as well as automation control technology are also unavoidable. Therefore, we also classify the technology from the monitoring perspective according to the four WHO domains: environmental, behavioral, physiological, and psychological. In this section, we introduce the typically used devices/sensors for each category.

2.1.1. Environmental Monitoring

Air quality sensors: Measuring pollutants indicates the quality of air. Pollutants include toxic and hazardous gases such as carbon monoxide (CO), carbon dioxide (CO_2), nitric oxide (NO), volatile organic compounds (VOCs), particulate matter (PM_{10} and $PM_{2.5}$), and ozone (O_3) [34]. Pollutants cause serious health risks depending on their concentration, the subject's health status, and the length of exposure [35, 36]. Nowadays, small devices of convenient forms with low power consumption support continuous and unobtrusive monitoring in particular for elderly, children, and people who are suffering from cardiovascular and respiratory diseases. This has pushed air sensors to become an inherent part of in-home monitoring. Based on the target applications, several factors are considered: selectivity, reliability, resolution, response time, reproducibility, price, etc. [37]. Common technologies utilize metal oxide semiconductors (MOS), electrochemical detection (EC), photoionization (PID), and infrared (IR) [38]. Due to its lower power consumption and price, but higher reliability and easier calibration, EC technology is used mostly. EC sensors have a minimum of two sensing and counter electrodes, which are contacted internally by electrolytes (i.e., liquid as an ion conductor) and externally via an electronic circuit. The electrodes affect certain chemical reactions at the so-called 3-phase boundary, where gas, catalyst, and electrolyte are present. Furthermore, EC sensors provide enhanced signal quality and have a longer lifetime [39].

Humidity and temperature sensors: Used in climate and weather evaluation, humidity indicates the likelihood of precipitation, dew, or moisture. An individual feels hotter under higher humidity, as it reduces the effectiveness of sweating to cool the body [40]. Furthermore, indoor humidity impacts temperature, air quality, health, and appliances [41]. Advanced semiconductor technology has reduced the dimensions and weights of sensors. Frequently, humidity and temperature sensors are combined. Thermal conductivity, resistance, or capacity are typical electrical effects used in these sensors [42]. Linear output voltage, stable output over long-term usage, and a wide range of measurements made capacitive technologies popular. The major sensor components are two curve shape electrodes made of aluminum, platinum, or chromium containing a porous dielectric substance (e.g., hygroscopic polymer film). The dielectric constant varies when humidity changes [43].

2.1.2. Behavioral Monitoring

Passive infrared (PIR) motion sensors: PIR sensors have a low power consumption and price. They detect objects through a changed light intensity [44]. Since the human body generates more infrared light than the indoor environment, this sensor is suitable to monitor human motion. The sensing component consists of a lens and a set of sensors with two slots. The slot is made from pyroelectric materials that are sensitive to infrared light. When the sensor is idle, both slots detect the same intensity, i.e., ambient radiation from the room or the walls. If a person passes by, the first slot generates a pulse. If the person leaves the sensing area, a negative differential is generated (Fig. 1). To monitor indoor behavior, PIR devices are attached to the living room, bedroom, kitchen, and specific facilities such as toilets or sinks (Fig. 2).

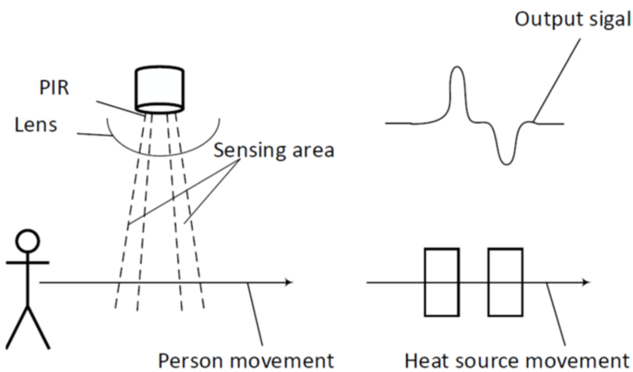

Figure 1. PIR sensing principle [43].

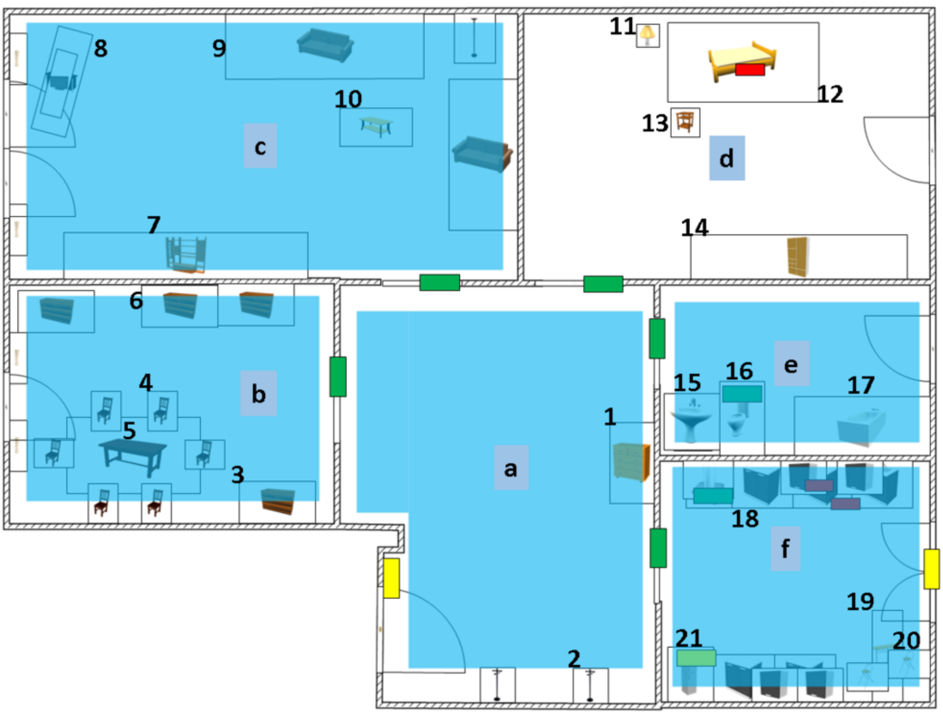

Figure 2. PIR placement in a smart home [46]. The green boxes show the positions of PIR sensors and the blue shadows are the areas under monitoring; the yellow boxes show the positions of contact sensors; red boxes show the position of vibration sensors. Areas and objects distributions in the smart hom; (a) hall: (1) drawer, (2) cloth hanger; (b) kitchen: (3) drawer, (4) dining seat, (5) dining table, (c) living room: (7) TV table, (8) rotating library, (9) sofa, (10) coffee table; (d) bedroom: (11) night light, (12) bed, (13) bedside table, (14) wardrobe; (e) toilet: (15) wash sink, (16) toilet, (17) tube, (f) working room: (18) drawer, (19) desk, (20) chair, (21) drawer.

Contact sensors: Humans open or close doors and windows, and simple contact sensors can track such behavior. The reed switch sensor consists of a contact pair in a glass hermetic shell (Fig. 3). One end of the contacts is fixed, while the other is covered with electro-conductive material and can move freely under the effect of a magnetic field [45]. Once a magnetic field is applied to the switch, the free end moves towards the fixed end. The switch is turned on, which yields a binary signal. Beside doors and windows, contact sensors also monitor the use of furniture or appliances such as cabinets and fridges.

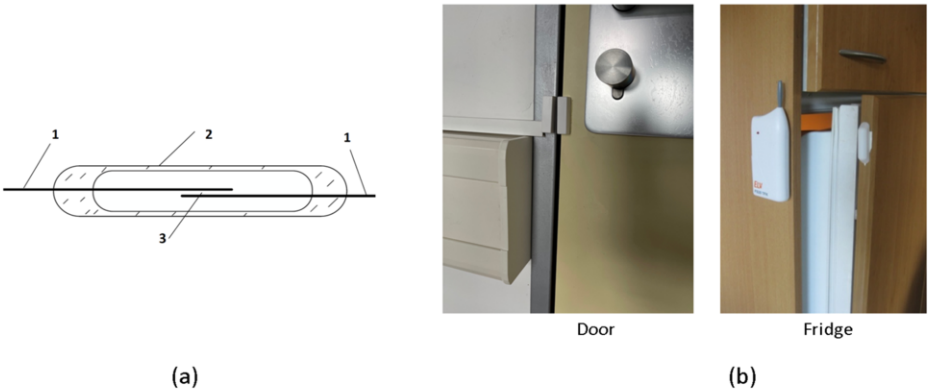

Figure 3. Reed switch. (a) construction: 1 – contact elements (springs) from permalloy; 2 – glass hermetic shell; 3 – working gap. Once there is a magnetic field applied on the switch, the working gap disappears and current passes. (b) application

Smart floors: Passive monitoring of behavior can be implemented resistively, capacitively, piezoelectrically, and triboelectrically [46]. Data includes location of the inhabitant, gait parameters (e.g., walking speed), and posture (e.g., fall). However, smart floors are costly. Specific locations include the bedroom, bathroom, and kitchen, where accidents occur frequently. Then, an alert is generated. Smart floors also create behavioral patterns for long-term monitoring.

2.1.3. Physiological monitoring

Electrocardiography (ECG): ECG is usually measured with wet or dry electrodes, which are in direct contact to the skin. In contrast, capacitive electrodes use the human body as one pole of the capacitor, and clothes or a gap between the skin as the other [47]. Sitting on a chair or lying in a bed with integrated cECG supports continuous monitoring of vital signs. In a cECG chair, the sensing and reference electrodes are attached to the backrest and the seating pad, respectively. In a cECG bed, all electrodes are layered beneath the bed sheet (Fig. 4). Using cECG, we can record the ECG unobtrusively and obtain significant health parameters such as the heart rate (HR) and the heart rate variability (HRV) [48, 49].

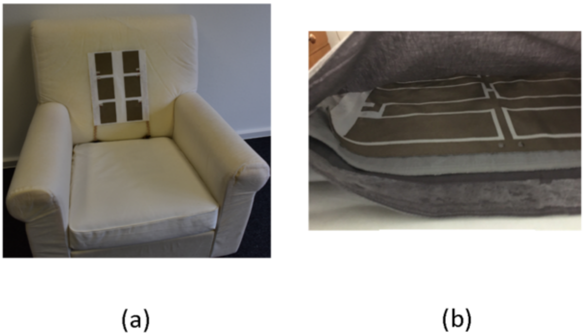

Figure 4. (a) cECG smart armchair and (b) smart bed. Capacitive electrodes are on the backside of the smart armchair and beneath the smart bed.

Ballistocardiography (BCG): Due to the physical law of conservation of momentum, the cardiac ejection of blood results in small velocity of the whole human body. BCG is a non-invasive method to measure such body motion in three dimensions (3D) [50]. However, most devices focus on the longitudinal, i.e., head-to-toe component, as it delivers heart rate and respiratory rate. Piezoelectric sensors and accelerometers are usually adopted to acquire a BCG signal. In smart beds, they are attached to the frame [51] or under the mattress [52].

2.1.4. Psychological monitoring

Psychological monitoring is realized indirectly using the approaches of the aforementioned domains. Physiological parameters can evidently reflect psychological performance. For example, the heart rate, galvanic skin response (GSR), and electroencephalography (EEG) are frequently used for psychological measurements. Also, behavioral changes indicate psychological health [53] (Fig. 5).

Some devices particularly support psychological monitoring. For instance, nighttime wandering monitoring systems (NWAS) support patients suffering from dementia. Nighttime wandering potentially endangers patients in terms of injury (e.g., fall), unattended home exits, and negatively impairs the caregivers' sleep [54]. The sensing delivers bed occupancy, inhabitant location, and use of objects. Fusing behavioral and physiological data yields context understanding and allows actions to calm down the patient, guide him/her back to the bed, and send an alarm to caregivers if the home is left [55].

2.1.5. Using Cameras in Emergency and for Physiological Measurement

According to the Department of Health and Human Services, approximately 28–35% of people aged 65 and over fall each year; and this figure increases to 32–42% for those over 70 years of age [56]. This requires robust approaches for automated event detection and timely delivery of first aid, and depth as well as video cameras use machine learning for fall detection [57–59]. Taufeeque et al. applied long short-term memory (LSTM) networks for human pose estimation and support multi-camera systems as well as multi-person scenes. Their results yielded an F1 score of 92.5%. [60].

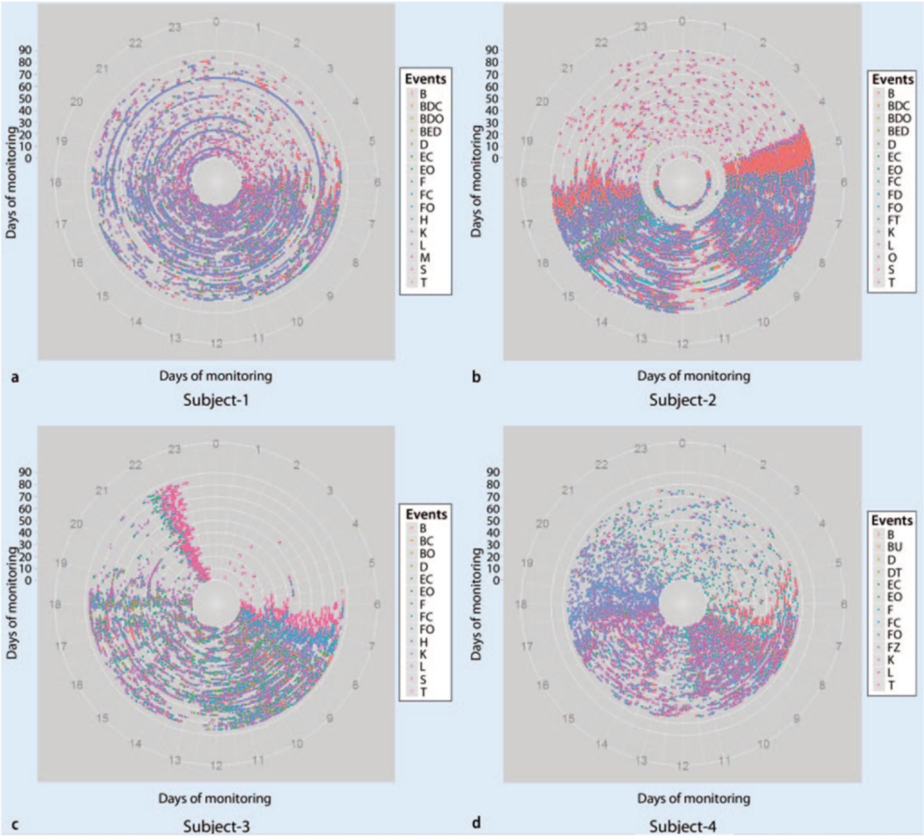

Figure 5. Four subjects' sensor data visualized by means of a spiral plot. The different colored dots represent single sensor events [53].

Furthermore, cameras can measure physiological parameters and vital signs indirectly. This includes heart rate and heart rate variability, SpO2, and others [61–63]. Such systems are applied in several environments, for instance smart cars ([64, 65]) and neonatal intensive care units [64, 65].

2.2. Data Integration and Management

A healthcare telemedicine system is a hierarchical multi-layer model for care and aid delivery [66]. The layers include (i) a network of sensors and sensing devices for measurement and monitoring, (ii) a gateway for aggregating the sensors' data, and (iii) a local server for fusion, processing, visualization, and interfacing the point of perception to external healthcare systems. The sensor network has two layers. The first layer aims at measurement, collection, and transmission. The second layer is an application for the first tier of local processing, fusion, and analysis. The decision-makers require data analysis. This is the consequence of complete monitoring, acquisition of extensive data from distributed sensing devices, and data processing under the umbrella of data fusion. The aim is instant event detection (e.g., fall) or long-term monitoring for predicting and preventing abnormalities [67]. In the following, we describe the components and the function of layers.

2.2.1. Sensor integration

A sensor is an edge-integrated node in the network. It measures physiological or non-physiological parameters and connects to an embedded system. It is not capable of data processing and transmission. A sensor neither has computational resources nor memory storage [68]. It differs from a sensing device in terms of memory, computational unit, operation, and processing [69, 70].

2.2.2. Sensing device integration

A sensing device is an embedded system connected to one or multiple sensors (on-board or add-on integration). The sensing device is an intelligent edge device to collect and pre-process data. Its functionality depends on the topology of the network. A sensing device may have restricted computational resources and memory storage. It is the first networking layer in a hierarchical data model.

An embedded system is a microprocessor-based computer hard- and software system that performs a dedicated function, either independently or as a part of a larger system architecture. Its core is an integrated circuit for real-time operations [71].

2.2.3. Data management

Measuring various parameters, sensing devices deliver an enormous amount of data (big data). We describe the data management in four stages:

1. Data acquisition and processing: Topology of the network, correlation of parameters, and applications address multi-level data acquisition and processing, as [72]:

- Low-level: On the lowest level, a single embedded system connects to several sensors related to one application for data processing. Synchronizing sensing devices, rate of sampling and transmission, the capability of processing and the topology are critical technical factors.
- Middle-level: The mid-level combines the processed data of several sensing devices from the previous stage. It implements pattern matching.
- High-level: The highest level links the point of perception (i.e., diagnostic space: smart home) to the external healthcare systems. It performs complex temporal-spatial fusion and bottom-top (sensor → gateway → server) data flow for long-term monitoring and early-stage detection (diagnosis → prediction → prevention) (Fig. 6). The external server as the third layer is optional and deployed according to the requirements at the point of perception.

2. Data transmission: In a hierarchical multi-layer model, we differentiate data transmission in the inter- and intra-connected network layers. T The intercommunication of sensing devices is hybrid: short-range wireless data transmission (e.g., Bluetooth, Bluetooth Low Energy (BLE), Zigbee) and bulky data transmission with security shield and compression over the long-range (3G/ 4G/ 5G cellular networks, Wi-Fi) [73].

3. Data synchronization: The hybrid topology improves network flexibility and sensor integrity but increases the complexity in terms of data management. Event detection and any change to the parameters are subject to data correlation among all WHO

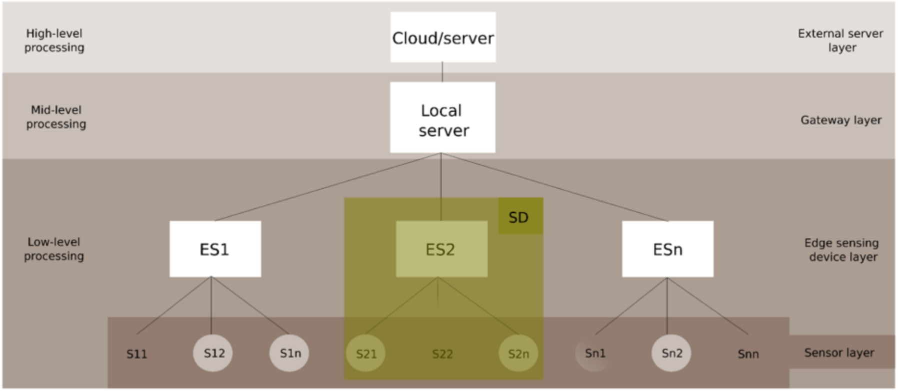

Figure 6. Multi-level data acquisition and processing in smart homes. The abbreviations stand for S: sensor, ES: embedded system, SD: sensing device.

QoLdomains. Thus, every embedded system delivers every parameter with a respective timestamp for synchronization [73].

4. Interfacing with healthcare systems: A complete chain of the healthcare system includes point of perception (i.e., smart home: alerting system), rescue team (responding system), and hospital (curing system). Therefore, a smart home as an alerting system involves responding and curing systems upon the occurrence of an emergency through opening the communication on the local server. The local server is also the bridge with external healthcare system through establishing a bidirectional communication for (i) delivering the emergency aid and rescue service; (ii) delivering care in real-time, and observing the rehabilitation progress by medical personnel; (iii) creating a personalized database by data collection from multi-sources (e.g., car, bike, and wearable) related to the user.

3. Application

We distinguish the applications in disease prevention and automated health alerts in smart homes into (i) health prognostics, (ii) emergency detection, and (iii) assistance and response. We differentiate the applications from long to short-term monitoring.

3.1. Long-term Health Prognostics

In current healthcare systems, a subject consults a doctor for disease diagnosis after the onset of the symptoms, and the level of discomfort is beyond a subjective threshold. This is problematic as many diseases (e.g., cancer) deliver symptomes at a very late stage, often too late for successful therapy and survival. Continuous measurement over the long term offers early stage detection of subtle changes. Simultaneous measurement of environmental, behavioral, physiological, and psychological parameters yields a high prognostic value. Although the environmental domain has a high value for respiratory diseases, this domain is typically not used for prognosis but for emergency detection. In the following, we give examples of prognostic measures in physiological monitoring.

We can assume the ECG as the modality with the highest prognostic value because of a more-or-less direct cardiac activity measurement. Besides, many diseases influence the cardiac system. Each cardiac cycle is represented by a pattern of waves (PQRST). The R-R interval defines the duration between two cardiac cycles and the reciprocal value is the HR. Other patterns allow insight into cardiac health. For instance, a prolonged QT interval is a predictor for sudden cardiac death [74].

Photoplethysmography (PPG) is an optical technique with lower diagnostic value than the ECG but it is more unobtrusive. We can derive theHR and the peripheral oxygen saturation (SpO2) from aPPG signal effortlessly. These parameters are used in emergency settings such as intensive care. SpO2 also shows a prognostic value, e.g., for predicting pulmonary fibrosis [75], respiratory failure [76], or arterial stiffness [77], which is a powerful predictor of cardiovascular mortality [78].

BCG is of value for health prognosis [79] but has not received dissemination comparable to ECG or PPG. This is because of the large number of confounding aspects. The reasons are lack of standardization, the complex origin of the waveform, and a low specificity and reliability for clinical applications [80]. Recently, developers integrated this method into wearable sensors [81] and household items [51].

We have identified a few research projects with prognostics based on devices sensing the behavioral domain. They focus on detecting unique events straightforwardly. However, there are several aspects of health that result in a measurable subtle change in behavior. Depression [82] and dementia [83] change gait, which is measurable by video cameras, smart floors, or distance sensors. Although researchers have proposed camera-based fall risk assessment [83] or disease detection [13], prognostic use of fused sensing devices from multiple domains has not yet been reported.

Use case: We have equipped a 3-room apartment (bedroom, bathroom, living room) with several sensing devices aiming at continuous monitoring for prognosis. We connect all sensors via a universal sensor node to a bus and aggregate the data into a local data warehouse. For physiological sensing, cECG sensors are integrated into the bed and chair [14] and conventional ECG is embedded into a “smart mirror”. This allows ECG monitoring in all rooms. We have installed video cameras with single-board computers. If the camera detects a face, it estimates the heart rate from skin color changes [84]. For behavioral sensing, we integrate three camera systems for pose recognition [16]. Furthermore, we embed contact sensors in each room, at doors and windows, showing the status (open/close). Furthermore, IR sensors detect activities within a room. We also use VoC, air humidity, temperatures, and luminosity sensors to measure the environmental conditions. Hence, we have covered all four WHO domains.

3.2. Short-term Emergency Detection

In this section, we focus on emergencies, aiming at real-time detection and alerting. Again, we consider all four domains. This type of event detection requires real-time sensing and processing of sensor data.

Regarding environmental monitoring, there are many sensing devices available for direct alarming gas, fire). Video cameras also can detect emergencies such as a fire [85]. In an emergency, high sensitivity and specificity are crucial. However, to date, there are only commercial solutions for automatic alerting, which are usually installed in public places such as hospitals, government buildings, or schools, but significantly less in private homes.

Regarding behavioral monitoring, there are several opportunities for emergency detection. Video cameras monitor resident's abnormal behavior, e.g., fall, heart attack [86] or seizure [87]. Smart floors and PIR sensors are also capable of detecting abnormal behavior in the elderly [88] or falls [89]. Secondary use of sensors in home automation, such as monitoring the status changes of simple switches (e.g. light switches) detect similar events [90]. However, there is not yet an alert based on this data. Physiological signals, foremost ECG, shows many cardiac diseases such as elevation of the ST interval [91], which indicated myocardial infarction (STEMI) Hyperkalemia [92], genetic disorders [93], and toxic events [94]can also be seen in the ECG. PPG also has excellent value for detecting emergencies [95]. It is used nowadays mostly in emergency departments and in-home event detection [96], e.g., for overnight measurements [97].

Psychological monitoring is less established in smart homes [29]. In addition, we are not aware of any commercial solution in the smart home for automatic alerting based on a combination of environmental, behavioral, physiological, or psychological sensing devices.

Use case: The International Standard Accident Number (ISAN) [98] aims to provide an emergency communication platform [99, 100] realizing interconnectivity between a smart home (alerting system), a responding system, and a curing system. We use technological, semantical, and syntactical interconnection of these systems to share the relevant emergency information. Our approach supports immediate emergency alerts without any humans in the loop. The core of our approach is the ISAN token, which is uniquely generated upon an event. It uniquely identifies an emergency and provides embedded data describing the accident circumstances (time, location, unique identifier of the alerting system, i.e., point of perception). A demonstrator has been implemented. Once the smart home detects an event (e.g., fall, STEMI), it generates the ISAN number automatically and sends it via the communication platform to the nearest responding and curing systems.

3.3. Assistance and Response

We aim at reducing the time between the occurrence of an emergency and the delivery of first aid. Automatic alerts shorten the time between the event and the call for assistance. Such systems have been commercialized already using bracelets or necklaces with a button that, once pressed, starts a voice connection (human to human) to an emergency center [101]. A similar project is an e-call system embedded in all cars manufactured in the EU [102]. Once the car inflates an airbag, the e-call system automatically establishes a telephone call with the emergency service (human to human) and transmits a minimum dataset (system to system). The systems can be triggered manually, too. Furthermore, smartphone apps provide such panic buttons.

On the contrary, we have described the smart home as a diagnostic space that automatically detects events and directly informs the responding system (system to system) without any humans in the loop.

However, we can also shorten the response time after the call for assistance has been received. Using the ISAN number, the smart home can provide floor maps and other information that helps the rescue team to deliver the first aid faster. This includes not only location but also navigation and additional health information such as ECG or heart rate [100].

In future applications, the smart home could also request for automatic assistance. Robotics and drone technologies have already shown effectiveness in the delivery of first aid kits [103, 104] and performing first aid, such as automatic cardiopulmonary resuscitation [105].

4. Discussion

The WHO defines six domains influencing health, well-being, and QoL. Sensor technology is capable of recording parameters from four of these domains: the environmental, behavioral, physiological, and psychological domains. There are mutual interactions among these domains.

4.1. Relationships Among the Four Domains

Environmental → Physiological/Behavioral/Psychological: The impact of air pollutants on the risks of cardiovascular and respiratory diseases, lung cancer, and early death is well identified and documented [106]. New research has emerged concerning the effect of air pollution on the brain and mental illness (e.g., depression) [107]. The determinants of psychological well-being have also been correlated with air pollution [108]. More precisely, higher levels of air pollution let people spend less time outside, which worse psychological distress by limited exposure to sunlight, reduced physical activity, and increased social isolation [109, 110].

Behavioral → Physiological: Physical activity decreases the risk of several non-communicable diseases, including obesity, cancer, type II diabetes, hypertension, chronic cardiovascular, and respiratory diseases [111]. However, despite a strong commitment of WHO and the European Union in supporting health-enhancing behavior regardless of gender, age, and social status, approximately 31% of adults and 80% of young people (age: 13-15 years) worldwide are physically inactive and do not comply with guidelines of healthy living [112, 113].

Psychological → Physiological: The psychological domain also influences physical activity [114]. For example, psychological stress increases the HRV as well as the blood pressure [115].

These examples show the intensive correlation and interaction of the four domains. The environment as an external domain affects the other domains (subject-related domains) but is itself not affected. Whether the aim of monitoring is long-term health prognostics and short-term emergency detection and assistance, the processing and decision-making is subject to data acquisition from multi sensing systems in multi domains. Thus, simultaneous monitoring of parameters in several domains is important.

4.2. Incomplete Monitoring in Related Work

However, current research aims mainly at recording in one domain [116] and to enhance the quality of data processing and analysis [22, 117]. Efficient acquisition of application-specific data is essential for the design of healthcare services [118]. Lack of appropriate data acquisition complies with incomplete monitoring of the domains [31].

Some studies aimed at monitoring user behavioral changes in daily routine by using sensors in home automation [119] [120]. Projects such as INCA [121] and Veterans Health Administration [122] implemented the infrastructure fulfilling telemedical requirements for disease management and care. FairforAge [123] and OASIS [124] are focused on the aging society at home and in work environments supporting mobility and life with cross-sectional topics on systems development. OASIS develops information and communication technology (ICT) architectures for products and services in aging societies. These leading projects cover three domains (environmental, behavioral, physiological) by observing daily living (ODL).

4.3. Our Vision: Complete Monitoring

We have introduced a concept on measuring all four WHO domains within a home. In our smart homes, we apply the bus system BASIS to connect all sensing devices. This yields the time synchronization of all measured data in all the four domains. The four-line bus has two lines for power supply and two lines for serial data transmission, and small bus couplers are bridging the sensing devices with BASIS. We use ambient sensors to extract behavioral patterns such as inactivity or motion. Our ambient sensors include PIR, light switches, ultrasonic distance, door and window connectors, and power consumption for the oven, fridge, and electrical outlets. We monitor the environmental domain by sensors such as VoC, air humidity, air temperature, and luminosity light.

There are three major concerns about the direct integration of sensing devices from the physiological and psychological domains: the devices (i) record the raw data at high sampling rates (e.g., ECG with typically 1 kHz); (ii) require higher computational power; (iii) support wireless data transmission, which BASIS does not. During the research phase, we add embedded systems (e.g., Raspberry Pi, NVIDIA Jetson) to the sensing devices and transfer onset and offset via the BASIS bus for time synchronization, while we transfer the raw data using Bluetooth, BLE, or Wi-Fi. In an application physe, the raw data is processed directly in the embedded system and not stored at all. This hybrid topology (wired/wireless) reduces latency and enables local and distributed on-board data processing and multi-layer fusion to detect an emergency in any layer. Therefore, we:

- process the simple tasks locally on the embedded systems, to reduce the network latency and bandwidth,
- reduce the potential risk of security, by multi-layer data fusion and not push all raw data to the external server,

This promotes the smart home concept to diagnostic spaces covering all four domains.

4.4. Future Trends in Healthcare System

Simultaneous monitoring of the four domains improves the semantic interoperability of the smart home as a diagnostic space in precise and valid diagnostics before occurrence. However, private spaces are also smart vehicles. Smart cars can be transformed into diagnostic spaces as they have a controller area network (CAN) bus which is similar to the BASIS in the smart homes [125]. Monitoring an individual in a smart diagnostic car will add valuable information supporting unobtrusive, continuous, and simultaneous measurements in all four domains while driving. Extending the continuous health monitoring to 24/7 specifies the role of wearable devices, e-bike, and smart offices (smart city). This complies with the anything, anyone, anywhere, and anytime (A4) approach [31]. In the near future, we expect more dynamic and mobile points of perception. Seamless integration of the environments is challenging with respect to privacy and security. However, we expect automated data fusion from multi-sources (e.g., smart home, smart office, smart car, e-bike, and smart wearable) at distributed locations, leading to a personalized database. This empowers valid diagnostics and decision-making. Real-time monitoring and event detection is supported by linking the point of perception to external healthcare systems. In particular, the responding and curing systems are involved for real-time care and emergency services delivery at the point of occurrence.

5. Conclusion

Integrating sensing devices that mutually measure parameters from the four WHO domains of health, well-being, and QoL is essential for disease prevention and automatic health alerts in smart homes and smart cars. We integrate medical and non-medical sensing devices. Enriching the sensory layer network and developing hierarchical multi-layer data fusion based on powerful computational nodes, supporting wired/wireless communication, facilitates on-board and distributed data acquisition and processing. This will reduce the traffic of raw data aggregation to high-level fusion. It also adds invaluable processed information at a lower level and shortens the processing time for information extraction out of the raw data. Bus-inherent synchronization supports data fusion for long-term diagnostics and event detection. The young and the elderly, the healthy and the disease-affected will benefit. In particular, we support the United Nations' 2030 Agenda for Sustainable Development [126], where the sustainable development goal (SDG) 3 is to ensure healthy lives and to promote well-being for all people of all ages as well as the WHO 13th General Programme of Work [127], which has three interconnected strategic priorities to ensure healthy lives and well-being for all: (i) achieving universal health coverage, (ii) addressing health emergencies, and (iii) promoting healthier populations.

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Innovative Sensor Technology for Emergency Detection in Life Science Laboratories

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Abstract. Chemical, analytical and biological laboratories use a variety of different solvents and gases. Many of these compounds are harmful or even toxic to laboratory personnel. Permanent monitoring of the air quality is therefore of great importance regarding the greatest possible occupational safety and the detection of dangerous situations in the work process. An increasing need exists for the development and application of small and portable sensor solutions that enable personal monitoring and that can be flexibly adapted to different environments and situations. Different sensor principles are available for the detection of gases and solvent vapors, which differ in terms of their selectivity and sensitivity. Besides simple sensing elements, integrated sensors and smart sensors are increasingly available, which, depending on their scope of functions, require a distinct effort in integration. This chapter gives an overview of available sensors and their integration options, and describes ready-to-use sensor systems for personal monitoring in life science laboratories.

Keywords. gas sensors, gas monitoring, laboratory automation, life sciences, laboratory monitoring

1. Introduction

Humans are regularly exposed to different toxic compounds in the indoor and outdoor environment. Poor air quality can cause various health problems, which can finally result in life-threatening and expensive emergency care. The development of suitable sensors for monitoring a wide variety of toxic components is therefore of enormous importance.

The classic pollutants in our air include nitrous gases, sulfur dioxide and hydrogen sulfide, which are released by natural processes or processes induced by humans (industrial exhaust gases, exhaust gases from combustion plants or motor vehicles, etc.).

In addition, contamination with toxic components can also arise in the work environment. This includes in particular chemical, analytical and biotechnological laboratories in which a wide variety of gases and solvents are used.

Carbon monoxide, for example, is produced in various chemical reactions or is used directly as a reaction gas. It is a highly toxic colorless, odorless, and tasteless gas. Human exposure to CO leads to the formation of carboxyhemoglobin, since CO is bound to hemoglobin with 250 times higher affinity than oxygen. The resulting insufficient supply

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of oxygen initially leads to headaches and dizziness. At high CO concentrations, unconsciousness and death occur.

Volatile organic compounds (VOC) is the collective term for organic substances that can easily vaporize at room or elevated temperatures. According to the World Health Organization (WHO) this includes all organic compounds with boiling points between 50-260 °C. Classic VOCs that are used in laboratories are e.g., hydrocarbons, alcohols, ethers or organic acids. Symptoms such as headache, hypersensitivity reactions, tiredness, decreased performance, sleep disorders and irritation of the respiratory tract are summarized under the term “sick building syndrome” [1]. The WHO does not define the clinical picture in an internationally binding manner. Effects on the nervous system are also known [2].

Another class of substances frequently used in laboratories are volatile halogenated hydrocarbons. These include, for example, chloroform, perchloroethylene or vinyl chloride (basic material for PVC production). These compounds form a component in many commercial products and chemical preparations, as well as in solvents and extraction agents. They can damage the ozone layer; some representatives (e.g., vinyl chloride) are also carcinogenic and mutagenic [3].

Dimethylformamide (DMF) is also a frequently used solvent. DMF is irritating to the skin, eyes and respiratory tract and can cause headache, nausea, dizziness, weakness, confusion, and a drop in blood pressure. Liver damage and alcohol intolerance reactions can occur [4].

Monitoring the air quality in laboratories is of particular importance both in preventing accidents with chemicals and in minimizing the exposure of laboratory personnel. Many sensory solutions have been developed for this purpose and are used to monitor room air and comply with limit values. The majority of classic systems are permanently installed systems. They enable entire rooms to be monitored, but are difficult to reconfigure if the laboratory environment changes. Such systems are also associated with high costs. In addition to permanently installed systems, there are also many transportable devices. These can be used flexibly in changing environments and changing applications. Due to their size, however, they cannot be used for personal monitoring of laboratory personnel either.

For the personal monitoring of laboratory personnel, the development of small sensor solutions that can be worn on the body or on clothing makes sense. While there are numerous wearable systems for personal monitoring that measure different physiological parameters, there are hardly any systems available for corresponding monitoring of chemical parameters. Suitable sensors must have the smallest possible dimensions. The sensor principles should be robust even under general environmental conditions. Sensitivity and selectivity should be appropriate to the applicable limit values for maximum concentrations of the various pollutants.

Hazardous situations for human can be categorized into oxygen deficiency/excess, explosion hazards and intoxications. Depending on the type of hazard, different measurement principles of gas sensor can be used [5] [6]. Oxygen measurements are often based on electrochemical principles. A higher risk of explosion especially exists in environments where combustible gases and vapors occur, as e.g., in the mining, chemical and oil refining industry. Here, often infrared and catalytic bead gas sensors are used. Intoxications include metal fumes as mercury, narcotic-acting gases and fumes as organic solvents, propane and butane, hydrides as arsine and phosphine or war gases as sarin. For these gases, primarily electrochemical and photoionization gas sensors are deployed.

2. Innovative Gas Sensors

Gas sensors belong to the class of chemical sensors and are used specifically for the detection of gaseous substances. Sensors for measuring physical quantities such as temperature, pressure, and acceleration are usually sealed watertight and airtight. Instead, gas sensors have to interact directly with their environment to detect the chemical component. This makes them much more susceptible to poisoning (environmental influences that make the sensor insensitive). In addition, they also show a certain cross-sensitivity (substances besides the target component that cause a sensor signal) and are characterized by corrosion, long-term drift, zero point drift and temperature drift [7].

Different principles can be used as measuring method. Physical principles use molecular properties such as the molecular mass, the diffusion behavior, the molecular structure (e.g., magnetic properties or paramagnetism), the molecular stability (as binding energies) or the molecular mobility for detection. Chemical measurement methods, on the other hand, use chemical properties such as reactivity, oxidizability, or reducibility.

The decisive factor for detecting hazardous gas situations is the correct selection of suitable measurement principles. Every principle is optimized for specific groups of gases with a characteristic behavior, and has consequently own advantages and limitations.

Depending on the target application, different criteria need to be considered for the sensor selection. The following key parameters are most important for the decision of a convenient sensor solution:

- **Detection range** – minimum and maximum of the allowed/detectable concentration
- **Sensitivity / resolution** – smallest change of the signal that can be detected/observed (often only one is given)
- **Accuracy / repeatability –** maximum deviation/variance (often only one is given)
- **Pre-operation time** – required time before the sensor is ready to use. For some gas sensors, a warm-up time of the heaters is required.
- **Response time** – required time of the sensor signal from zero to commonly 90% (T90) of the full-scale by exposing the sensor to an instantaneous full-scale concentration change [8]
- **Recovery time** – required time of the sensor to fall back to the baseline or to 10% of final value after step removal of measured variable [9][8]
- **Sensor lifetime** – expected duration of the sensor's operation; an often seen specification is around 5 years, depending on the principle and the using conditions
- **Environmental conditions** – required working range for environmental parameters such as temperature, humidity, and atmospheric pressure

For the use of sensors for personal monitoring, the sensor systems should be as small as possible in their design.

2.1. Catalytic Bead Gas Sensors

For the detection of combustible gases such as natural gas, methane, butane, propane or hydrogen, the catalytic bead method is particularly suitable, since here the combustible characteristics of gases are exploited. Especially in the detection of hydrocarbons of the lower explosive level (LEL) or hydrogen (H_2) this method is used to monitor explosion limits [10][11].

The sensors consist of two platinum heating coils (detector and reference coil), which are enclosed by ceramic beads (smaller than one millimeter), also designated as pellistors (combination of pellet and resistor). The detector bead additionally is coated by a catalytic active substance, e.g., platinum, palladium or metal oxides such as manganese oxide [12]. The reference bead remains passive without a catalytic substance. Both pellistors are encapsulated by an explosion-proof housing with a sintered metal flame arrester on the gas exchange side. This is necessary since minor explosions can arise, which should not have impacts on the environment.

In the measurement process, the coils are usually heated up to 300-500 °C, depending on the target gas [13]. The catalyst of the detector bead effects a decrease in the activation energy, and intermediate states of the reaction arise on its surface. This influences the speed of reaction, depending on the temperature and the concentration of the reactants, and leads to the combustion of the absorbed gases on the catalysts surface. Through the combustion, the temperature around the detector bead increases, resulting in an increase in the resistance of the coil. No change in temperature and resistance is observed for the reference bead. Environmental effects such as temperature fluctuations have the same influence to both pellistors and their resistance. By utilization a Wheatstone bridge (half bridge) these effects are compensated and the resulting bridge voltage (by resistance change of pellistors) is quantitatively proportional to the concentration of the combustible gases in the chamber (see Figure 1) [14].

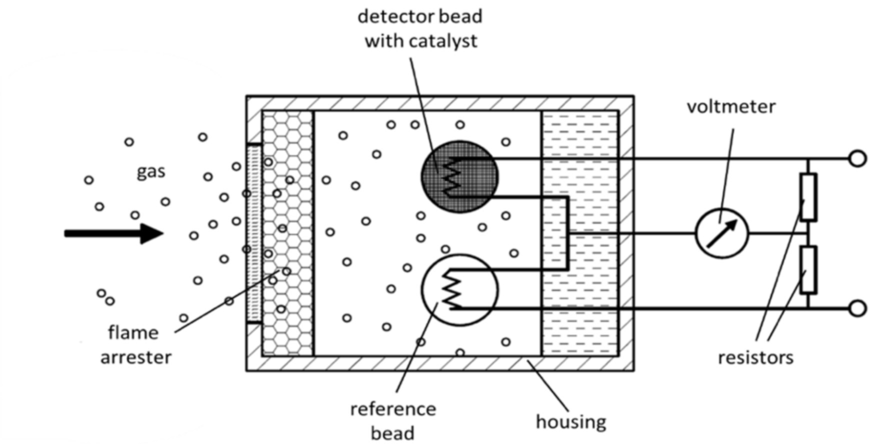

Figure 1. Principle of a catalytic bead sensor.

Catalytic bead sensors are inexpensive and robust and can easily be calibrated due to the linear sensor reaction depending on the gas concentration. A necessary condition for using catalytic bead sensors is the presence of oxygen, since it is required for the burning process. With less than 10 seconds, the response time of catalytic bead sensors is relatively short [15]. The average lifetime of these sensors is commonly 5 years [16], which can be significantly reduced by catalyst poisoning, whereby the catalysts are partially or completely deactivated by gases containing sulfides, halides, and silicones [15]. A disadvantage is their low sensitivity in the percentage range, since relatively high gas concentrations are necessary for a sufficiently high heat release. They also show only a low selectivity: every gas that burns on the catalyst surface of the pellistor and causes a measurable heat release is registered as an increase in resistance, so that a selective determination of the gas type is difficult. Due to the required heating, these sensors consume a significant electrical power, which reduces their use in mobile applications.

Catalytic bead sensors are often used for the detection of flammable gases, such as methane. Examples are the SGX VQ21TB (SGX Sensortech, Neuchatel, Switzerland) or the Figaro TGS681x (Figaro USA, Inc., Arlington Heights, IL USA).

2.2. Electrochemical Gas Sensors

Electrochemical gas sensors (also: electrochemical cells, EC sensors) work similarly to batteries or fuel cells. The basic components of an electrochemical sensor are a working electrode, a counter electrode, and usually also a reference electrode. These electrodes are enclosed in the sensor housing and are in contact with a liquid electrolyte. The working electrode sits on the inside of a porous hydrophobic membrane that allows gas to pass through, but not the electrolyte (see Figure 2) [17][18].

Once the gas gets in contact with the sensor, it flows through the membrane to the working electrode. Depending on the type of gas, it is either

- oxidized (e.g., $CO + H_2O \rightarrow CO_2 + 2H^+ + 2e^-$) or
- reduced (e.g., $O_2 + 2\,H_2O + 4e^- \rightarrow 4\,OH^-$)

at the measuring electrode. The resulting ions (H^+, OH^-) diffuse through the liquid electrolyte and are

- reduced (e.g., $O_2 + 4\,H^+ + 4\,e^- \rightarrow 2\,H_2O$) or
- oxidized (e.g., $4\,OH^- + Pb \rightarrow PbO_2 + 2\,H_2O + 4\,e^-$).

at the counter electrode. A current flow is created between the two electrodes, which is proportional to the gas concentration [19][20].

To prevent the measured values from drifting, a reference electrode is used that generates a constant potential. The gas concentrations are displayed in part per million (ppm) for toxic gas sensors and in percent by volume for oxygen. The great advantage of electrochemical gas sensors is their high specificity and sensitivity to target gases. Due to their principle of action, there is little or no cross-sensitivity to other substances. Further, these sensors consume low power and offer an intrinsically safe operation. Because of their capacity for miniaturization [13] they have ideal features for mobile sensor solutions. A drawback of electrochemical gas sensors is their high sensitivity to humidity and gas concentrations (electrode poisoning). In addition, the temperature dependence of the electrochemical potential has to be considered. These factors can lead to irreversible damages and offset the baseline readings or influence sensors response time [21].

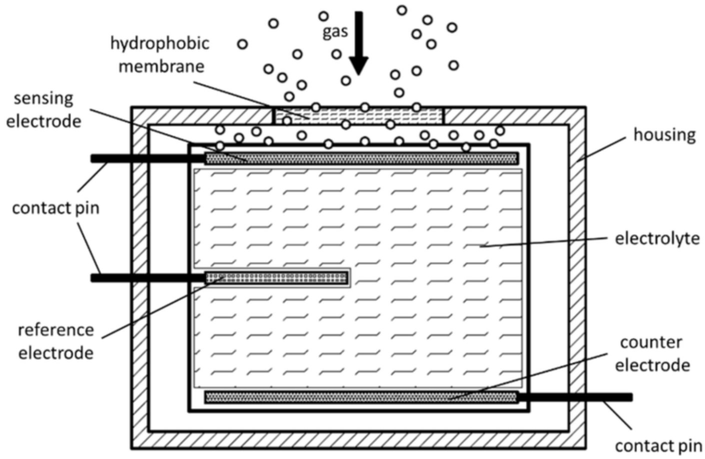

Figure 2. Principle of an electrochemical gas sensor.

The electrochemical gas sensors include the ZE08-CH 20 (Winsen Electronics Technology Co., Ltd., Zhengzhou, China), which is used for the determination of formaldehyde. The measuring range is between 0 and 5 ppm, with a resolution of <0.01 ppm. The interference with alcohol and carbon monoxide is disadvantageous.

Another representative of this group is the SPEC Sensor Package (SPEC Sensors LLC, Newark, CA, USA) for the determination of ethanol in the range up to 1,000 ppm with a resolution of <5 ppm and a service life of 5-10 years.

Small electrochemical sensors are also available for the detection of carbon monoxide (CO: 0-2,000 ppm), hydrogen sulfide (H_2S: 0-1,000 ppm) and nitrogen oxides (NO: 0-250 ppm; NO_2: 0-2,000 ppm) as well as sulfur dioxide (SO_2: 0-2,000 ppm). In addition, these air quality sensors detect oxygen (O_2: 0-30%), hydrogen (H_2: 0-1,000 ppm), chlorine (Cl_2: 0-200 ppm) and chlorine dioxide (ClO_2: 0-1 ppm) (SGX Sensortech, Neuchatel, Switzerland).

2.3. Photoionization Gas Sensors

By exposing gases to ultraviolet light (UV) the ionization of specific molecules can be observed, which is practically used for the detection of chemical compounds by the photoionization detection (PID). This principle is primarily used for the detection of harmful VOC's in the environmental air [22].

The base of this measurement method is a UV light source and two electrodes (sensing and counter electrode). The components are positioned in a measurement chamber, which is continuously supplied by environmental gas molecules. If the gas molecules enter the chamber, they are exposed to the UV-light inside. The UV lamp emits photons with a sufficiently high energy to strike out an electron and to form positively charged ions (see Figure 3). Often light sources with 10.6 eV are used since a wide range of harmful substances respond to it. In contrast, this energy is not high enough to ionize classical air compounds such as nitrogen, oxygen or noble gases. These light sources have the longest life expectancy, of approximately 6,000 hours [23]. The electrodes establish an electric field in the measurement chamber, and an ionization current arises from the ionized molecules. The resulting intensity of the ionization current is directly proportional to the concentration of the ionized gases [24][25]. The so-called response factor represents the sensitivity of the sensor relating to a reference substance (mostly isobutene) and allows the determination of the gas concentration. This is important if the target gas cannot be used for calibration or different gases are detected by one sensor. The determination of a specific gas concentration requires the separation of the target gas, since otherwise the concentration of all ionizable gases (depending on the UV lamp's photon energy) in the chamber are added up.

Modern PID solutions are already capable of measuring concentrations of organic compounds around 1-10 ppb and have typical response times of a few seconds [26]. The size of the ionization chambers typically is between 40-200 µL [27] but can be reduced to a few microliters (0.5-10 µL [24]). Accordingly, this method is suitable for portable gas detection solutions.

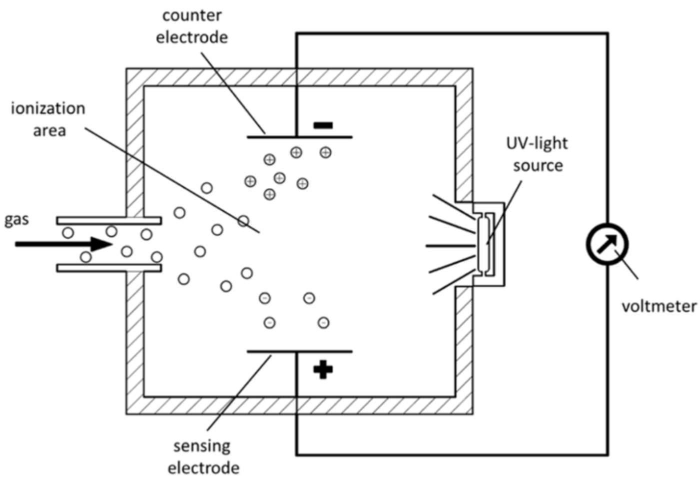

Figure 3. Principle of a photoionization sensor.

An example of a photoionization detector is the ION MiniPID2 (Ion Science, Royston, UK) for the detection of highly volatile organic compounds (VOC). Different versions allow detection in ranges from 0 to 40 ppm, 0 to 100 ppm or even up to 4,000 ppm; the detection limit is 100 part per billion (ppb). The 11.7 eV MiniPID2 extends the range of detectable compounds with chlorinated hydrocarbons, unsaturated fluorocarbons, formaldehyde, ethylene, and methanol. The sensors can be used in the temperature range from -40 °C to +65 °C with humidity from 0 to 99% RH. The ION MiniPID2 HS achieves better detection limits with 0.5 ppb, although it can only be used in the range up to 3 ppm. It is well suited for clean rooms and the detection of volatile contaminants. The lifespan of these sensors is over 5 years.

2.4. Non-dispersive Infrared Gas Sensors

One characteristic of most gas molecules is their absorption of light of specific wavelengths. If a photon hits the gas molecule, the photon's energy stimulates the molecule to oscillate. Some gases can absorb visible light if the concentration is high enough (e.g., chlorine appears in yellow-green and iodine vapor in violet) but generally the absorption occurs in the infrared area. Typical absorption lines are 9.6 µm for ozone (O_3) [28], 3.3 µm or around 7.8 µm for methane (CH_4) and 4.24 µm for carbon dioxide (CO_2) [29][30][31]. This behavior can be used effectively to differentiate gases. The selectivity of this method is limited, since several gases show similar absorption lines as e.g., CO_2 and H2O, at 2.7 µm [32].

An established optical gas-detection method is the so called NDIR-approach (non-dispersive infrared). It is especially convenient for determining the concentration of hydrocarbons, carbon monoxide and carbon dioxide.

Main parts of this sensor are a broadband infrared light source, a measurement cuvette (sample chamber), two bandwidth filters and two infrared detectors (measurement and reference detector). The cuvette connects the opposite positioned light source and the detectors in such a way that the emitted light has to pass the whole cuvette to reach the detector's site. In front of each detector, a narrow bandwidth filter is positioned, which only lets pass through a specific spectrum of the emitted light. The spectrum of the filters is different, so that the measurement filter can be selected for a specific absorption wavelength of the target gas. The reference filter uses a wavelength, which is not affected by the target gas, and is detected by the reference detector (see Figure 4).

In the measuring process, the cuvette leads the gas flow lengthwise to the emitted light. If the target gas passes the cuvette, the gas-specific wavelength of the emitted light will be absorbed and cannot be detected by the measurement detector. The reference detector in this case does detect light, and confirms the detection. If influences such as power and temperature fluctuations, polluted optical parts or dust disturb the measurement, both detectors are affected in the same way [32][33].

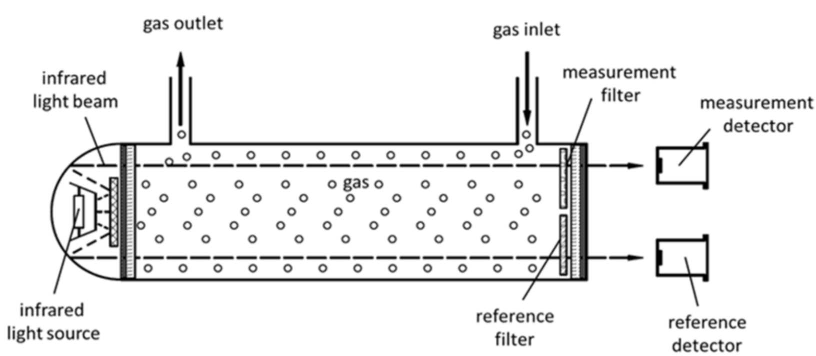

Figure 4. Principle of an NDIR gas sensor with two infrared detectors.

The NDIR method is a robust and cost-effective way to measure different gases with a medium resolution. The reaction time of these sensors is roughly around 20 seconds. By using a reference detector, many disturbances can be recognized and used to avoid false detections. This method also allows small constructions, which can be used for portable sensor solutions. One restriction of this method is the condition that the required gases need to absorb infrared light and that the wavelengths of these gases need to be known. Measuring several gases in parallel is possible but restricted since for every gas, an own filter-detector unit needs to be installed. Further, the length of the cuvette is very close to the absorption characteristic of the gas [34]. A combination of gases with different absorption characteristic requires a separation of the measurement canals with own cuvette and filter-detector unit [35].

An example of non-dispersive portable IR sensors is the SGX IR12 GM (SGX Sensortech, Neuchatel, Switzerland) for the detection of methane and hydrocarbons with a minimum detection level of 30 ppm methane (CH_4). A further example is the IRC-A1 sensor (Alphasense, Sensor Technology House, Essex, UK) for the measurement of carbon dioxide (CO_2) in the range of 0 to 5,000 ppm.

2.5. Metal Oxide Semiconductor Gas Sensors

Under the influence of gas, some metal oxides, such as tin(IV) oxide (SnO_2) or titanium dioxide (TiO_2), but also organic semiconductor materials, show a change in their conductivity. Oxygen vacancies in the crystal structure of the oxides act like n-doping of the material. This effect is used in metal oxide semiconductor gas sensors (MOS) to detect gases [36].

In a first step, oxygen molecules from the ambient air are adsorbed onto the sensor surface. The oxygen accepts electrons from the inside of the semiconductor and is therefore negatively charged. As for an n-type semiconductor (SnO_2), this reduces the charge carrier density, which leads to the formation of a depletion zone and lowers the conductivity in the edge zone (see Figure 5). If the surface of the semiconductor is exposed to a reducing gas, this reacts with the resulting oxygen ions, changing the conductivity. While reducing gases such as carbon monoxide or hydrogen increase the conductivity, it decreases in the case of oxidizing gases such as oxygen, oxygen producing gases or fluorine. Due to the correlation between the gas concentration and the change in conductivity, a quantitative determination of the concentrations can be carried out in addition to the determination of the gas. To enable a reaction between the ambient gases and the sensitive material and for controlling the selectivity [37] an operating temperature between 250°C and 450°C [38] is required, thus usually a platinum heater is included [37].

One of the most known MOS sensors based on tin oxide is the "Figaro sensor" developed by Naoyoshi Taguchi [39]. Depending on the design, these sensors can be used to detect natural gas and methane gas (type TGS 813), but also to determine alcohol, ammonia, etc.. MOS sensors are quite inexpensive due to the possibility of mass production. They are characterized by high sensitivity in the ppm range and a long service life [40]. One disadvantage is the non-linear sensor reaction depending on the gas concentration, which makes calibration considerably more difficult. In addition, there is a certain cross-sensitivity, especially regarding air humidity. The selectivity of the sensors is low so that they can only be used for screening purposes or the determination of known compounds. The sensitivity of the semiconductor for a certain gas can be changed via the temperature of the semiconductor.

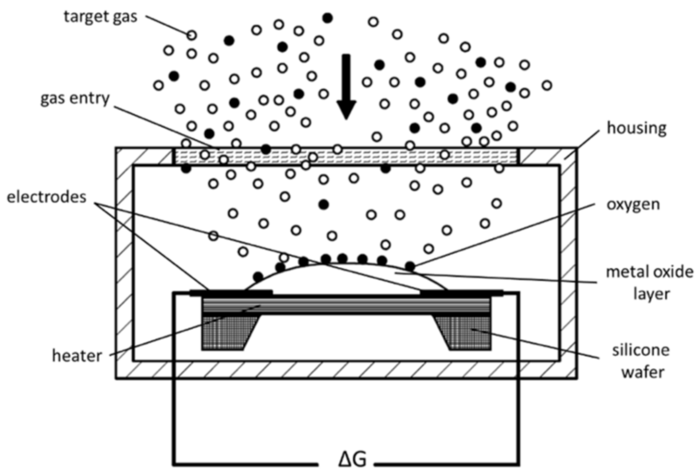

Figure 5. Principle of a metal-oxide gas sensor.

Another disadvantage is the high-energy consumption due to the required operating temperature. Miniaturization and the use of thin-film technology [41] can be used here to reduce the energy demands. The reduction of energy consumption of MOS gas sensors is a topical issue in research regarding the growing interest in adapting gas sensors for wearable devices [42][43].

The MiCS 5524 (SGX Sensortech, Switzerland) is an example of a MOS sensor which is used for indoor air quality monitoring. It allows the measurement of carbon monoxide (CO, 1-1,000 ppm), ethanol (C_2H_5OH, 10-500 ppm), hydrogen (H_2, 1-1,000 ppm), ammonia (NH_3, 1-500 ppm), methane (CH_4, >1,000 ppm). The MOS sensor TSG 8100 (Figaro USA, Inc., USA) for detecting air contaminants detects similar gases in the range of 1-100 ppm.

2.6. Graphene-Based Gas Sensors

Another type of gas sensors is based on graphene. Due to properties such as high surface-to-volume ratio, low electrical noise and remarkable transport properties related to the two-dimensional structure, graphene is an interesting material for different new applications. Numerous sensor applications are known for the determination of different biochemical components such as glucose in tears or sweat [44], lactate in sweat [45], ascorbic acid in tear films [46] or cortisol in sweat or saliva [47].

Ko et al. showed in a study that graphene can easily absorb/desorb NO_x molecules [48]. The conductivity of graphene layers changed depending on the concentration of NO_2 molecules. The resulting graphene-based sensors were characterized by a fast response, good reversibility, selectivity and high sensitivity. With UV LEDs and silicon microelectronics, this new technology can be used for the development of nano-sized gas sensors with very high sensitivity.

Ultrasensitive NO_2 gas sensors based on epitaxial graphene have been reported by Novikov et al. [49]. An optimized graphene/metal contact configuration resulted in a low contact resistance. A significant improvement of the sensing sensitivity was further achieved by complementary annealing of the sensor at 120 °C in the carrier gas flow. The limit of detection was estimated to be 0.6 ppt.

A graphene-based sensor has also been reported for environmental monitoring [50]. The prototype showed fast and reproducible measurements of NO_2 in environmentally relevant concentrations between 5 and 50 ppb.

NO_2 sensors are operated in ambient environments. Thus, possible cross-selectivities have to be minimized. A study conducted by Melios et al. showed that graphene has similar sensitivities for NO_2 and SO_2 at 70 °C. However, operating the sensor at higher temperatures at 150 °C significantly enhanced the sensitivity for NO_2. In addition, higher temperatures could also decrease the sensitivity of typical concentrations of CO in ambient air [51].

Other sensors have been developed for the determination of ammonia (NH_3) [52][53]. The level of detection (LOD) was determined at 500 ppb. The determination of hydrogen with LOD of 20 ppm was reported by Chung et al. [54]. Ren et al. described the determination of sulfur dioxide using a graphene-based sensor [55]. A detailed review of graphene-based sensors for the determination of different toxic gases and organic vapors including methanol, acetone and toluene can be found in [56].

2.7. Summary

The sensor market has developed very dynamically recently. The focus was on ever-increasing miniaturization. Smaller sensors form the basis for personal monitoring of people in their workplaces.

Numerous technologies are now available for determining different compounds. Unfortunately, the majority of the sensors do not have sufficient selectivity, which would be necessary for the determination of individual compounds. Chemical sensors are the exception, which, due to their very selective operating principle, can be used specifically for the quantitative detection of a wide variety of different inorganic and organic compounds.

Table 1 shows a summarizing overview of compounds and suitable sensors.

3. Hardware for Sensor Integration

3.1. General Requirements

Depending on the target application, specific sensors can be selected. For their integration into technical solutions, different selection criteria need to be considered. These parameters may differ depending on the technical measurement principle. One of the most important parameters for the sensor operation is the energy supply, which is required for the vast majority of gas sensors. Typical voltages are 1.8 V, 3.3 V or 5V. The power consumption – required electrical energy – is another important parameter.

For the determination of the sampling rate, it is important to consider that the response time of the sensors commonly requires several seconds to reach the final value, depending on the principle and the construction. A change in the sensor's sampling rate often has an influence on the sensor's behavior and consequently requires an individual calibration.

Table 1. Selected sensor principles for the determination of different inorganic and organic. components

Compound	Sensor Principle Detection Range ppm	Example
Inorganic Gases		
Ammonia	EC / 0-200 ppm	FECS44-200[a]
Carbon dioxide	IR / 0-5%	IR601[b]
Carbon monoxide	EC / 0-1,000 ppm	FECS40-1000[a]
Chlorine	EC / 0-10 ppm	FECS45-10[a]
Hydrogen	MOS / 1-30 ppm	TGS 2600[a]
Hydrogen Sulfide	EC / 0-100 ppm	FECS50-100[a]
Nitric oxide	EC / 0-300 ppm	FECS41-250[a]
Nitrogen dioxide	EC / 0-30 ppm	FECS42-20[a]
Oxygen	EC / 0-100%	KE-25[a]
Sulfur dioxide	EC / 0-20 ppm	FECS43-20[a]
Organic Gases and Solvents		
Acetylene	IR / 0-100 ppm	IR604[b]
Alcohol / Solvent vapors	MOS / 50-5,000 ppm	TGS2620[a]
Aromatic compounds	PID / 5ppb-100 ppm	10 eV MiniPID2[c]
Butane / Propane	MOS / 1-25%	TGS 2610-C00[a]
	CAT / 0-100%	TGS6810-D00[a]
Chlorinated hydrocarbons	PID / 0.1-100 ppm	11.7 eV MiniPID2[c]
	MOS / 5-100 ppm	TGS3830[a]
Chlorofluorocarbons	MOS / 5-100 ppm	TGS 3830[a]
Combustible gases	CAT / 0-100%	VQ549ZD[b]
Ethanol	MOS / 1-30 ppm	TGS 2602[a]
	MOS / 10-500 ppm	MiCS 5524[b]
Formaldehyde	PID /0.1-100 ppm	11.7 eV MiniPID2[c]
Methane	MOS / 1-25%	TGS 2611[a]
	CAT / 0-5%	MP7217[b]

[a] Figaro (Arlington Heights, USA); [b] SGX Sensortech (Neuchatel, Switzerland); [c] Ion Science (Royston, UK)
EC: electrochemical; MOS: metal oxide semiconductor; CAT: Pellistor; IR: Infrared

Output signal and data interfaces have to be defined to deliver the measurement results, depending on the sensor's technical configuration. This includes analog signals, pulse width modulation signals, serial interfaces as UART (Universal Asynchronous Receiver Transmitter) or busses for embedded systems as I^2C (Inter-Integrated Circuits) or SPI (Serial Peripheral Interface). Commonly, analog interfaces or I^2C are used. Available sensor interfaces are strongly dependent on the sensor’s configuration and equipment. While simple analog interfaces do not require the analog to digital conversion or further processing effort, but protocols often require the inclusion of small microcontrollers.

Finally, the mounting technology is of importance. This can be realized by through hole technology (THT) or surface-mount technology (SMT). The decision for a mounting technology is decisive regarding the final construction size, which is significantly smaller using SMT.

Other parameters as environmental conditions or sensor life-time also can influence the sensor’s integration. Additional sensors might be required to monitor different environmental parameters for correcting the measurement results. In case of lower sensor life times, it is recommended to use an exchangeable design for the sensor.

3.2. Sensor Types

Generally, three types of sensors can be categorized – sensing elements, integrated sensors and smart sensors (see Figure 6) [57]. These three types differ in their functionalities.

Gas sensing elements, which work on the base of measurement principles as introduced in section 2, receive a signal or stimulus and respond in a distinctive manner. They generally require a further signal conditioning and often the adaption of standard interfaces or busses for their integration. The signal conditioning includes a bundle of measures to adapt and to optimize the signal of the sensing element for the subsequent processing steps. Depending on the sensors' individual characteristic, these measures need to be considered in the sensor electronic.

Integrated sensors already have signal conditioning measures. This approach allows the sensors to send signals that can be used immediately, without an additional circuit design for signal amplification or processing. The combination of sensing and signal processing enables an easy integration. Since the data acquisition method is already integrated, the development time for a new device can be reduced. Integrated sensors can be designed for space and weight saving compared to other solutions. Another advantage is their easy replaceability in case of malfunctions or errors. For integrated sensors, often sensor modules (small PCBs including a sensing element) are provided by manufactures or third-party companies, which contain the required electronics.

If, in addition to sensing and signal conditioning, signal processing is also integrated into the sensor, they are defined as *smart sensors.* Such complex sensors usually contain microprocessors or microcontrollers with a low-power consumption. Thus, the implementation of device internal interfaces as UART, SPI or I^2C or external interfaces as USB (Universal Serial Bus) are available. The microcontrollers are can not only realize bus communications, they also offer the implementation of a software-based data processing [58] such as data fusion, signal conditioning parts, auto-calibration procedures or even threshold monitoring.

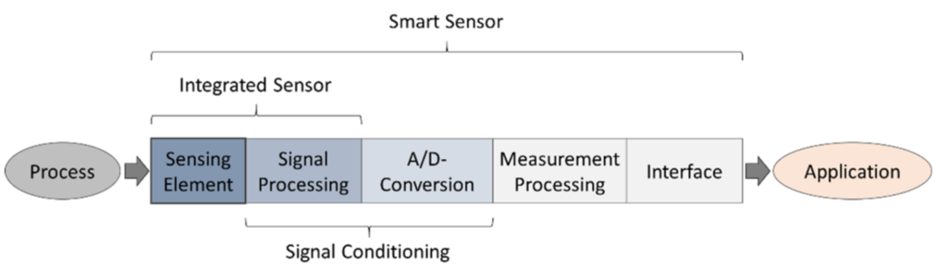

Figure 6. Simplified processing chain between sensing element and smart sensors.

For external communication, smart sensors / modules can also be equipped with active and passive radio interfaces, including Bluetooth or WLAN. This enables an easy transmission of the data obtained for visualization purposes, data storage, and data evaluation.

By integrating sensing, signal conditioning and signal processing, the entire demanding task of such sensors should be performed without an external computer.

Reasons for this include miniaturization, decentralization, an increase in reliability, a reduction in costs or an improvement in flexibility.

3.3. Integration of Sensing Elements

Since sensing elements only enable the recording of measured values, all signal conditioning and signal processing functions and the voltage supply must be implemented. The adaption and stabilization of the voltage input is an important base to ensure a safe and correct operation. This also includes the consideration of the sensor's power consumption, which can be relatively high due to the often implemented heaters, depending on the used principle. For such heater-related sensing principles, it can be important to provide a heating regulator that compensates different tempered environments for accurate measurements. The vast majority of the currently available sensing elements are through hole components, whereby their installation is simpler but also requires more space.

The required conditioning of the output signal strongly depends on the application demands (e.g., accuracy) and the aimed design of the target device (e.g., size, power consumption). Signal conditioning includes several measures, such as the signal amplification, level adjustment, signal conversion, filtering and analog/digital conversion (ADC), if required. Not all measures are always required or considered, depending on the characteristic of the used principles. Often it is, for example, necessary to convert electrical resistances or currents into a voltage signal or to linearize non-linear relations between voltage and concentration. High demands on the accuracy and reliability of the sensor results also increase the requirements for the sensor's integration. Exact measurements often depend on environmental conditions as temperature and humidity and have to be considered for data correction. The increasing miniaturization of the sensing elements also influences the signal output. E.g., smaller electrode areas inside the sensing element lead to a smaller sensor response relative to the noise [59]. By amplification and filtering of this voltage signal, an adequate sensor output has to be generated.

A general but significant condition for the integration of sensing elements is its optimal positioning. First of all, it needs to be ensured that the sensing element is sufficiently supplied by gas flow around. In some cases, pumps are used to guarantee an optimal and continuous gas flow for the measurement. Further, it is also important to make sure that no other heating element (e.g., transistors, other gas sensors) is close to the sensing element to avoid a mutual interference.

3.4. Integration of Integrated Sensors/Sensor Modules

As already introduced in section 3.2 integrated sensors contain already signal conditioning measures. Indeed, only a limited number of simple integrated gas sensors (not smart) in monolithic design can be found on the market (see Table 2). Instead, sensor boards, often from the manufactures, assume this task and equip the sensing elements with the required measures. Technically, both solutions can comprise the same measures, but regarding the installation size and the connection options, they differ. Modules are larger than monolithic solutions and often are installed via plug connectors, whereas monolithic solutions often are made for soldering.

Generally, integrated sensors/sensor modules support the hardware integration since basic conditioning measures do not have to be considered, whereby not all measures are necessarily included. Moreover, the adaption and stabilization of the voltage supply can be part of the integrated sensor/sensor module. If it is not integrated or the available voltage does not fit to the target device, an adaption is required. For the output signal, these solutions offer commonly an analog front-end interface with a predefined voltage range, which is suitable for analog inputs of microcontrollers.

Some signal conditioning measures need not necessarily to be realized by hardware and can be realized by the microcontroller. This opens up further opportunities to simplify and optimize the integration, which are often handled in smart sensors.

The installation conditions, introduced in section 3.1, for positioning the sensor regarding the gas flow and other temperature sources also apply to integrated sensors. In Table 2 some examples for integrating sensor modules are presented.

Table 2. Integrated sensors/sensor modules

Properties	**Spec ULPSM-NO2**	**Figaro CGM6812-B00**	**SGX Sensortech* MP-7217-TC**	**Winsen MQ-4**
Detected Gas	NO_2	combustible gases	methane	methane, liquefied natural gas (LNG)
Principle	EC	CAT	CAT	MOS
Construction Type	module	module	module	integrated
Power Supply	3±0.2V DC	5±0.2V DC	3±0.1V DC	≤ 24V DC (5±0.1V DC recommended)
Signal Output	analog (0-3V)	analog (1-4.5V)	analog 0-60 mV	analog (2.5V～4.0V)
Power Consumption	30±15μW	≤1.5W	≤ 126mW	≤ 950mW
Measurement Range	0-20 ppm	0-14,000 ppm for H_2	5% volume Methane in Air	300-10,000ppm
Response Time	<30 sec.	≤ 30 sec.	< 12 sec.	N/A
Special Features	on-board temperature sensor		on-board temperature sensor	

MOS: metal oxide semiconductor; EC: electrochemical; NDIR: non-dispersive infra-red
* sensor also uses thermal conductivity as sensing principle

3.5. Integration of Smart Sensors

Smart sensors, or also called integrated smart sensors, contain the features of simple integrated sensors and use microcontrollers as additional processing units. Similar to the integrated sensors, smart sensors are also available as monolithic and module solution, whereas here more monolithic solution can be found than for the integrated sensors. The advantage of smart sensors using the monolithic approach is a significant reduction of the sensor's construction size (see Table 3) and hence they usually based on surface mount technology.

Using smart sensor/sensor modules supports their hardware integration similar to the integrated sensors. Due to an integrated processing unit, recommended procedures from the manufacturers for the handling are already included and do not have to be considered for the integration. So for example a closed-loop temperature control for possibly included heaters, software-based signal conditioning as filtering or linearization, compensation of changing environmental parameters (by using additional temperature, humidity, and atmospheric pressure sensors), automatic drift-compensation and calibration procedures can be implemented to achieve better/optimized measurement results. Due to the included processing unit for the data transmission commonly used standardized, internal digital interface as UART, SPI or I^2C also can be realized. These protocols allow a comprehensive transfer of some information (measurement values and status information such as measuring status or heater stability status) to a central processing unit, where the data of all involved sensors of the device run together and are processed. Especially for the integration of several sensors bus solutions (e.g., SPI, I^2C) are recommended, since the wiring effort can be significantly reduced. Besides the reduced hardware implementation, the integration effort for smart sensors primarily refers to the software-related adaption of the appropriated transfer protocols by the subsequent processing unit. One restriction which can arise by using smart sensors is that sensing and processing is encapsulated, and no individual post-processing can be performed. To enable extensive options for post-processing, some smart sensors also provide raw data and the manufacturers offer libraries for the processing or individual adjustment of the calibration line.

Regarding the position of the sensors on an oriented circuit board (PCB), it is recommended to comply with the installation conditions (sufficient gas-flow, avoiding temperature influence) as introduced in section 3.1. Especially the tiny small monolithic smart-sensor solutions are vulnerable to foreign temperature sources, and it is useful to separate them and therefore also milling the PCB around the sensor is recommended to reduce the thermal conduction.

In Table 3 examples for smart sensors are presented that partially contain the explained features. However, the Bosch BME 680 sensor has by far the most extensive range of functions and features in the comparison.

Table 3. Smart sensors/sensor modules

Properties	**Bosch BME 680**	**Sensirion SGP 30**	**Spec IOT-CO-1000**	**Sensirion SCD30**
Measured Data	VOC gases (CO_2), temperature, humidity, pressure	TVOC gases, CO_2eq	CO	CO_2, temperature, humidity
Principle	MOS	MOS	EC	NDIR
Construction Type	chip	chip	module	module
Power Supply	1.71-3.6 V	1.62-1.98 V	2.6-3.6 V	3.3-5.5 V
Power Consumption	0.09-12 mA (depending on operation mode)	48.8 mA at 1.8V (measurement mode)	12 mW for continuous sampling	19 mA for 1 meas. per 2 s
Interfaces	I^2C, SPI	I^2C	UART	UART, I^2C
Measurement Range	N/A	VOC: 0-60,000 ppb CO_2eq: 400-60,000 ppm	0-1,000 ppm	400-1,000 ppm

MOS: metal oxide semiconductor; EC: electrochemical; NDIR: non-dispersive infra-red

3.6. Summary

The integration of gas sensors into a target device depends on the planned operation purpose and consequently on its target properties (e.g., target gases, size, power consumption, accuracy). In accordance with these properties, suitable gas-sensor principles and types have to be found. The sensor types can be divided into single sensing elements, integrated sensors and smart sensors, which differ in the included processing features. While sensing elements only include the sensing principle, integrated sensors additionally also cover signal-conditioning features, which convert and optimize the output signal and commonly provide a voltage-based analog front-end interface. Smart sensors generally contain the functions of integrated sensors and are extended by a processing unit. The processing unit allows a digital post-processing, including temperature regulation, baseline compensation, auto-calibration (or integrated calibration lines), and allows the provision of internal digital interfaces such as I^2C or SPI.

Depending on the selected sensor type, the sensor integration requires a varying level of integration effort. With smart sensor solutions, especially for gas sensing, where many factors can influence the measurement (e.g., by sensor drift, temperature, and humidity), many procedures are covered and encapsulated in one chip or module. The integration can be reduced to the provision of the power supply and the adaption of the output protocol, which partially or completely needs to be considered for the integration of single sensing elements or integrated sensors.

However, independent of the sensor's construction type, the positioning of the sensor is most important. It is necessary to position the sensor in such a way that a continuous gas flow around the sensor is given. Further, the thermal conduction of elements around the sensor, who radiates heat, should be avoided or compensated by suitable measures.

4. Ready-to-Use Sensor Solutions

4.1. Definition and Integration of Sensor Devices

Sensor devices are complete systems which, in addition to the actual sensor data acquisition and all processing steps, also enable the visualization and evaluation of the data. The integration of gas-sensor devices primarily focuses on their connection to application-related infrastructures. The simplest integration scenario is the direct connection between one sensor device and one sensor device node. The sensor device node is a processing system such as a computer, server/cloud or mobile device. The most important condition for the integration is the compatibility of the participants' interfaces. Some interfaces have established as standards for such applications such as USB, Ethernet, wireless LAN and Bluetooth Low Energy (BLE) [60]. For low-energy requirements with wireless communication also specifications such as 6LoWPAN (acronym for: IPv6 over Low power Wireless Personal Area Network) [61], ZigBee [62] or ANT/ANT+ are used especially for wearable applications. In some cases also cellular communication standards (3G, 4G, 5G) are included in the sensor devices to permit a higher independence from local networks [63]. The used protocols and profiles on the interfaces can vary and range from the Bluetooth GATT-Profile (Generic Attribute protocol) via TCP/IP (Transmission Control Protocol/Internet Protocol) to HTTP-based/-conform web standards (including SOAP and REST) [64], which should not be further enlarged here. The implementation of such protocols as part of the sensor-device integration strongly depends on the application and the provided features of the device. The usual approach is that the sensor-device node uses a polling routine, in which the sensor device transfers data on request. In contrast, Smart Connected Sensors (SCS) are devices that automatically use cloud services to send their data to a service platform. Here, the measurement data are processed and used for long-term analyzes and as comparison values. The integration effort for such sensor devices is reduced to a minimum if the service is configured. Authorized users can access this data via programming interfaces. Additional functions can also be managed in the cloud, and reference and limit values can be entered for comparison and alarms. By integrating sensing, signal conditioning and signal processing, the entire demanding task of such sensors can be performed without an external computer. Additional functions can also be managed in the cloud, and reference and limit values can be entered for comparison and alarms.

In many applications, the sensor-device nodes collect data from several distributed sensor devices, which allow a wide area-covering monitoring, for example, to check the general air quality or to detect hazardous gas situations. At least in these cases, an addressing for the sensor devices is required to differentiate the devices and to allocate their positions. A further important point for the integration of sensor devices is the consideration of data security, especially if data are safety related and if they are transmitted via web or other open networks. In this case, measures for the data anonymization or encryption and the manipulation protection, if necessary, have to be considered.

The sensing function combined with such connectivity features allows a simple coupling with computers, smart devices and their presence in networks. The ability to network also offers the possibility that sensor data can be directly distributed worldwide. Some solutions also provide battery options, and integrated data storage for a mobile operation. Especially such sensor solution benefit from the miniaturization of the sensing elements, the corresponding reduced power consumption and the integration of conditioning and processing features.

Today, app-based methods are usually used. This also enables the use in actual mobile monitoring systems. Sensor devices are therefore intended for use in different areas without the need for further integration work.

4.2. Examples for Gas Sensor Devices

Due to the currently great demand for gas-sensor devices, because of the increasing desire for a safe and sufficient air quality [65], solution for gas monitoring in different environments can be found. On the commercial market as well as in research, the interest can be indicated by the wide variety.

A flexible gas sensor platform for the measurement of different gases, including carbon monoxide, oxygen, ammonia, fluorine, or chlorine dioxide is the TIDA-00056 (Texas Instruments, Dallas, Texas, USA) [66]. The system sensors can be changed whereby Texas Instruments recommends the electrochemical gas sensors Alphasense A2 (Alphasense Ltd, Great Notley, UK) for oxygen (range: 0.1-20.9% O_2) and Alphasense CO-AF for carbon monoxide (range: 0-5,000 ppm CO). Prepared for a wide range of wireless interfaces as Bluetooth Low Energy (BLE), Zigbee RF4CE, 6LoWPAN and

ANT and equipped with standard coin cell battery, this device is optimized for mobile applications. The gas concentrations can be monitored via a gas sensor mobile APP.

A further ready-to-use sensor is the bluSensor® AIQ (Salzburg, Austria), which combines the measurement of humidity and temperature using the Sensirion SHTC3 and TVOC (total volatile organic compounds) using Sensirion SGP30 (range: 0-60,000 ppb TVOC and 400-60,000 ppm CO_2eq). The sensor system is made for air quality measurement and is available with USB and wireless communication (Wi-Fi and Bluetooth) interfaces. bluSensor® AIQ is a stationary system which is supplied by USB. It has different colored lights inside that indicates if thresholds are exceeded.

The Wireless CO_2 Sensor PS-3208 (Pasco Scientific, Roseville, CA, USA) bases on the non-dispersive infrared (NDIR) technology. It measures CO_2 in the range from 0 to 100,000 ppm and is designed as a data logger equipped with a lithium-polymer battery for up to 24 h operation. The data can be retrieved via USB. An integrated Bluetooth 4.0 interface allows transferring the data directly to a terminal device such as a smartphone.

In October 2020, NASA presented the first prototype of a new portable device for the determination of different gases [67]. The smartphone sized 'E-Nose Breath Analyzer' was developed for the diagnosis of breathing gases and enables the determination of 16 different chemicals including methane, hydrazine, formaldehyde, acetone, benzene, toluene, or malathion at room temperature within seconds. An array of electrochemical sensors combined with sensors for humidity, temperature, and pressure is used for real-time breath analysis [68]. The system is a further development of the electronic noses, which were developed for the indoor air monitoring of the Space Station [69].

Numerous scientific papers have been published on the determination of toxic gases using smartphones. Azzarelli et al. described a wireless gas detection with a smartphone via RF communication. The sensing strategy employs chemiresponsive nanomaterials integrated into the circuitry of commercial near-field communication tags. Thus, a portable, and inexpensive detection of gases such as ammonia, hydrogen peroxide, cyclohexanone, and water could be achieved at part-per-thousand and part-per-million concentrations [70]. A smartphone coupled handheld array reader for the determination of different toxic gases was reported by Devadhasan et al. The system uses a colorimetric monitoring approach and includes a complementary metal oxide (CMOS) image sensor. Toxic gases, including hydrogen fluoride (HF), chlorine (Cl_2), ammonia (NH_3), and formaldehyde (CH_2O) were detected using titanium nanoparticles coated with chemically responsive dyes. The different compounds could be detected with detection limits of 1 ppm for each gas. The measured signals are transferred via a specific app to a smartphone for the display of the results [71]. Suárez et al. developed a Bluetooth gas sensing module for air quality monitoring. Besides humidity and ambient temperature sensors, the prototype included four gas detection sensors (MiCS-4514, MiCS-5526 and MiCS-5914, SGX Sensortech, Corcelles-Cormondreche, Switzerland). The system has been tested with ten volatile organic compounds, including acetone, benzene, ethanol, ethyl acetate, formaldehyde, and toluene. Depending on the compound's success rates, between 88.33% and 92.22% could be achieved using a BackPropagation Learning algorithm and Radial-Basis based Neural Networks [72]. A miniaturized electronic nose with digital gas sensors for the determination of different concentrations of NOx has also been reported [73]. Four metal oxide sensors have been used: BME680 (Bosch Sensortec GmbH, Reutlingen, Germany), SGP30 (Sensirion, Staefa, Switzerland), CCS811 (Sciosense B.V., Eindhoven, Netherlands, and iAQ-Core (Sciosense B.V., Eindhoven, Netherlands). A Bluetooth low-energy communication module was developed to enable the data transfer from the sensor module to the smartphone application. Suitable algorithms for data normalization and feature extraction were integrated. Machine learning algorithms were used to classify the data retrieved from the sensing. Test measurements were performed for concentrations between 40 $\mu g/m^3$ and 200 $\mu g/m^3$ NO_2 and 7.7 $\mu g/m^3$ to 77 $\mu g/m^3$ for NO. Interferences in the determination of the two gases could be seen for some concentrations.

A wearable sensor solution combining the measurement of gas (CO and NO_2), sound level as well as temperature, air humidity and pressure is presented in [74]. Aim of the development was the monitoring of environmental parameter in usual routine (as work or at home) and its influence on the humans body and the mental strain by a wrist-worn device [75]. Especially in work environments, the exposure of gases can reach critical thresholds. Thus, the sensors detect NO_2 up to 5 ppm and CO up to 1,600 ppm (Spec Sensor LLC, Newark, CA, USA).

A mobile gas-sensor device was further developed to ensure the occupational safety in automated laboratory environments [76]. The module's design allows the integration of smaller sub-modules equipped with gas-sensors for example BME680 (Bosch Sensortec GmbH, Reutlingen, Germany), SGP30 (Sensirion, Staefa, Switzerland) and MICS-5524 (Amphenol SGX Sensortech). As interface for the sensor modules, the device supports SPI, I^2C or analog signals. Thus, the sensor device can be used at different potentially dangerous positions or added to mobile robots that work with chemical compounds to detect hazardous situations for humans. Currently, the sensor only uses a USB interface, but wireless LAN and Bluetooth interfaces will be available soon. A central management system collects the measured gas concentrations combined with the location information of the distributed sensor devices and realizes the post-processing and visualization of the data. The system also includes an alert management to inform about areas where often no staff is present.

5. Summary

The trend towards monitoring numerous parameters in our working and living environment continues uninterrupted. Numerous commercial solutions exist for the monitoring of physiological data and movement profiles, which can be easily used and operated by the user. So far, however, there are only a few suitable solutions for continuous monitoring of environmental pollution. In addition to the classic inorganic gases such as NOx or CO, this also includes organic components that can cause severe safety problems or lead to corresponding health problem.

Theoretically, different sensory principles can be used for monitoring gases and solvent vapors. Catalytic bead sensors use changes in resistance caused by catalytic combustion reactions, which are proportional to the concentration of the compounds to be determined. Photoionization detectors ionize compounds using UV light from a gas discharge lamp. NIR sensors in turn use different absorption wavelengths of chemical compounds. Metal oxide semiconductor sensors use the substance and concentration-dependent change in the conductivity of inorganic or organic materials. Electrochemical sensors work on the principle of galvanic cells; depending on the principle, an electrochemical reaction causes a voltage change or a current.

For the exact qualitative and quantitative detection of individual compounds, sufficient selectivity is required that has little or no cross-sensitivities. This is only possible to a limited extent with the above-mentioned operating principles. For the response of catalytic bead sensors, a heat development is required; this occurs with all substances that are flammable. This only enables a differentiation between flammable / non-flammable gases; a further targeted detection of individual compounds is not possible. NIR-based sensors enable a better selection of different compounds through the targeted selection of the wavelengths to be measured. It should be noted here, however, that there may be overlaps in the measurement signal due to similar absorption ranges of different compounds. Electrochemical sensors show excellent selectivity due to their operating principle. They can be specifically tailored to the determination of individual components. However, this type of sensor has so far mainly been used for the determination of inorganic gases.

Extensive developments in the field of metal oxide semiconductor sensors can be seen in recent years. They can be mass-produced, are therefore very cheap and have small dimensions, which makes them ideal for use in mobile solutions. The selectivity of this type of sensor is limited; the underlying operating principle only enables a distinction to be made between oxidizing and reducing gases, which increase or decrease the conductivity of the sensor material.

While numerous sensors are available for the selective determination of different gases, only limited selective sensors are available for the detection of solvents and solvent vapors. The majority of organic compounds can be detected using classic VOC sensors. Owing to the lack of selectivity, however, it is often only possible to determine sum parameters.

Sensors can be divided into different categories. Simple sensing elements only enable the pure conversion of measured values, but do not have any functionality for data conditioning or data processing. Integrated sensors represent combinations of sensing elements with data conditioning (amplification, etc.) Processes. Smart sensors / sensor modules are usually equipped with microcontrollers that have extensive functionality for data processing. Usually, they also have the option of external communication for data transmission to external and higher-level entities. The different functional scope of the sensor elements and modules used must be considered for their integration. By integrating such sensor solutions into a further microcontroller structure, which handles application-related sub-processes (configuration by users, display or indicate results, external communication for data transmission), they can be used as 'ready-to-use' systems for monitoring environmental parameters. In addition to commercial systems, there is a large amount of research activities in this area, which often combine different sensor elements.

Current and future developments in the field of monitoring systems show two main goals. Initially, the focus of the research is on increasing the selectivity of the sensors to enable better identification of individual compounds - even in mixtures. In the area of MOS sensors, this is done by testing different materials for the sensor surfaces. Different coatings can influence the responsiveness of the sensors and thus achieve a higher selectivity. Another possibility is to vary the operating parameters, which can also lead to different reactions with different substances. In addition, sensor arrays are increasingly being used; the measurement data are evaluated here using artificial intelligence methods. Graphen-based sensors will also be an interesting alternative in the future, as probe molecules can be integrated through electrochemical functionalization, which can be used for the selective determination of individual compounds according to the key-lock principle.

In addition to increasing the selectivity of the sensors, their miniaturization is of great importance, which is a prerequisite for their use in portable systems. By using semiconductor and graphene technology, this is already possible for the actual sensing elements. However, there are still limits in the miniaturization of complete sensors in the area of energy supply. In addition to the energy required for the communication protocols, the required power consumption of the sensors is particularly important. Depending on the sensor principle used, this can be large and thus requires the power supply (usually batteries) to be dimensioned accordingly.

The user interfaces are also important for the acceptance of the sensors. Cloud-based solutions for data storage as well as suitable app-based user interfaces are the essential aspects.

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Early Warning System for Emergency Care: Designing a Timely Monitoring Mobile-Based System

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Abstract. Early Warning Scores (EWSs) systems support the timely detection of patient deterioration and rapid response of the care team. Due to the mobility nature of healthcare settings, there has been a growing tendency to use mobile-based devices in these settings. This chapter aimed to design a mobile-based EWS application (app). This was a descriptive study to design the architecture of the proposed EWS app. The design of architecture was done using the Unified Modeling Language diagrams including a class diagram, use-case diagram, and activity diagram. We evaluated the architecture using the ARID scenario-based evaluation method. The proposed EWS application (app) was the integration of three EWSs, including NEWS2, PEWS, and MEOWS. The workflow of these EWSs systems was designed and integrated into a single app. Also, the static structure of the proposed EWS app was designed by class diagram and the behavioral structure was depicted by use-case and activity diagrams. The class diagram showed the system components and their relationships. However, the use-case diagram displayed the app's interaction with its environment, and the activity diagram illustrated how the EWS app processes were carried out. Evaluation results showed the possibility of designing the architecture for the proposed EWS app. In our app, the EWSs were designed in the clinician's workflow, and it was integrated with the patient's Electronic Health Record (EHR). These factors may lead to more use of EWSs. Considering the frequency of alerts represented to clinicians and the user-friendly design of the app, some suggestions can be considered by EWS systems developers in the future.

Keywords. early warning system, unified modeling language, mobile-based application, mHealth, patient deterioration

1. Introduction

Researches showed a high rate of adverse events incidence in hospitalized patients[1, 2]. Derangement of vital signs is the first clinical change that occurs when the patient's deterioration becomes worse[3]. Physiological parameters derangement from pre-defined thresholds such as heart rate, respiratory rate, body temperature, and so forth usually occurs a few hours before the incidence of a clinical adverse event, such as death

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[3, 6]. Therefore, the rapid identification of basic physiological parameters derangement, along with the timely response of the care team, can have a valuable role in the prevention and control of adverse conditions [7, 9]. This is the goal of Early Warning Scores (EWSs) that are also known as "track and trigger" systems [4,10]. EWSs are tools, assessing the change of a patient's vital signs and alerting the care team if necessary[11]. EWSs systems allocate a score to the health status of a patient based on her/his vital signs derangement. The larger the patient's EWSs score, the higher risk of the patient's deterioration [12,13]. Based on the patient's score, the EWS system recommendations vary, including the escalation of patient's assessment, required expertise clinicians, or rapid reaction of the care team [14,16]. There are many EWSs systems for assessing adults patients' deterioration, such as the National Early Warning Score (NEWS)[17] and Vital Pac Early Warning System (ViEWS)[18]. These EWSs systems are only used for adults. Due to the differences in physiological response in children under 16 and pregnant women, the EWSs systems have been developed for them separately[16]. Modified Early Obstetric Warning System (MEOWS)[19], Maternal Early Warning Trigger (MEWT)[20] as well as Pediatric Advanced Warning Score (PAWS)[21], and Irish Pediatric Early Warning System (PEWS)[22] are examples of EWSs systems for pregnant and pediatric patients, respectively.

There are many approaches to collect vital signs information in a hospital or pre-hospital settings including manual data collection using spreadsheets or using technological approaches such as tablets, personal digital assistants (PDA), and other mHealth equipment[23]. Concerning the mobile nature of healthcare delivery (in multiple places by several clinicians) there is an increasing tendency to use mobile devices in healthcare workflow[24, 26]. The use of mobile devices such as smartphones and PDAs by clinicians not only provides a portable device in the mobile healthcare setting but also has a positive impact on rapid response, error prevention, communication, and data management and accessibility[25]. The results of reviews on the use of handheld devices by medical students and residents in France, the United Kingdom, Ireland, the United States, and Canada have shown that 75-95% of them used personal smartphones in their clinical workflow[24], [27–31]. Integrating EHR with the EWS system allows clinicians especially nurses to document their vital sign assessment in the patient's EHR. This leads to the significant impact of using EWS because of its integration with clinicians' workflow[32,33]. mPEWS-InPro is an EWS mobile-based application for assessing children's deterioration. This EWS system uses the modified Pediatric Early Warning System (mPEWS)-InPro for detecting changes in children's vital signs. This app was developed as a mobile-based app to prevail over the communication problem of care team members. The system has been validated by 108 pediatric patients' information which indicated the high degree of accuracy for this mobile-based system (95%, CI: 0.865 to 1.000, p = 0.001) [34]. Dia-AID is another EWS mobile-based system that was developed to monitor the health status of diabetes patients. This app was a question-answering (Q&A) system that helped diabetes patients by Q&A service to enhance the patient's information about diabetes, assessing patients' risk and managing their health data. The Dia-AID showed a better performance in comparison with the baseline methods[35].

Concerning the existence of several EWSs systems for different patient categories (based on age and sex and therefore the pregnancy status of women) and the growing trends to use the mobile-based system in healthcare settings, in this chapter a mobile-based EWSs app was proposed and designed to support the possibility of assessing the deterioration status of adults, children (patients under 16), and pregnant women. Thus, this app can be used for a wide range of patients in emergency care without the need to open different EWSs systems. Based on the patient's features, such as age and pregnancy status, the system automatically presents the proper EWSs system to its users. Besides, the proposed EWS app is integrated with the EHR system of patients to record the patient's physiological parameters to include the nurse's workflow.

2. Material and Methods

We have designed the EWS system using the Unified Modeling Language (UML) diagram. UML is a standard language to describe a system plan, visualization, specification, construction, and documentation of a software system[36]. UML has many diagrams to support the documentation of the architecture and behavior of a system. The UML diagram can be categorized as structural and behavioral diagrams. Structural diagrams display the static structure of objects, classes, or components of a system, while the behavioral diagrams present the object interactions with each other and with the environment as well as dynamic aspects of a system[37]. A study showed that the basics of a system can be represented using the five types of UML diagrams including activity diagram (that depicts the activities in a process or data processing), use-case diagram (that presents the interaction between the system and its environment), sequence diagram (that shows the interaction between users and system as well as between system components), class diagram (that displays the object classes in the system and their relationship) and state diagram (that illustrates how the system reacts to the internal and external events)[38]. In this chapter, the class, use-case, and activity diagrams are used to design the proposed EWS system.

Our system is composed of three main modules including the EWS system for adults, children (under 16), and pregnant women. We selected the NEWS2[16], PEWS[22], and MEOWS[19] as the EWSs systems for each module, respectively. Having the escalation guide is the most important criterion for the EWSs selection. Also, our design was according to the latest version of each EWS scoring system guideline.

We summarized the basic physiological parameters, assessed by the three EWSs in Table 1. The NEWS2 is a track and trigger system that calculates the aggregated scores of an adult patient's vital signs and generates appropriate recommendations for the care team based on the patient's health status. The care escalation triggers when the score of patients in one physiological parameter is three or the aggregated score is five to seven. Its configurations cannot be used for children (under 16) and pregnant women[16], [39]. However, the NEWS2 score isn't reliable for patients with spinal cord injury, especially tetraplegia or high paraplegia[39]. The NEWS2 scoring system chart is available from [40].

Table 1. The basic physiological parameters assessed in selected EWSs

Named of EWSs Systems	Target Patients	Basic physiological parameters
NEWS2 [40]	Adults	Respiratory rate, Oxygen saturation, Systolic blood pressure, Pulse rate, Level of consciousness or new-onset confusion (ACVPU), Temperature.
PEWS [41]	Children under 16	**Core PEWS parameters:** Concern, Respiratory rate, Respiratory effort, Oxygen therapy, Heart rate, Conscious level (AVPU) **Additional Parameters:**

		Oxygen saturation, Central capillary refill time, Blood pressure (systolic), Skin color, Temperature
MEOWS [19]	Pregnant women	Temperature, Systolic blood pressure, Diastolic blood pressure, Heart rate, Respiratory rate, Oxygen saturations, Urine, Proteinuria, Urinalysis, Edema, Amniotic fluid, Neuro response (AVPU), Pain score, Lochia, Looks unwell, Trigger

***ACVPU**: Alert, Confusion, Voice, Pain, Unresponsive; **AVPU**: Alert, Voice, Pain, Unresponsive

The PEWS score cannot be used for adults or neonates. The PEWS score shouldn't replace or undermine the clinician's decision and concerns. Additional parameters are considered for case-by-case children and based on current health condition, treatments, and interventions as well as her/his predicted clinical status[41]. The PEWS scoring chart was shown in[22].

Compared with the other two EWSs systems, MEOWS checks more numbers of physiological parameters to determine the level of pregnant women's deterioration. The MEOWS scoring and trigger chart were described in [19].

The scenario-based method was used to evaluate the designed architecture. The method is suitable to combine the different interpretations of users from the software capabilities and create a common view of it [42]. A scenario describes the stakeholder's interaction with the designed system. Active Review for Intermediate Design (ARID) is a scenario-based method [43]–[45]. The ARID method concentrates on the detailed design of various parts of the system. Therefore, it can be used to evaluate incomplete architectures in two stages including pre-meeting sessions and review sessions. In the pre-meeting phase, the members of the review session and the scenarios that must be presented at the review session are determined and generally, the preparation for the review session is provided. In the review session, the reviewers and stakeholders evaluate the designed architecture for the system[43].

Two medical informatics professions and one nurse participated in the review session. Three scenarios were selected for evaluation of the proposed architecture described in Table 2. In the first and third scenarios, the clinician assesses a new patient but in the second scenario, an existing patient is assessed. In all scenarios, the clinician saves the results in the patient's EHR.

Table 2. Selected scenarios for evaluation of proposed EWS

#	Patient age	Patient gender	Patient pregnancy status	Other physiological parameters
1	13	Female	-	Concern = yes, Respiratory rate = 32 (Breath per minute) Tachypnea , Respiratory effort = mild, Oxygen therapy < = 2L, Heart rate = 105, Conscious level (AVPU) = Alert, Blood pressure (systolic) = 112 mmHg, Temperature = 38.6 °C,
2	42	Male	-	Respiratory rate = 15, Oxygen saturation = 84.5% (No COVID-19), Systolic blood pressure = 117 mmHg, Pulse rate = 84, Level of consciousness or new-onset confusion (ACVPU) = patient is more confused than before now, Temperature = 38.7 °C.
3	36	Female	Yes	Temperature = 37.5 °C, Systolic blood pressure = 138 mmHg, Diastolic blood pressure = 85 mmHg, Heart rate = 81, Respiratory rate = 15(Breath per minute), Urine = No, Edema = No, Amniotic fluid = clear, Neuro response (AVPU) = Alert, Pain score = 1, Lochia = Normal, Looks unwell = Yes,

3. Results

When a clinician uses our system, automatically the proper EWS system based on the patient's characteristic will be applied. The designed EWS system is implemented as a rule-based system to determine the severity of a patient's deterioration. An overview of the designed EWS is shown in Figure 1.

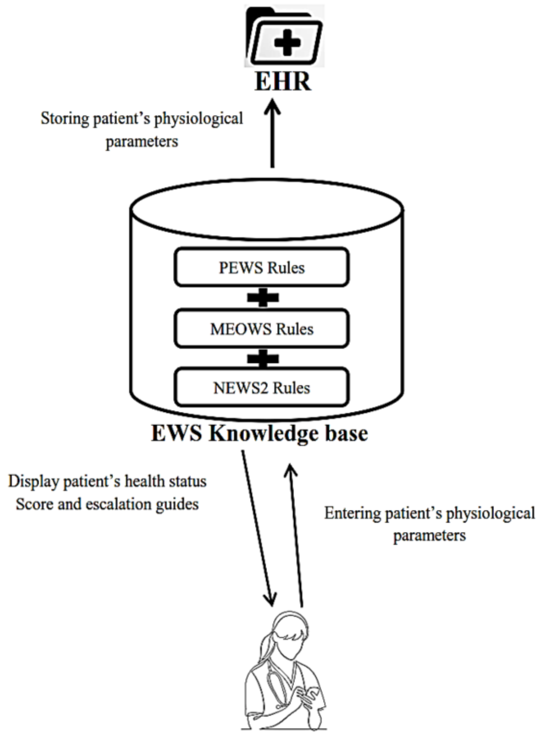

Figure 1. Overview architecture of proposed EWS system. The clinician uses the EWS app. According to the patient's information including age and pregnancy status, appropriate rules in the EWS knowledge base will be used. Finally, the clinician can store the patient's vital signs in her/his EHR.

The main stakeholders of developed EWS will be the nurses and multidisciplinary clinical team in hospital wards and ambulances as well as patients. This system can be used as a Clinical Decision Support System (CDSS) helping nurses to manage the patient's deterioration.

The flowchart of the designed EWS is illustrated in Figure 2. NEWS2 is not reliable to be used for patients having spinal cord injury, especially tetraplegia or high paraplegia. Thus, the EWS system exits if a patient has at least one of these diseases. PEWS and NEWS2 follow almost the same work logic, such that they take the values of a patient's vital signs and calculate the sum of different parameters scores. Unlike the two previous EWSs that calculate the aggregated score of a patient's vital signs, MEOWS counts the number of vital signs with the values in the yellow and red areas. If two patients' vital signs have values in the yellow range or one in the red range, then the trigger system is activated.

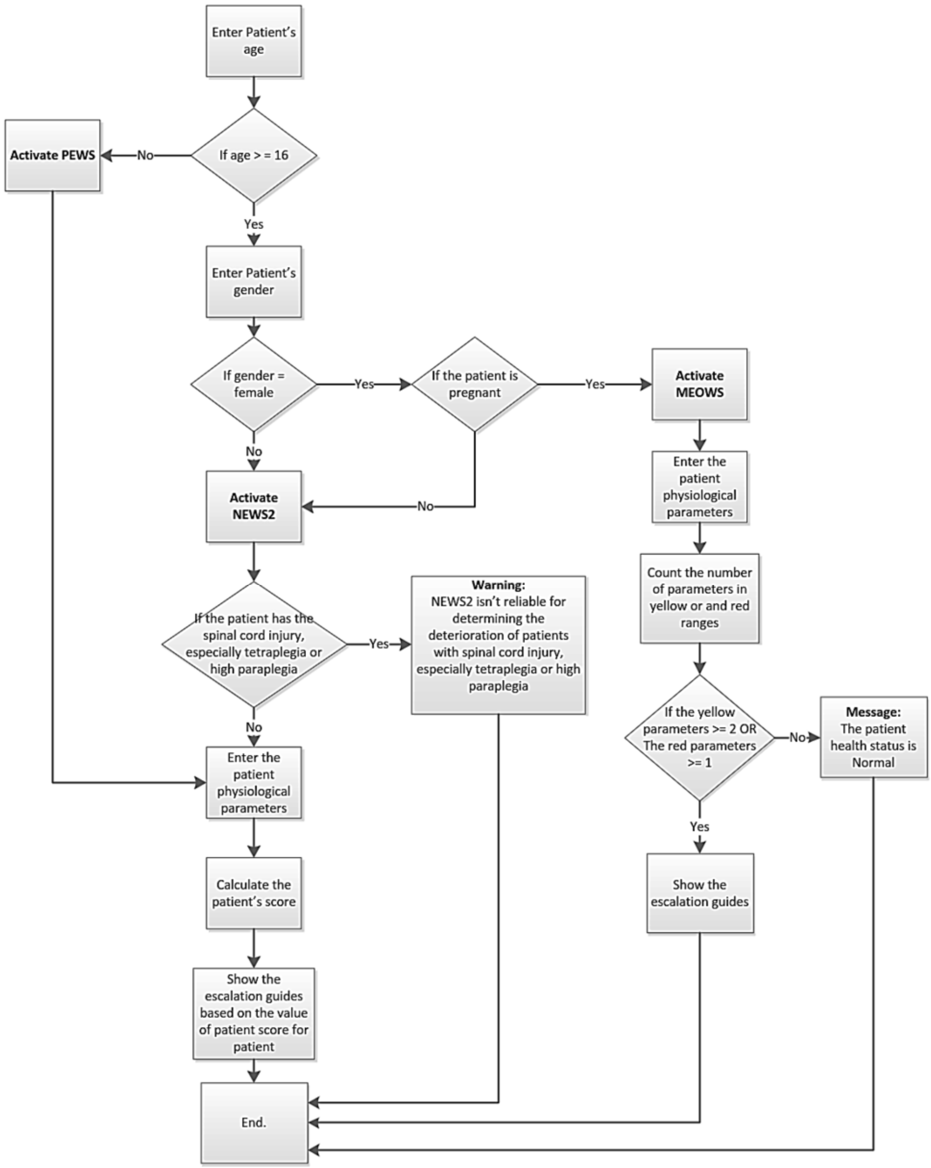

Figure 2. The flowchart of the developed EWS system.

The static structure of the proposed EWS uses a class diagram. Each class represents an entity in the system (see Figure 3). The "person" is an abstract class that represents the mutual features of "clinician" and "patient" classes. In other words, both "clinician" and "patient" inheritance the "person" class features. The numbers used on the connection between two classes indicate the number of each class involved in the relationship. For example, each clinician can assess "n" patient(s) and each patient can be assessed by "n" clinician(s). The "question form" class has a mandatory relationship with the "EWS App" class. This means that the existence of the "question form" class depends on the existence of the "EWS App" class.

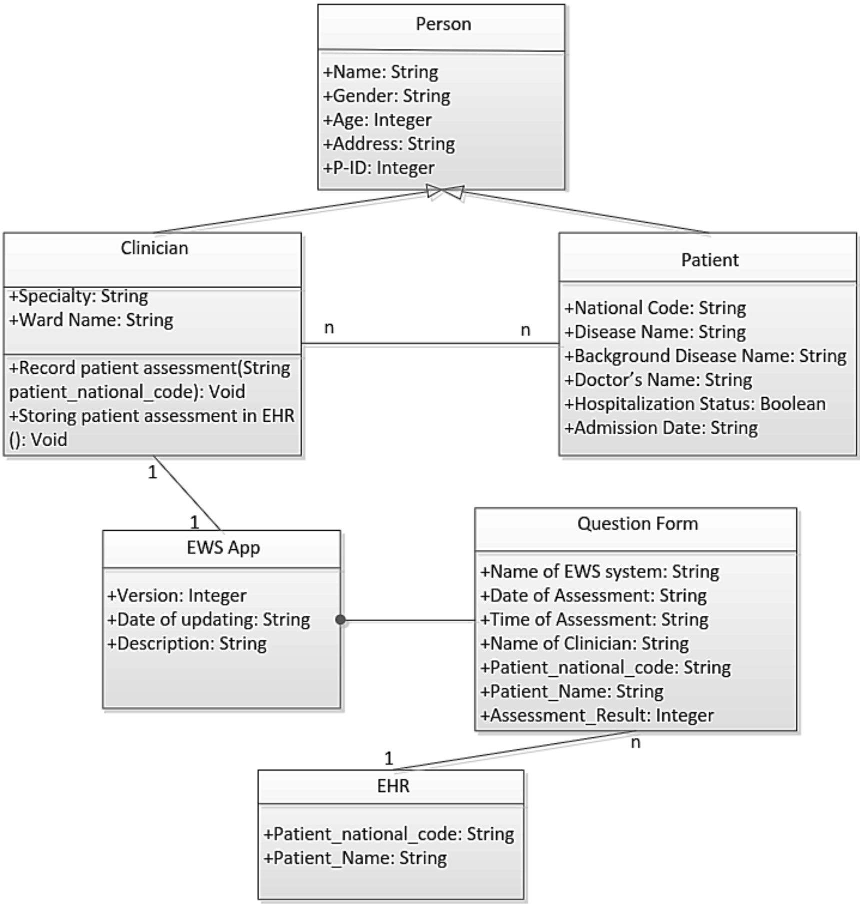

Figure 3. The static structure of the proposed EWS system.

The use-cases are based on the clinician viewpoint (see Figure 4). Figure 5 illustrates how a clinician can assess a new or existing patient, recording the measurements in the EHR and reviewing the trend of physiological parameters for an existing patient.

As shown in figure 5, after login, a clinician can add a new patient to the EWS system. Therefore, she/he must enter the patient's identifier code such as the national ID code. The system examines whether the patient already exists in the EWS system. If the patient is a new case, first the clinician must enter the patient's demographic information. Based on the patient's information, including the patient's age and pregnancy status, the system shows the proper EWS questions (NEWS2, PEWS, or MEOWS) for vital signs assessment. The clinician stores the assessment of the vital signs in the patient's EHR. For patients that are already available in the EWS system, the clinician can also request to view the trend of physiological parameters changes.

To analyze the first scenario, the clinician login to the EWS app (see Table 2 based on Figure 5). Because of assessing a new patient in this scenario, the patient's national ID code and demographic information are entered. The patient's age less than 16 activates the PEWS scoring system. Due to the patient's temperature over 38.5 °C and

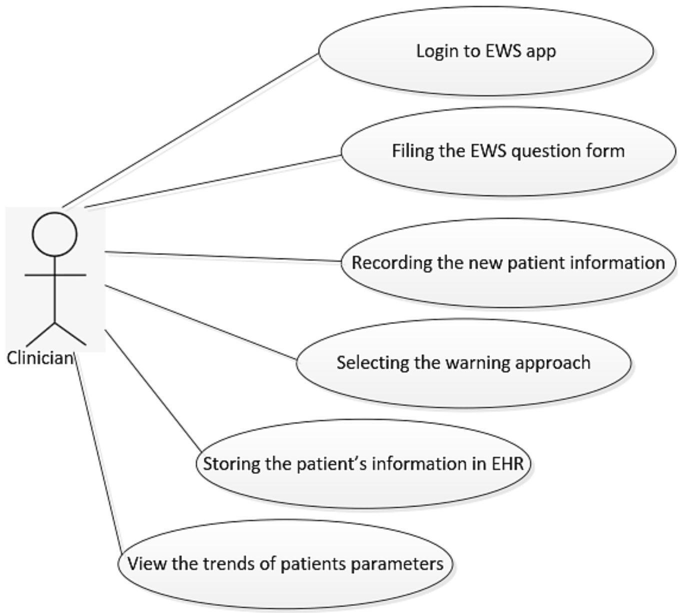

Figure 4: The proposed EWS use-cases from the clinician viewpoint.

tachypnea, the child has sepsis (according to the physiological parameters used to sepsis diagnosis[22]). Based on the scoring chart of PEWS in[22], each physiological parameter of patient scores. Thus, the general score of patients in the first scenario is 5. As shown in[22] two other warnings are triggered (Table 3). Finally, the clinician stores the results in the patient's EHR.

To analyze the second scenario, based on the designed activity diagram (Figure 5 and Table 2), the clinician login to the EWS app. As the patient has already registered in the EWS system, by entering the patient's national ID code, the NEWS2 is activated (because the patient's age is more than 16 and his gender is male). The patient's SpO_2 is in the 88-92 interval. Accordingly, scale 2 is used to score the patient's SpO_2=2 (the patient is not infected with COVID-19, based on the [40]). The clinician decides on the patient confusion. Therefore, based on the confusion assessment in NEWS2[40], the consciousness score is 3. Also, based on the NEWS2 chart [40], the patient temperature score is 1. Thus, the general score of the patient in the second scenario is 6. As a result, five warnings are triggered (Table 3). Finally, the clinician stores the results in the patient's EHR.

To analyze the last scenario, the clinician enters the patient's national ID code and demographic information, because a new patient is assessed in this scenario (see Table 2 based on Figure 5). The patient pregnancy status activates the MEOWS system. Due to her unwell appearance and based on the MEOWS scoring chart in[19] the patient gives one yellow color (in MEOWS the numbers of yellow and red colors are counted based on the women's health parameters); other physiological parameters are in the normal range. In this scenario, the pregnant woman takes one yellow color, and based on the MEOWS chart in[19] the triggered message states that her health status is normal. Finally, the clinician stores the results in the patient's EHR.

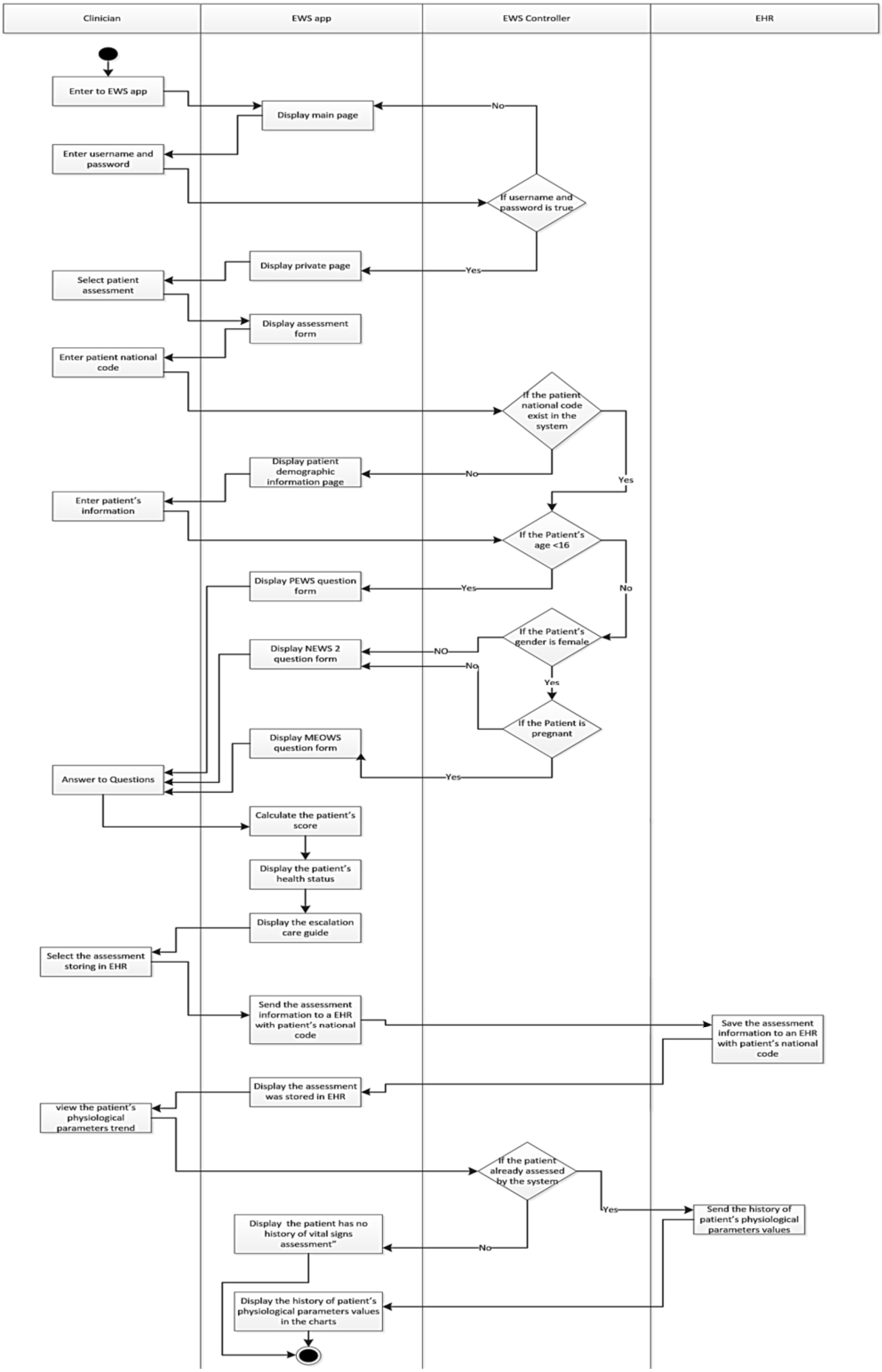

Figure 5. The process of a patient assessment by the proposed EWS app.

Table 3. Analysis results of selected scenarios

#	Patient age	Patient gender	Patient pregnancy status	Other physiological parameters (score)	Total Score	Triggered warnings
1	13	Female	-	Concern = yes (1), Respiratory rate = 32 (Breath per minute) Tachypnea (1), Respiratory effort = mild (1), Oxygen therapy < = 2L (1), Heart rate = 105 (0), Conscious level (AVPU) = Alert (0), Blood pressure (systolic) = 112 mmHg (0), Temperature = 38.6 °C	5	**Sepsis warnings: Within 60 minutes:** **Warning 1:** Take IO or IV blood samples **Warning 2:** Measure the urine output **Warning 3:** Take early SENIOR input **Warning 4:** Give high oxygen flow **Warning 5:** Give IV/IO fluids and consider initial inotropic support **Warning 6:** Give a wide range of IV/IO antimicrobials **General warnings:** **Warning1:** The patient should be assessed at least once every 30 minutes by a nurse and an on-call physician. **Warning2:** Need to urgent medical assessment
2	42	Male	-	Respiratory rate = 15 (0), Oxygen saturation = 84.5% (No COVID-19) (2), Systolic blood pressure = 117 mmHg (0), Pulse rate = 84 (0), Level of consciousness or new-onset confusion (ACVPU) = patient is more confused than before now (3), Temperature = 38.7 °C (1).		**Warning 1:** The patient clinical risk is moderate **Warning 2:** Need to assess the patient at least once an hour **Warning 3:** Need to immediate assessment by the ward physician or the nurse of the acute care team to decide about intensifying the clinical care **Warning 4:** Immediate need and intervention by a clinical team for management of sepsis and immediate transfer to a hospital or clinical area with a high level of care in the hospital **Warning 5:** Transformation of the patient to an environment with more monitoring facilities should be considered

3	36	Female	Yes	Temperature = 37.5 °C (white color), Systolic blood pressure = 138 mmHg (white color), Diastolic blood pressure = 85 mmHg (white color), Heart rate = 81 (white color), Respiratory rate = 15 (Breath per minute) (white color), Urine = No (white color), Edema = No (white color), Amniotic fluid = clear (white color), Neuro response (AVPU) = Alert (white color), Pain score = 1 (white color), Lochia = Normal (white color), Looks unwell = Yes (Yellow color),	**Warning 1:** The patient's health status is Normal.

4. Discussion

EWSs systems are used by nurses in hospitals and ambulance care. These systems help to rapidly identify and manage the patient's deterioration by assessing her/his vital signs. Therefore, EWSs provide the possibility of rapid intervention of treatment team to patient's status changes and can prevent the consequence adverse events such as unplanned intensive care unit (ICU), cardiac arrest, and mortality of hospitalized patient [46], [47]. Unlike the previous works that concentrate on only one group of patients, for example, diabetes[35], children[34], pregnant women[48] or adults[49], the designed EWS system in this chapter was the integration of three EWSs systems for adults, children, and pregnant women. the system can help to monitor and manage a wide range of hospitalized patients without the need of switching EWS system by the app user. The designed app automatically loads the appropriate EWS system for each patient based on the patient's features, such as age and pregnancy status. This feature improves the EWSs system's ease of use by clinicians.
Similar to mPEWS-InPro[34] and Dia-AID[35], the proposed EWS was developed as a mobile-based app to meet the healthcare requirements concerning the communication needs of clinicians especially in multidisciplinary treatment teams [34], the mobile nature of healthcare delivery[24]–[26] and the tendency of healthcare providers to use the mobile-devices in their workflow[24], [27]–[31].

Using EWSs systems leads to efficient recording and assessing the patient's physiological parameters as well as improving the response time of the treatment team to the patient's deterioration[46]. Also, studies have shown that in the short term, the EWSs systems increase the nurse's knowledge and competence about rapid response and their confidence in identifying the clinical deterioration and how to respond in these conditions[50]. Therefore, EWSs systems can have a positive impact on nurses' performance, confidence, and knowledge[46], [50]. Also, the integration of the EWSs system with patients' EHR can have a key role in enhancing the impact of EWSs on nurses. EWSs systems can facilitate the regular recording of patients' vital signs in EHRs, which help nurses to document their measurements and have a better response to patients' status changes concerning the physiological parameters.

The user-friendly design of EWS applications, their interoperability, and real-time communication are the important features for developing an EWS system[51]. The proposed EWS app was integrated with EHR, following the standards interfaces and frameworks such as Fast Healthcare Interoperability Resources (FHIR) is necessary to provide the interoperability in the system. Also, using user-centric design methods that engaged the end-users and other stakeholders of a health app in its design and development[52] is a good solution to develop a user-friendly app.

Alert fatigue is an important process affecting an alert system operation in healthcare settings. When the number of a system's alarms is high, the users don't attention to them and alert fatigue occurs[53]. Therefore, alert fatigue leads to ignoring the important alerts of systems that can reduce the system's effectiveness and may have consequences adverse events for patients[54]. A trade-off between reducing the alert's burden and providing the important alerts is a challenge of developing an alerting system[55]. The health setting emergency status (such as a hospital ward, ICU, or ambulance) and the goal of using EWS are important factors in determining the frequency of alerts in EWSs. When the EWS system is used in a hospital ward, and one of the goals is to enhance the nurses' knowledge and confidence, it seems that increasing the sensitivity by presenting more alert is of priority. But in the emergency use of EWS such as ambulance and where the EWSs users are the more experienced clinicians; it is desirable to reduce the alerts burden. Some studies suggested that the EWSs apps should be developed in such a way that its users can set the alerts presentation approach (for example, similar to Capan et al[55] maximum, medium or minimum alert presentation) based on their need. In the initial use of the EWS app, the users can set the app to give the maximum alerts, and over the time and with increasing the EWS's user experience or depend on the health settings and related workload and time sensitive of these settings, the EWS's users can choose the options to display fewer alerts.

The evaluation of our EWS app was carried out by a scenario-based method in the very early stage of developing the app. Implementation of a prototype of a designed EWS app and its evaluation with a real dataset from an emergency unit can provide better insight into the performance and accuracy of our EWS app design.

5. Conclusion

Early detection of patient deterioration in clinical settings can prevent adverse events such as ICU admission or patient mortality. As the vital signs may change a few hours before adverse events [56], the EWSs help to regular monitoring of the patients' physiological parameters. Concerning the tendency to use the mobile device in healthcare settings as well as the mobility of care delivery by several healthcare providers, the goal of this chapter was to design a mobile-based application as an EWS system. The proposed EWS system integrated three EWs systems (NEWS2, PEWS, and MEOWS) to cover adults, children, and pregnant women. Also, the proposed EWSs app was designed in such a way that was integrated with EHR. The clinician can choose their proper warning approach depending on their goal of using the EWS system and the condition (such as workload and time-sensitivity) of their work setting. Integration of EWSs in the workflow of clinicians in a way that it automatically activates the most appropriate EWS system based on the patient status (not as a separate app), as well as its interoperability with other health systems such as patients EHR, can lead to the more using of them. Developing such systems that are integrated with EHR can help to the rapid response of the care team to patient deterioration and better management of patients in acute care. This chapter can have valuable recommendations such as selecting the alert presentation approach, considering a user-centric design approach, and designing the user-friendly interface for EWSs system developers.

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Part 3

Virtual Emergency Registries

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Social Media and the Internet of Things for Emergency and Disaster Medicine Management

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Abstract. Social Media and the Internet of Things are nowadays full and strong components of day-to-day life worldwide. Both allow communicating with others 24 hours a day, 7 days a week without distance limitations. During the last decade, on-site citizens have shared disaster-related first reports on social media. Official institutions are using the same framework for delivering up-to-date and follow-up directives. Moreover, monitoring health risks, patients, and systems behavior in real-time over the Internet-of-Things allows detecting different levels of anomalies that might lead to critical events that need to be managed as an emergency. Emergency and disaster medicines deal with broad and complex medical, surgical, mental health, epidemiological, managerial, and communicational issues. Social Media platforms and the Internet of Things are technologies that increase cyber-physical interactions between individuals, machines, and their environment. The generated data over time are massive and are supporting the emergency or disaster mitigation process. This chapter deals with, in the first section, the social media platforms, and the Internet of Things. Then, at a second one, the concepts of emergency, disaster medicine and management are discussed. In the following two sections, we discuss applications and usages of social media and IoT technologies for improving the management (preparedness, response, recovery, mitigation) of emergencies and disasters as fundamental keys and pillars for efficiently handling the managerial information flow in emergency and disaster contexts.

Keywords. social media; Internet-of-Things; online social networking; community networks; disasters; emergencies; risk management; hazard management

1. Introduction

Social Media (SM) and the Internet-of-Things (IoT) are full and strong components of day-to-day life worldwide. Both allow communicating with others people and systems 24 hours a day and 7 days a week without strongly feeling distance limitations.

During the last decade, with the increase emergence of, on-site citizens have shared disaster-related first reports on SM. Official institutions are using the same framework for delivering up-to-date and follow-up directives in case of disruptive events. Moreover, monitoring health risks, patients, and systems behavior in real-time over the IoT allows

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detecting different levels of anomalies that might lead to critical events that need to be managed as a crisis. This must involve generally emergency and disaster medicines practitioners. These specialties are dealing at the same time and at different scales, with medical, surgical, psychological, psychiatric, public health, epidemiological, managerial, and communicational issues. In this context, social media platforms (SMPs) and the IoT are technologies that increase the cyber-physical interactions between individuals, machines, and their environment. The generated data over time are massive and are supporting the emergency or disaster mitigation process.

In this chapter, we define the SMPs and the IoT in the first section. In the second section, we introduce the concept of disaster. In the last part, we highlight the nowadays relationships between Social Media and the Internet and how they are vital and new fundamental pillars for efficiently handling emergency and disaster information-flow management.

2. Social Media Platforms and the Internet-of-Things

Social Media platforms and the Internet-of-Things are technology-based domains connecting the real and the virtual worlds and taking the interactions between individuals (e.g., humans, animals), machines (e.g., computers, smartphones, transportation vectors, home appliances), and their environments (e.g., living spaces, roads, working places) to the cyber-physical dimension [1,2].

2.1. Social Media Platforms

Today, Social Media platforms macrocosm is driven by high levels of interactivity, dynamicity, and ubiquitously. SMPs are at the crossroad of instant messengers, multimedia sharing systems, and "open-air public speaking" [3]. The individual or collective "shares" (e.g., text messages, pictures, photos, sound records, videos, documents, hyperlinks) can publish and read 24 hours a day, 7 days a week, 365 days a year, all around the world in an abundance of languages supported by the SMPs.

The users of the SMPs can be individuals acting for themselves and organizations represented by one or more than one individual. Signing-up is free and then allows each user to connect with others known or unknown in the real world.

The social media ecosystem comprises:

- News websites (e.g., "BBC News" [4], "CNN World" [5], "Der Spiegel" [6]),
- Collaborative encyclopedias (e.g., Wikipedia [7]), and
- Social networking services (SNS) provide different functionalities and services. For example:
    - Facebook as a polyvalent and grand public focused platform [8];
    - Flickr [9], Instagram [10], or Pinterest [11] as video and picture sharing platforms);
    - Twitter [12] or Tumblr [13] as blogging services; LinkedIn focusing on professional networking and services [14];
    - Reddit [15] as a mix of the previously highlighted platforms and which enable news aggregation, web content rating, and blogging/discussion website;

   ○ Telegram [16], as an instant messaging and a video-telephony platform, also allows creating or joining groups and channels supporting broadcasting to an unlimited number of subscribers).

2.2. *The Internet-of-Things*

Even though the Internet is a cyber-physical system, most communication is human-to-human based (a.k.a, the Internet-of-People or IoP). Nonetheless, the constant increase of the connectability of machines, devices, and components (a.k.a. objects), each one with its unique identifier, is taking the IoP to the IoT wherein humans are a minority [17].

The Internet-of-Things is a global space-expanding platform itself each time a newly identified object joins the whole. Moreover, IoT continuously integrates more automated data processing and generates new information and knowledge support for decision-making.

The main aim of an IoT-centric society is to have an integrated architecture allowing moving from the well-established Human-to-Human (H2H) or Human-to-Machine, (a.k.a. H2M or Human-to-Thing) paradigms to a Machine-to-Machine (a.k.a. M2M). Therefore, humans move the tails of the overall communications and decision-making processes. To do such a thing, the IoT must solve real-life problems by establishing, developing, implementing, and deploying robust architectures. This evolutionary and integrative process is based on the collaboration between the academia and the industry by defining translational and interoperability standards that are usable in a wide range of application fields, such as health, medicine, transportation, manufacturing, homeland security, and infrastructure safety, and more [17–19]. This revolution brings humanity to a ubiquitous computing and communication-centered era. The crucial part of the IoT as an M2M environment is changing populations' way of life by morphing them to a kind of abstraction of themselves giving inputs to machines, to "things". This is inducing huge ethical issues which are out of scope in the current chapter [20,21]

Nonetheless, the Internet-of-Things is more than a Machine-to-Machine assembly. The IoT is a whole integrating at different levels of complex hardware and software technologies [22], such as:

- Wired and wireless networks of sensors and actuators [23],
- Identification and tracking technologies, e.g., Radio Frequency Identification techniques (RFID) [24];
- Communication protocols [23,25,26];
- Distributed intelligence enhancing small devices' capabilities [27–29].

2.3. *Social Media and the Internet-of-Things as a Whole*

Social Media and the Internet-of-Things are a whole, a System-of-Systems.

SMPs interact with their users mainly by using mobile and ubiquitous systems (i.e., smartphones, tablets, computers, home appliances such as televisions) to run their applications and collect data.

If we focus on smartphones, they are all-in-one tools. A smartphone acts as a phone, but also as a small computer (e.g., for browsing the web), a telemonitoring system comprising different sensors (e.g., cameras, accelerometer, barometer, gyroscope; magnetometer; Global Positioning System (GPS) units, proximity sensors, light sensors, Light Detection and Ranging (LIDAR) sensors, biometric sensors, for fingerprint sensor or facial recognition and using optical, capacitive and ultrasonic technologies; and more in the next future).

Besides, the current cellular communication technologies (4G and 5G networks) [30] are crucial for allowing to get and share updates on social media in near real-time and comprising environmental data collected by the plenty of sensors available on the IoT ultimate tool known as smartphone [31].

To sum up, Social Media and the Internet-of-Things are now deeply integrated from the perspective of the day-to-day users, looking at them as the Internet.

Looking at this Social Internet-of-Things is challenging when we consider it as pervasive, fully connected, and having autonomous intelligence. This extensive integration and penetration in people's life can offer some kind of safety feeling (having systems taking care of our well-being). Still, because of their openness, they are targets for cyber-attacks [32]. Both are central points to explore when social media and IoT tools and systems are used for emergency and disaster management (EDM).

3. Emergency and Disaster Medicine and Management

In the following section, we define some concepts related to emergency and disaster medicine and management. We focus then on integrating social media and the internet-of-Things in these fields.

Emergency medicine and disaster medicine are both multidisciplinary specialties. Their common challenge is to look simultaneously and handle medical, surgical, psychological, psychiatrically, public health, and epidemiological, managerial, and communicational issues. Disasters are disruptive, sudden, and complex emergencies. Let us consider nano-disasters with impacts at the individual level. This kind of event is defined from our perspective as an emergency (for emergency medicine) affecting directly one or a few individuals. Disaster Medicine relates to mega-disasters with consequences at different population levels, with at least a few thousand people involved [33]. The COVID-19 pandemic involves both [34,35].

Uncertainty in action induces risk and hazard, engendering disruptive and unusual events such as an emergency and a disaster. These events induce losses of human life, damages to infrastructures and economic activities, and may negatively affect the environment. Several scales were defined and implemented over time for quantifying and categorizing the severity, the complexity, and the impacts of disasters [36,37].

The fundamental differences between an emergency and a disaster reside in scales and capacities to handle it efficiently.

Emergencies and disasters have variable and heterogeneous impacts and consequences on human activities, depending on the event scales. It is possible to classify them according to the number of directions or collateral casualties. On one hand, an accident impacting a small number of individuals (from one to ten) in a small area (less than a square kilometer) must be considered as a nano-disaster or minor disaster and can be handled as an emergency. On the other hand, a significant national or global event affecting a large population, such as at least a few tens to hundreds of thousands of people must be qualified as a large-scale disaster, mega-disaster [33,38]. Table 1 shows some examples of natural, man-made, and the combination of both kinds of disasters (at different scales).

Table 1: Examples of natural, man-made, and the combination of both kinds of disasters (at different scales)

Nature forces	Combinations of disasters caused by natural forces and man-made	Man-Made (anthropogenic) [39]
Climat phenomenons (hurricanes, floods [40], extreme heats)	Natech disasters for "Natural Hazard Triggering Technological Disasters" [41,42]	Residential or industrial casualties (fires, explosions, "Nuclear, Radiological, Biological or Chemical" hazards) [43]
Seismological events (earthquakes, landslides, volcanic eruptions) [44]	Technological Hazard triggering Natural disaster [43]	Transport accidents and calamities (Air, Maritime, Road, Railway) [45]
Epidemics and Pandemics (Influenza [46], Plague, Smallpox, Coronaviruses [47])		Cyber-attacks of any kind of (healthcare) infrastructures such as Hostech disasters ("Hostile Hazard Triggering Technological Disasters") [48,49]
		Societal events such as conflicts or acts of terrorism [50]

However, the main difference between an emergency and a disaster is related to how the resources allow efficient managing this event. In that way, the understanding of risks of small and large scales enables the development of preparedness plans. These one must be suitable for managing the event in short delays and taking in charge of casualties from the event area to a well-fitted infrastructure (e.g. field or permanent hospital for medical and surgical cases, emergency accommodation, or socio-psychological support, in other cases). The large-scale events usually exceed the involved community's abilities and capabilities (local resources).

The emergency preparedness plan (EPP) or the disaster preparation plan (DPP) are based on the continuous mitigation of previous disruptive events. Nowadays, the EPPs and the DPPs give technologies a critical position, like the Emergency and Disaster Response/Recovery Plans (e.g., ERPs and DRPs). In social media, the IoT, and more globally in the ubiquitous and mobile health technologies era, technologies support EDM from end to end. These vectors facilitate the event report, the dispatch of first responders and on-field medical teams, search-and-rescue, evacuation, hospitalization, discharge, and follow-up.

4. Social Media as Emergency and Disaster Management Platforms

Through search engines and social networks, the Internet is used to monitor, predict, and survey changes in populations (a.k.a. infoveillance [51,52]). This is used to get early disease outbreak warnings and follow its dissemination and resilience [53]. Social Media and Social Networks Services are powerful tools, allowing the mass to connect, interact, and collaborate. We have used them worldwide for the last two decades in different forms (e.g., blogs, chat rooms, discussion forums, wikis, YouTube Channels, LinkedIn, Facebook, and Twitter) [54].

Social Media as an ecosystem is a well-known vector for communicating and sharing evidence-based healthcare information and recommendations [55]. Nevertheless, efficient and effective health-related communication must be monitored and controlled for the "quality and reliability" of published and disseminated information [56]. Considering the fundamental human rights of communication over the social networks, and more globally over social media, between healthcare information customers and providers [57] must encourage the community to be active in developing relevant and constantly up-to-date policies for protecting confidentiality and privacy [58–60].

Reported data and information flowing from a disaster scene at its first instants are disorganized, where the event effects the perceptions and witnesses on-scene such as victims, witnesses, first responders, and off-scene with the emergency services dispatchers getting preliminary reports, media and more particularly social media arena players publishing breaking news. Additionally, concerning the number of people involved, the event generates massive data, information, and knowledge.

Because of this "chaos", data and information management and retrieval processes are challenged, raising the need to develop knowledge management infrastructure, allowing collecting, storing, and screening social media data in near real-time.

As an example, a social media historian helps to deal with the preparedness and mitigation of EDM [61]. A Historian is a software environment that allows recording, storing, retrieving, and analyzing events, sequences of events, and processes by time and domain in a factual database. Accordingly, the primary sources of the current historian-based disaster management systems are based on online social media, particularly online social networks [62–64].

Social media-based historians can support emergency and disaster research to better understand individual and collective behaviors during these unusual events; this must improve their mitigations and enhance preparedness for future similar events.

As one illustration of the potential of these kinds of applied historians for previous disaster mitigation and future one preparedness, earthquakes are natural and relatively frequently occurring disasters, having many types of impacts and consequences from an extensive range of societal perspectives.

The availability of disaster-related data is essential, at any time resolution and update, more particularly near real-time events, both for the public and all regional and extra-regional emergency organizations. Social Media comprises news-based television and radio channels having a website and social network pages. These last ones are also resources of data and information related to emergencies and disasters of any kind. In earthquakes, in-depth details are delivered with a relatively long delay compared with governmental and scientific websites. Nevertheless, the population is more confident when these sources publish warnings and reports [65].

A disaster ontology was developed as a first step and evaluated by domain experts reviewing March 11, 2011, Fukushima disaster [66]. This disaster is the umbrella title of a series of events following an earthquake in northern Japan and a tsunami. One of the associated events is a major nuclear accident, the world's most serious accident since the Chernobyl disaster of 1986 [67], and the medical impacts were and are still consequent [66,67]. A central issue identified from the "Fukushima disaster" is the number of sequential events and combined effects. From the "disasters" ontology perspective, the different types of disasters and their subtypes can influence one another. In "Fukushima", a natural disaster such as a geophysical event (i.e., an earthquake) induced another natural disaster, a hydrological one (i.e., a tsunami) resulting in a set of technological and industrial disasters (i.e., a nuclear plant accident, explosions, and fires of infrastructures). We can link this overall case to medical ontologies for reporting health conditions (such as physical and psychological trauma, epidemic disease) of individuals and populations.

This disaster ontology was evaluated on 37,144 messages extracted from social media and specifically from Twitter for ten days in April 2018. These tweets comprised the keyword “earthquake” (with and without hashtag -#earthquake-). The hashtag-keyword “#earthquake” was present in 74.64% of the tweets, having a median length of 140. 53.91% are re-tweets (not original messages), and 1.19% replied to another tweet. The geolocation coordinates were attached to 11.57% of the tweets of the sample. The density and the volume of the messages published on Twitter related to the earthquakes changed over time, and spikes indicated unusual events. They were associated with reports of earthquakes of various intensities on governmental and scientific websites. Common occurrences of different kinds of disasters have been noticed, such as “earthquake” and “tsunami” appearing together in 0.92% of messages, “earthquake” and “nuclear” in 0.52%. Furthermore, emergency and disaster medicine-related terms such as “injuries”, “injured”, “dead”, “death”, “suffer”, “healthcare”, “medical”, “emergency” “survival kit”, “emergency kit”, “first aid” appear in average 0.04% [61].

Using Social Media as a whole for reporting hazardous events can support the mitigation of these events and improve the preparedness for future potential ones. Analyzing, in near real-time, the contents of a massive volume of messages published over social media may allow us to understand the needs of the event field/scene and the assistance that can be provided. However, a key issue of using social media data and information is the difference in the quality of the different kinds of sources affecting their reliability. However, social media can self-regulate misinformation through the masses during these disruptive events [68].

In other terms, social media has changed the information dissemination pathways in case of emergencies and disasters. They transformed how emergencies and disasters are tracked and managed. For example, smartphone applications are used during disruptive events (e.g., hearth attack, car accident, terrorist attack) for alerting, asking for assistance, and reporting quickly, simply and efficiently to emergency services.

For example, Facebook [69] and Twitter [70], provide crisis communication tools and information sources. These tools are activated in case of terror attacks such as the attacks in Paris on November 13, 2015 [71] or during the typhoon Mangkhut, which struck Hong Kong in September 2018 [72]. This feature of the social media platforms allows users in an area affected by a crisis to mark themselves or others as safe.

Nowadays, SMPs integrate more than interpersonal communication services. They are storing data that can be investigated for (1) mitigating particular events, (2) surveilling changes in population behaviors, and (3) helping, for example, decision-makers to adapt their communication strategies to enhance population compliance and resilience to recommendations and directives in case of an emergency or a disaster. Moreover, most of the SMPs are used over mobile applications installed on smartphones and tablets with embedded sensors and receivers that make them connected objects of the Internet-of-Things and their users as members of the Internet-of-People (another kind of things).

5. The Internet of Things for Hazardous Events Detection

The Internet-of-Things is the whole of all the devices connected and controlled by and over the Internet. The "IoT power" resides in the product of the interactions between communicating devices and complex systems (Cyber-Physical Systems). This ecosystem affects the global level, systems design and engineering [73], economic [74], and resources management [75].

In the context of EDM, the whole IoT is a game-changer. IoT generates large volumes of data that must be collected, stored, extracted, and processed by analytics technologies. The results of this analyses support decision support systems (DSS) for improving, for example, emergency response operations [76,77]. As one example, smart cities are designed in such a way the same can contribute to enhance emergency and disaster resilience. Indeed, smart cities are integrating to their management platforms, IoT systems located in different places such as smart buildings [78-79] or roads for safety and traffic management [80,81].

In a smart building, IoT-based systems are able, for example, to detect and to generate alerts about

- Fire or floods in a building,
- Air pollution beyond the threshold level in the specific areas,
- Earthquakes and tsunamis.

In smart healthcare and focusing on emergency and disaster medicine and management, IoT-based systems are able, for example,

- To support distant monitoring and diagnostic [82-84]; particularly in an era like the current COVID-19 pandemic one [85–88];
- To deal with vehicle accident detection, reporting [80];
- To collect road loads for computing a continuously updated (medical) emergency evacuation path [80,83,89];

The Internet-of-Things in Emergency Medical Care and Services (used too in disaster medicine and management) is a part of the new healthcare information systems.

In emergency and disaster medicine, time, availability, and accuracy of contextual information are critical for increasing the chances of successfully providing the most adapted care in the shortest delay. Nonetheless, this is dependent on completeness, consistency, conformity, accuracy, integrity and the timeliness of the data and the information received and collected from the emergency call by dispatch to the emergency department admission. The Internet-of-Medical Things (IoMT) allows collecting and real-time data preprocessing from the patient and its environment for on-field monitoring and diagnosis support. In other terms, the IoMT platforms provide a telemedicine emergency management framework and patient-centric-information-based care services [90].

Accordingly, developing new and improving existing IoT systems and services for enhancing the emergency and disaster medicine and management practice must be based on telemedicine (as the main component of smart healthcare). The IoT-based telemedicine allows providing the on-scene healthcare practitioners (EMTs, paramedics, nurses, and physicians) with distant added-value expertise [91]. Firstly, the patient's historical data is accessible online (e.g., on a smartphone or a tablet) for supporting efficient initial diagnosis and treatment. Secondly, all the IoMT such as biological and physiological sensors (comprising imaging such as ultrasound) measurements can be used [85–87]:

- Immediately by decision-support systems, and
- Uploaded into the patient's electronic health record (EHR) for or later follow-up.

In such a way, many benefits are expected from the IoT and the IoMT in emergency medicine and management to move to a proactive practice. The COVID-19 pandemic is an essential trigger for developing policies facilitating the implementation of these new technologies for ensuring continuous, efficient, and effective delivery of care in a social distancing context (less physical contact between patients and healthcare practitioners, and fewer visits to medical clinics). Also, in parallel, it is critical to consider using the IoT and specifically IoMT in daily usage. Over and above that for handling emergencies and disasters, we require looking at architectures, security aspects of the health-data generated and exchanged.

6. Conclusions

One key challenge in using Social Media and the Internet-of-(Medical) Things in Emergency Medicine and Management relies primarily on data and information quality. Reports about hazardous events are produced by and on various channels, such as the traditional media (e.g., newspapers, radio, and television), social media, social networks (e.g., Twitter, Facebook, Snapchat, and Instagram), and IoT sensors.

- Traditional media and Social Media are allowing institutions and the mass to **broadcast disruptive event reports**.
- The **IoT/IoMT are social media components** by being integrated in the mobile devices hosting their applications and so permitting sharing the collected data collected.
- **Decision-making can be affected by the quality of data**, information, and knowledge collected and generated by healthcare professionals, journalists and by the population.
- **The "Social Internet-of-Things" is pervasive, fully connected, and has an autonomous and collective intelligence.**
  - This extensive integration and penetration in people's lives can offer **safety and security feelings** (having systems taking care of our well-being).
  - But, the openness of Social Media, IoT, and so Social IoT are good **candidates for cyber-attacks** [32]. Accordingly, using these technologies in emergency and disaster medical practice and management must consider developing additional layers dealing with the security of the systems from end to end (cyber-defense against attacks and network management for handling real-time communication failures).
- An additional new pillar of delivering emergency care and disaster management relies on the technological "**Quality of Service**" provided currently by Social Media and IoT devices and systems as a part of the alert, operation, and management processing [92].

The opportunities and the prospects of Social Media and IoT/IoMT in the practice of emergency and disaster medicine and management are numberless and still not fully defined and are still open research issues [93].

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Investigating the Components of Virtual Emergency Department

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Abstract. The prediction of the demography of Spain shows that Spain will experience an aging population soon. Aging is a condition of chronic disease resulting in overcrowding Emergency Department. Despite chronic diseases, Covid-19 became a serious issue for emergency Department staff and health care providers. All of these matters emphasized the importance of the Virtual Emergency Department which can provide faster and more affordable medical services while everyone can keep the social distance as much as possible. In this chapter, we investigated the role of IT in the healthcare system and the possible suggested solutions. We have studied the existing telemedicine, e-health, machine learning algorithms and in the end, their combination to built an integrated virtual emergency department to cover all the aspects. We have proposed a model for this integrated model and studied the possibility of success in each step including admission, triage, diagnoses, and clinical advice based on literature.

Keywords. Virtual Emergency Department, Smart Triage, Smart Diagnoses, Telemedicine, AI in Health Care System

1. Introduction

1.1. Importance of Virtual Emergency Departments in Pandemic

The main entrance to the health care system is the Emergency Department (ED), in which the quality of treatment directly affects the quality of the healthcare system. Overcrowding in EDs is a global multi-factorial issue causes (i) extended length of stay (LOS), and (ii) delay in medical care and treatment for chronically ill patients, frustration, and short-term mortality among patients. Our statistical analysis of the Parc Tauli Hospital's data set reveals that almost 70% of ED visits are non-urgent patients who do not need emergency care. Authors in [1] reported that 91.5% of patients who visited EDs within five days had mild or moderate symptoms.
Coronavirus (COVID-19) was first identified in China in 2019 and soon became a pandemic. Spain has undergone three outbreaks in the spring and fall of 2020, with the third wave in January 2021, which undermined the ED's response capability. The studies show that frequent visits of COVID-19 patients at Al4 or Al5 levels or patients with mild symptoms overwhelmed EDs and raised the risk of transmission.

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WHO on reports, on average, every person infected with COVID-19 exposes 2 or 2.5 persons. Besides the risk of exposure, Covid-19 affects the mental health of society widely. A survey indicates that 36% of the participants reported moderate to severe psychological impact, 25% impacted with mild to severe anxiety levels, and 41% showed depressive symptoms, and 41% felt stressed [2,3,4].

1.2. Contributions of The Virtual Emergency Departments Globally

Since the beginning of the pandemic, many countries began to strictly follow the evaluation, investigation, and implementation of the VED. For example, many EDs in Ontario use virtual follow-ups for discharged patients, virtual psychiatry consulting, and virtual appointments to the pediatric emergency department. The London Health Sciences Centre (LHSC) also opened an after-hour virtual "ED waiting room" integrated into their departmental electronic medical platform. SickKids in Toronto similarly rolled out virtual subspecialty consultations for children physically in the ED. The Virtual Emergency Department (VED) provides remote health services to non-emergency patients via video call using smart devices. The examination of this type of patient with long-distance care allows virtual clinical follow-up and consultation to provide care seekers with faster care services from home, eliminating travel time and ED wait times while maintaining social distance for pandemic management. The VED can also provide 24-hour service, which improves the healthcare system's efficiency and reduces LOS.

1.3. Motivation and Contribution

To the best of our knowledge, current studies are insufficient for presenting a comprehensive VED model with detailed modelling parameters. We recently proposed a comprehensive VED model validated using real-time data analysis from the Parc Tauli Hospital data set, with each stage of the ED elaborated separately. We use cutting-edge artificial intelligence classification and clustering algorithms to propose the method.

2. Materials and Methods

2.1. Traditional Process in ED

Patients visit ED by themselves or an ambulance. There are three main stages in the ED, including registration and admission, triage and then treatment. The patient's registration is followed by triage. The triage phase in ED specifies the treatment area (i.e., area A and B in Fig. 1). Patients with acuity levels (ALs) 1, 2 and 3 are assigned to Area A and stay in care-boxes during all hospitalization. Patients with ALs 4 and 5 belong to area B for receiving treatment. All patients in the admission and triage phases have the same nurses and healthcare staff. After triage, in diagnoses and treatment stages, separate doctors and assistant nurses serve at each Area while sharing the same test service resources such as laboratory test and X-Ray [5].

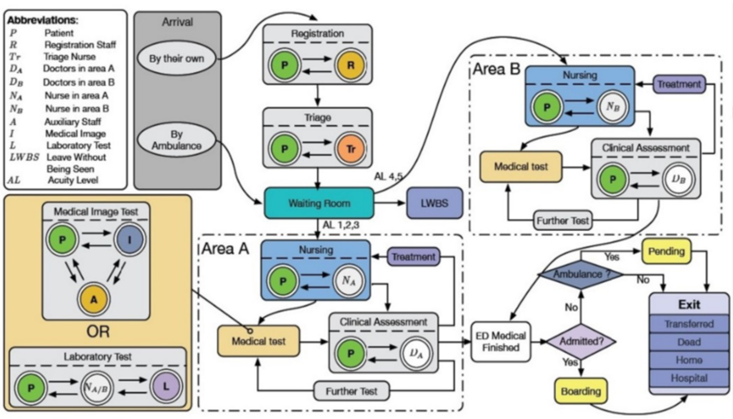

Figure 1. ED model modeled the actions and interactions between different elements of the system including patients, healthcare staff, and physical resources of ED. Urgent patient receive treatment in areas A and B were designed for non-urgent patients and have their own allocated staff [5].

2.2. *Who Benefits from VED*

The VED concept began with providing medical services to 1) rural areas with no access to the care system, 2) after-hours care needs, 3) chronic care monitoring, and 4) after surgery or post-acute passive monitoring. Participants in these four categories do not have life-threatening conditions. However, it has recently become a hot topic to provide virtual medical services to all types of patients. Patients with severe symptoms, on the other hand, should go to the nearest emergency department. The following are the life-threatening signs, according to Ontario Emergency Services: respiration problems, high body temperature, difficulty speaking or swallowing, neck stiffness or severe headache, fatal injuries, new or worsening seizures, possible broken bones (i.e., bones or joints look different, cannot put weight on injury), vomiting and inability to drink fluids, loss or change of vision, numbness or weakness of the face or body, inability to walk, new confusion or memory problems, pregnancy and labour problems, opioid pain medicine prescriptions or renewals

2.3. *Non-Urgent Arrival Patients: Clinical Data Collection and Analyzes*

The analysis of ED visits with varying acuity levels is required to clarify the importance and influence of VED on ED quality. This information revealed a correlation between the number of non-urgent arrival patients and ED saturation. A study shows that 30% of ED visits in USA are unnecessary, and it is preventable [6]. Another study reports that 67% of the visit to an ED in Iran are non-urgent patients [7]. However, statistical analyzes of clinical data collected from (Parc Tauli hospital) indicate that 70% of total ED visits are patients with ALs 4 and 5 (Table 1) [8]. In the triage step, patients are classified into five acuity levels (ALs) , where patients with ALs 1, 2, and 3 are considered urgent patients and prioritized to receive treatment and/or physical resources according to the Spanish triage system. Patients with ALs 4 and 5 are classified as non-urgent patients who have a lower priority to receive treatment and/or physical resources [9,10].

Table 1. Classification of patients visiting the ED based on their level of urgency (Spanish Triage System). The data represent 1 year of ED visits (collected from Parc Tauli Hospital in Sabadell/Spain)

Acuity Level	Type of Attention	ED Visits	Number of Visit
AL1	I-resuscitation	0.39	530
AL2	II-emergent	4.36	5,905
AL3	III-urgent	25.37	34,394
AL4	IV- less urgent	50.33	68,228
AL5	V-non-urgent	19.55	26,509

2.4. General Model of VED

VED follows the same steps as ED but using remote infrastructure technology for monitoring. A telemedicine setup will require basic infrastructures such as an internet connection, a video platform, smart devices, and telecommunication technology support. Patients seeking medical care or recommendations log on/into a hospital webpage/app to start a virtual visit from their own device. After the connection, the patient would be (i) registered, (ii) triage, (iii) diagnosed and (iv) treated/advised by an automatic system or online medical staff. If necessary, prescriptions or lab tests is organized, and the patient is redirected to an in-person emergency department or an appointment with a primary care provider. Figure2 shows the different stage of VED which each stage has been elaborated as follows:

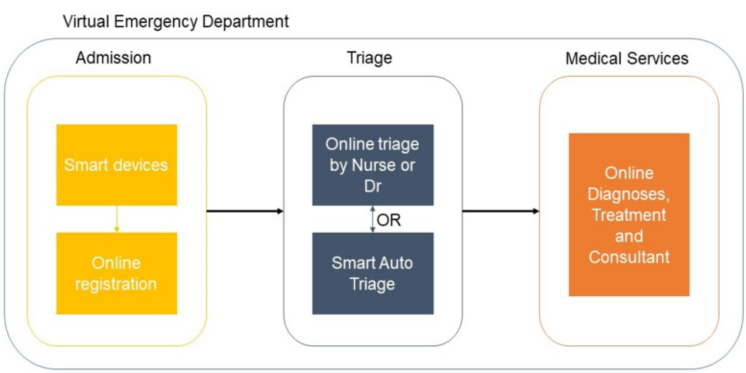

Figure 2. ED is composed of three main sub-model including admission, triage and medical services (diagnoses, treatment, consultation, medical test and so on)

2.4.1. Registration

When a patient enters an ED, he/she must be admitted to ED and stays in the waiting room. There are patients frequently visiting ED, usually without an appointment. However, they should be admitted every time. Managing the registration is a solution to optimize the time-efficient service providing. Online registration helps care providers manage patients' entrance and organize the less/non-urgent visit in not-hectic time. It also reduces there-admission and waiting room time. To do online registration, a smart device and internet connection are needed. Patients themselves or their families can easily connect to the website or app, sign up and enter some information such as personal data, historical medical data, and fill up the pages with current symptoms and signs of the patient requesting the visit.

2.4.2. Virtual Triage

The triage stage starts after collecting health information from patients or his/her family. This information is acquired by answering a few questions about the health status. The questions such as how quickly your symptoms developed, how long you have had them, and whether they have changed recently are also asked to rectify the degrees of urgency [12,13]. Virtual triage could be implemented through (i) attending physician virtually and remotely; (ii) an artificial intelligence platform and automate smart model such as machine learning algorithms. Some patients, especially older people, use VED to be monitored after surgery. For such a purpose, the quantity of the vital signs such as electrocardiogram, heart rate, blood pressure, respiration rate, blood oxygen saturation, blood glucose, skin perspiration, body temperature, motion evaluation, cardiac implantable devices, and ambient parameters are required. Wearable Health Devices (WHDs) help them measuring these parameters and transfer them to the medical staff for real-time and remote health tracking.

2.4.3. Online Clinical Service

The next step after the successful triage is the diagnosis. The system could automatically assist the system, live communication type - involving a physician - or a non-real-time consultation. Generally, the type of implementation depends on several factors, such as the severity and type of disease and patient willingness. A non-real-time option includes the clinical analysis, result of the medical test, and medical recommendation. The result is sent as a text message or an email to care seekers.

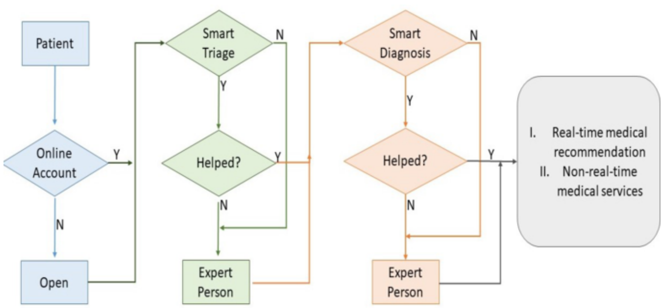

Figure 3. VED model is merged of automated model through (machine learning algorithm) and telemedicine

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3. Importance of Artificial Intelligence in VED

In emergency department studies, the use of AI-based solutions and platforms is rapidly increasing. As a subset of AI, Machine Learning (ML) has grown in popularity in medicine. As a result, its classification algorithms are employed in prediction, triage, and diagnosis. These algorithms contribute to decision-making, whether independently or minimize the uncertainty of medical staff in manual working.

3.1. AI-based Solution in Triage

The Spanish triage system, which is similar to the Canadian system, is known as the Emergency Severity Index (ESI), and it is a five-level emergency department (ED). The triage algorithm divides patients into five clinically relevant groups ranging from 1 (most urgent) to 5 (least urgent) (least urgent). The classification is determined by acuity and resource requirements. Figure 3 [14,15] represents the algorithm.

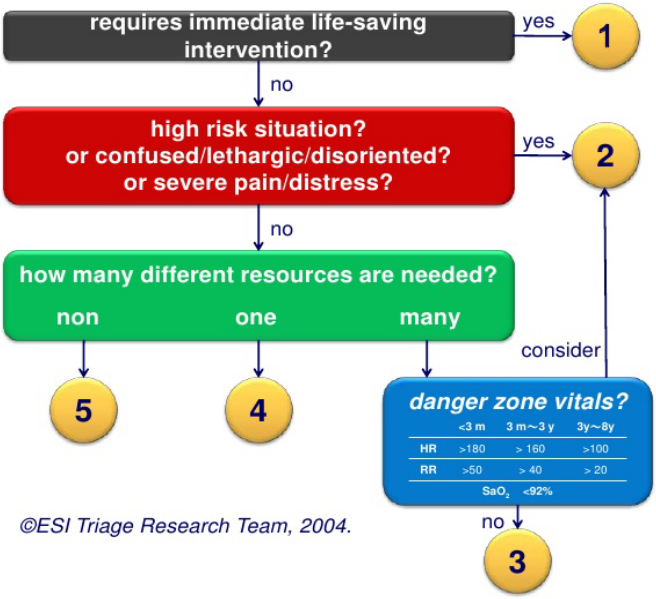

Figure 4. Canadian(similar to Spanish) triage system classifiys the patient in five categories based on their severity and need of resources. [14]

A team from Harvard Medical School investigated machine learning prediction models using routinely available ED triage data. They have collected data from the ED component National Hospital and Ambulatory Medical Care Survey (NHAMCS) between 2007 and 2015. 70% of triage data was used for training as predictors (e.g., demographics, triage vital signs, chief complaints, and comorbidities), and the remaining 30% of ED data was used for the test. As the reference model, a logistic regression model based on ESI data had been developed. The clinical outcomes were split into two categories: critical care and hospitalization. In this study, they assessed each model's predictive performance, using the Area Under the receiver-operating-characteristics Curve (AUC) and net benefit (decision curves). The AUC is a measurement to evaluate a classifier's ability to distinguish between the positive and negative classes; the higher the AUC, the better the performance of the model. Decision curve analysis with the key concept net benefit also is a method to measure prediction models and diagnostic tests. In both outcome predictions (critical care and hospitalization), all four machine learning models outperformed the reference model. The result of the study is shown in the Table2:

A research team in Korea has investigated the different machine learning models to predict the Korean Triage Acuity Scales (KTAS) levels. This team collected a data

Table 2. Result of AI solution in triage

Outcome and Model	AUC (Area Under Curve)
Critical care outcome	
References model	0.74 (.072- 0.75)
Lasso regression	0.84 (0.83 – 0.85)
Random forest	0.85 (0.84 – 0.87))
Gradient boosted decision tree	0.85 (0.83 – 0.86)
Deep neural networking	0.86 (0.85 – 0.87)
Hospitalization outcome	
References model	0.69 (0.68 – 0.69)
Lasso regression	0.81 (0.80 – 0.81)
Random forest	0.81 (0.81 – 0.82)
Gradient boosted decision tree	0.82 (0.82 – 0.83)
Deep neural networking	0.82 (0.82 – 0.83)

set from a single emergency department of a tertiary university hospital from November 2016 to June 2019. They classified the data into three types of (i) only structured data, (ii) only text of nursing triage notes, and (iii) a mix of both structured data and nursing triage notes. The data set was analyzed to develop Logistic regression, random forest, and XGBoost and predict the KTAS level [16]. The models with the highest AUROC (Area under the receiver operating characteristic curve) were the random forest and XGBoost models trained on the entire dataset obtained the highest AUROC (Area under the receiver operating characteristic curve) (AUROC = 0.922, 95% confidence interval 0.917–0.925 and AUROC = 0.922, 95% confidence interval 0.918–0.925, respectively). The result (Table3) demonstrates that machine learning can strongly predict the KTAS level at triage, which provides us with many possibilities of uses [16]. Another study [17] collected the

Table 3. Result of AI solution in Korean triage acuity scales

Model	AUROC
Logistic regression(clinical data)	0.8812
Logistic regression (text data)	0.8595
Logistic regression (all data)	0.9053
Random forest (all data)	0.9220
XGBoost (all data)	0.9220

information from different ML models in triage and compared each algorithm's accuracy with others. These algorithms include Decision Tree, Support Vector Machine, Random Forest, Naïve Bayes Classifier, and Bayesian Network. The comparison of accuracy is shown in Table 4.

The abilities of artificial intelligence and machine learning techniques can be used in medicine. Especially, these techniques may have a significant contribution in emergency medicine and some critical issues, including disease prediction, admission or discharge prediction, and patient triage. By early prediction and diagnosis of high-risk diseases such as AKI, Sepsis, pneumonia, and contagious diseases such as influenza, necessary interventions can be performed more rapidly in ED to prevent multiple disease progression complications. Different machine learning algorithms such as Logistic regression,

Table 4. Different models used in machine learning-based triage systems

Model	Accuracy
Decision tree	84.0%
Support vector machine	84.0%
Random forest	AUC: 0.73 – 0.92
Naive Bayes classifier	Accuracy: 87.9%
Bayesian network	Accuracy:86.9%

Bayesian network, deep learning have been deployed with high accuracy ranging from 70% to 90%.

3.2. AI-based Solution in Diagnoses

Using AI and ML classifiers such as Fuzzy Logic System, Decision Tree, SVM (support vector machine), K-nearest neighbours (KNN), PNN (probabilistic neural network), and RBFNN (radial basis function nueral network) facilitates predicting various diseases, such as Parkinson's disease, liver disease, heart disease, breast cancer, and lung cancer. The result especially, the prediction of cancers with the slightest uncertainty, have been admissible [18]. Many ML algorithms, including Naive Bayes classifier (gaussNB), LDA (linear discriminant analysis), KNN, quadratic discriminant analysis (QDA), SVM (nu-SVC), MLP1, linear SVM (LinSVM), Random Forest, logistic regression, and C-SVC as a type of SVM (called SVC) have been tested under the same condition in a study [19,20]. MLP1 is a multilayer perception algorithm with one hidden layer that the hidden layer included a maximum of 200 neurons. In the end, the nu-SVM algorithm gained the best accuracy with 93.08% and the highest F1-score rate of 0.9151 In another study, the accuracy of ML in detecting some of the most important diseases have been compared. The diseases in this study are acute kidney injury (AKI), chronic obstructive pulmonary disease (COPD), and asthma, urinary tract infection (UTI), Sepsis and influenza. We summarize the results in Tables 5-8.

AKI: Many types of research investigated the detection, prediction, and diagnosis of AKI. They have been applied different methods and models to discover the most precise algorithm. In these studies, the algorithm such as Multinomial naıve Bayes (MNB), L1-/L2- regularization, SVM, Logistic Regression (LR), Random Forest (RF), Gradient Boosting and Decision Tree (GBDT), support vector machines, Gradient Boosting Machine, Deep learning, and architecture knowledge-guided deep learning was used to design the model. The best result of each study is shown in Table 5.

Table 5. prediction and diagnosis of AKI

Algorithm	Result
Boosted ensembles of decision trees	AUC; 0.72 – 0.87
Logistic regression	AUC: 0.77
Gradient boosting machine	AUC: 0.73 – 0.97
Deep learning	Accuracy: 99.1%
Logistic regression	AUC: 0.74
Binary logistic regression	Sensitivity: 96.6% Specificity: 95.7%

Influenza: is an infectious disease affecting many people every year, and it can cause epidemics due to its contagious nature. Two different studies have been performed: natural language processing and different classifiers were used in a combined manner. In the second one, seven classifiers, including Naïve Bayes, Bayesian network with the K2 algorithm, Efficient Bayesian Multivariate Classification, Artificial Neural Networks, Logistic Regression, SVM, and Random forests were applied, and the results were compared with each other. The first study reports a Bayesian network classifier (naïve Bayes) with an AUC of which was 0.79 and showed the highest value among the nine experiments. Moreover, in the second one, Bayesian (naïve base) showed better performance with an AUC of about 92-93%.

Table 6. Influenza – algorithm with highest AUC

Algorithm	AUC
Bayesian Classifier	0.92-0.93
Bayesian network classifier (naïve Bayes)	0.79

Sepsis: A machine learning-based method has been proposed for the prediction and diagnosis of Sepsis, which can improve patients' treatment procedure. Using a gradient tree boosting algorithm, three levels of Sepsis are detected. Features used in this method include values of 6 vital signs in EDs, general wards, and ICU, and, eventually, the Area under the ROC value for Sepsis and severe Sepsis are 0.92 and 0.87, respectively. Applying SVM to a bag of words is more effective than other methods, and the AUC values for test and train data are 0.86 and 0.89, respectively.

Table 7. Sepsis: algorithm with highest AUC

Algorithm	Accuracy
Gradient tree boosting	AUC: 0.87-0.92
Support vector machine	AUC: 0.86

COPD and Asthma: Asthma condition and COPD exacerbation in EDs has been assessed in different studies using different machine learning methods such as Lasso regression, random forest, and boosting, and deep neural network, Gradient-Boosted Decision Tree, Naïve Bayes, and some models have been developed based on available data. The models with the best results are presented.

Table 8. COPD and Asthma: The most accurate result

Algorithm	Result
Random forest	C-statistic: 0.84
Logistic regression	Accuracy: 89.1%
Naïve Bayes	Accuracy: 70.7%
Tree-based decision model	AUC: 0.83

UTI- To predict UTI, seven machine learning algorithms including Random forest, extreme gradient boosting, adaptive boosting, elastic net, support vector machine, logistic regression, and neural network. Results showed that among the mentioned algorithms, the XGBOOT algorithm provided the best efficacy with an AUC of 0.90.

4. Discussion

In order to reduce pressure on ED and enhance its performance, several solutions have been suggested. Some solutions incorporate patients by redirecting them to different wards, increasing resources (e.g., physicians, nurses, and physical resources), and applying operational research methods. Nevertheless, those methods can not only solve the problem of budget but also social distance issues for communicable diseases such as Covid-19 stay unchanged. It has been reported proximately, the average cost of a VED per visit is about $40 to $50, while the average estimated cost of in-person acute care is $136 to $176 [30].

4.1. Utilizing Telemedicine to Support VED

While not identical, telehealth, telemedicine, m-health, e-health, and Miot (Medicine Internet of things) terms, they may be used interchangeably. Telehealth is the distribution of both Health Resources and Services Administration such as video conferences, videophone for consultation, home monitoring of patients, robotic surgery, treatment via digital instrument, live feed and application combinations [21,22]. Telemedicine is a subgroup of telehealth limited to only long-distance clinical services such as diagnosing and monitoring patients. E-health is defined as a healthcare practice supported by electronic processes and communication, including internet medicine and all virtual things related to medical and services that can search, find, and understand the health information by using electronic sources to solve a health problem [24]. MHealth (mobile health) uses mobile communication devices, such as mobile phones, tablet computers and wearable devices (e.g. smartwatches), for health services, information, and data collection, which is a sub-segment of e-health. It uses information and communication technology (ICT), such as computers, mobile phones, to provide health services and information [25]. The Internet of Medical Things (IoMT) merges medical devices and applications to obtain accurate diagnoses, fewer mistakes and lower costs of care. IoMT allows patients to send their health information to the physician to follow up and prevent chronic illnesses [26]. With the different definitions, all of these could be used in the proposed VED via electronic, smart, communication and mobile or wearable devices and technology to provide virtual and accurate health care services. Some programs and applications such as Jefferson Health, Mount Sinai, Kaiser Permanente, Cleveland Clinic, Providence have been developed and allow clinicians to see patients at home. Doctors and nurses can provide medical recommendation, Triage through web-conferencing, automate triage, monitor the patients in ICU, making the medical decision by accessing the specialist, giving consultations, permitting the patient to schedule a video visit on demand, and even provide the possibility for clinicians to work from home [27]. At present, coordinating of the testing system, pharmacy, insurance and payment regulation, and coherence among all the components are parts of unsolved issues [28]. The average number of VED visits per patient is 1.3 visits/year. Unfortunately, not many types of research have been conducted to investigate an integrated VED objectively. VED allows health care is timesaving for both staff and patients and less costly with minimum touch, and, in many cases, more effective than other health care options. Specifically, it can be important for patients with less of an emergency condition who are transmitters and can impose a significant burden on EDs.

4.2. VED Vision: from Testbed to Real Application; Requirements

No telemedicine program and application can be conducted overnight, but all the discussed researches and studies represent that partially VED is implemented and used in some countries and EDs for some particular type of diseases successfully. However, a central, allied, and integrated healthcare system is missing to unify all the sub-models and types of diseases. The existing systems already helped the care seeker and giver with faster clinical services, but still, it does not provide them with all needs of patients. To fulfill all the requirement, the entire existing sub-segment incorporating automated and/or online initial intake, triage, diagnoses, treatment, monitoring via video, web, phone, smart, and/or wearable devices should be concatenated and then unified with transport and ambulance system management, pharmacies delivery system and insurance and finance department. Despite Internet and electronic devices, a secure database is needed.

4.3. Problem and Limitation of VED

The health care system requires the collection and massive storage of personal health information. It may be sensitive and potentially embarrassing. Thus, medical data protection is one of the concerns of both caregivers and care seekers. Insecure data could lead not only to data breaches but also to fatalities in people relying on medical devices. Clinicians also need to rely on technology when ensured security and fully compliant with privacy laws. Besides, both caregivers and care seekers have to be trained for using the virtual system. However, the VED is unable to test and examine patients and might cause a delay in treatment. VED relies on the technology of measurement and data. Therefore, the methods' performance depends not only on the efficiency of the algorithm but also on data quality and conditions of implementation. The structure of data (supervised and unsupervised) and medical reports may significantly impact the results.

5. Conclusion

A model had been designed and developed to integrate existing sub-segment models and merge an intelligent automatic system with telemedicine and mhealth. The proposed model has studied the possibility and probability of success in each sub-segment according to related researches. Machine learning is highly recommended to triage, diagnose and decision-making especially for for most common diseases. In general, the machine learning model methods were superior in predicting critical care, triage, and diagnoses, thereby achieving better clinical care and optimal resource utilization.The system can ease self-care management, accelerate the clinical services, and organize self-quarantine while in-person visits become the last option. Decreasing the non-urgent visit also provides the urgent visit with a better quality of medical services and result in patient satisfaction. The smart algorithms minimize the failure while caregivers making decisions. VED enable people from different locations to have the equal access to the healthcare system and connect to specialist easier. However, the uncompleted data and shortage of information have significant implications on the accuracy of all studies. Therefore, no definitive answer is gained about the most accurate method.

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Part 4

Future Challenges and Opportunities in A&EI

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Challenges and Opportunities of Patient Safety Event Reporting

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Abstract. The World Health Organization (WHO) announced the first-ever World Patient Safety Day on September 17, 2019, which remarks a global campaign to create an awareness of patient safety and urges people to show their commitment to making healthcare safer. Reporting medical incidents or patient safety events (PSE) has been recommended as an effective approach for the detection of patterns, discovery of underlying factors, and generation of solutions. It is believed that PSE reporting systems (e-reporting) could be a good resource to share and to learn from the reporting if the event data are collected in a properly structured format. Unfortunately, the prevalence of underreporting and low quality of the reports have become barriers to ultimately achieve the goal of preventing and reducing medical incidents. This chapter describes the efforts that have been made to improve e-reporting through informatics approaches, including a review of PSE taxonomies and conceptual frameworks, studies of medication events, patient falls, and PSE involved in health information technologies, as well as discussions of design requirements for future e-reporting systems.

Keywords. patient safety, event reporting, healthcare quality

1. Why Patient Safety Event Reporting?

Medical error is one of the leading causes of death in the US [1] and many other countries in the world [2]. The reduction of medical errors and patient safety events has become a major concern in healthcare today [3–5]. It is believed that patient safety event reporting (e-reporting) systems could be a good resource to share and to learn from the errors. When the event data are collected in a properly structured format, the reports could be useful for the detection of patterns, discovery of underlying factors, and generation of solutions [6,7]. Effectively gathering information from previous lessons and timely informing the subsequent action are the two major goals for the design, development, and utilization of such a system [8].

To achieve the goal of preventing and reducing medical errors, e-reporting systems should be secure, easy to use, and effective [9], that is, confidential or anonymous, with excellent user acceptance, and used in a meaningful way. Being able to facilitate learning from past mistakes is critical to e-reporting systems to eventually decrease recurring incidents. Unfortunately, common issues of e-reporting mainly focus on underreporting and low-quality reporting. The quality of voluntary reports is just as significant as the

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number of submissions [10].

2. Barriers of Event Reporting

Lack of instructions and training in event reporting, event analysis, and use of reporting systems undermines the motivation of reporters, accounting for under-reporting and low-quality [11].

At the organization level, the culture of blame and resistance to sharing have been identified as barriers to e-reporting [12]. Likewise, the management policy on mandatory and non-confidential reporting of medical incidents, in fact, discourages front-line clinicians from reporting internally [13]. Last, but not least, the psychological stress that healthcare staff experience while discussing mistakes with their supervising managers, such as fear of embarrassment and loss of reputation or job [11,12], should not be ignored.

At the technology level, current e-reporting systems were not built based on a consensus of conceptual frameworks. In some cases, underreporting can occur just as a result of reporters unable to identify a proper classification or definition[10]. Several medical incidents, patient safety event taxonomies, or conceptual frameworks are available for the development of e-reporting systems [14]. Unfortunately, in practice, so many taxonomies that lack consistency may impede the interoperability among different e-reporting systems at a larger scope. Selecting “other” or “miscellaneous” as an incident category is a common problem and posed barriers for computerized analysis [10]. Classification and definition used in e-reporting systems play a key role in assuring the quality of reports and may even determine whether an event is recognized or ignored [15,16].

Furthermore, existing e-reporting systems are mainly template-based, with a combination of open-ended and structured questions, aimed at maximizing the consistency and minimizing the variation in the level of details. Inevitably, it may have the unintended effect of homogenizing incident descriptions with a loss of details [8]. As a result, most e-reporting systems cannot synthesize incident data to generate actionable knowledge [10], [12,17]. In our systematic review of peer-reviewed publications and publicly accessible web pages, none of the reviewed reporting systems have any features that facilitate learning from mistakes or provide actionable feedback to reporters [8]. Despite numerous studies suggest instituting a “just culture” that encourages learning, non-punishment, few studies have investigated system difficulty and inefficiency regarding ease of use, ease of understanding, and their relations with the level of details in reporting [11] and it is rare to find research investigating data-driven learning features in e-reporting[17][18][19].

2.1. Learning Purpose of Event Reporting

Since 2000, numerous e-reporting systems have been developed based on the recommendations from the IOM’s report. Nevertheless, most of the systems just function as a primary data repository of the reported events with little or extremely limited evidence to show that event reporting can improve patient safety, and how much influence it can make remains unclear [20]. Therefore, learning from errors is still an intuitive way to avoid the recurrence of errors. Root cause analysis (RCA) cannot be carried out unless an occurrence of safety events has been reported in detail, based on which further actions of improvement will become possible.

Studies on e-reporting systems have been limited and fragmented. Most of them were based on qualitative studies [21][22][23]. Thus, it has been equivocal regarding how to build an effective event reporting system to assist in overcoming the technical barriers and achieving the expected learning effect. The barriers identified are worth an extensive discussion so that timely knowledge support could be offered and reporting motivation could be enhanced [24]. In addition, it has been unclear in terms of long-term evaluation strategies based on the event reporting systems, triggering the uncertainty about the real effect of the systems. There have been questions regarding how to mitigate or resolve these issues, and accordingly, design a set of learning-oriented and user-centered features to enhance reporting motivation.

2.2. Design Features of E-reporting Systems

A systematic review of reporting systems introduced the systems implemented between the years 2000-2011 in healthcare institutions across the world, including the United States, Netherlands, Canada, United Kingdom, Germany, Australia, China, and Japan. The use of e-reporting systems was not limited to a particular clinical area. For example, some of them focus on general patient safety events and some others focus on specific areas, such as anesthesia events and radiation oncology events. The system design features were identified as 'widgets', i.e. drop-down lists, checkboxes, or radio buttons used to replace plain text input for users' convenience when appropriate, other features include 'anonymity or confidentiality', 'validator', 'reference', 'review notification', and 'hierarchy'[8]. Similar to the evolvement of paper charts to electronic health records (EHR), the features show a trend of the advancement of user-centered design. The designs in the early stages (stages 0–2) simply transformed paper forms into e-forms where the features ensuring data quality (stages 3–6) were not pervasive. It was found that 12 out of all 48 (25%) identified e-reporting systems were actually electronic copies of paper-based reporting forms rather than interactive systems.

2.3. Data Quality of E-reporting Systems

Data quality in general regarding accuracy, completeness, and timeliness has been the main concern in event reporting, meaning flaws in terms of functionality and usability that could be treated per the user-centered perspectives. Data quality in an e-reporting system is defined as a multidimensional concept, including accuracy, completeness, and timeliness. We define the three data quality dimensions as follows:

- Accuracy: the degree of proximity of a given patient safety event report to corresponding real-world occurrences. The reporting accuracy is subject to user errors and cognitive limitations in memory and reasoning, including but not limited to typographical errors, memory decay, causal attribution, and hindsight biases. The accuracy of e-reporting could be improved if these contributing factors are incorporated into design considerations with good usability and functionality.
- Completeness*:* the degree to which a given patient safety event report includes necessary information describing the corresponding real-world event to be sufficiently valid for the purpose of analysis and generation of intervention. The completeness could be enhanced if its criteria are explicitly delineated and properly represented to the reporters with the help of interface features.

- Timeliness: the degree to which a patient safety event is reported on time for root cause analysis and the generation of real-time intervention. The timeliness could be enhanced by improving the efficiency of the reporting process and offering a smooth review process to generate actionable knowledge.

The quality and rate of event reporting can be greatly affected by the user interface associated with human factors [10,25]. It was argued that an effective design of e-reporting systems should support the social-cognitive process of potential reporters [16,26], meaning e-reporting systems should guide a reporter to go through the reporting details step-by-step without costing additional time and efforts. A well-designed system tends to generate data of high quality. Likewise, a well-designed e-reporting system could serve as a facilitator to enhance data quality for understanding and trending the data about patient safety events. Unfortunately, by far, the design features of e-reporting systems have been addressed in a fragmented way across studies.

3. Taxonomy for Event Reporting

Despite the potential of e-reporting systems, narrative reports are severely under-utilized. The current classifications for event reporting are difficult for reporters to understand and utilize, which constrains the quality of reports and may result in misleading and wrong information in the reports. Moreover, the high workload of clinical duties, also known as competing priorities, spares less time for clinicians to complete reports of high quality. Last but not the least, e-reporting systems do not provide timely feedback to reporters as a regular system function, such as process of reporting, analysis of the cases, and recommended interventions [11,24].

Taxonomies, classifications, and terminologies can be used to determine the spectrum of data elements. The International Classification for Patient Safety (ICPS) [27] of the WHO and the Common Formats of the Agency of Healthcare Research and Quality (AHRQ) [6] provide widely accepted concepts, terms, and frameworks for patient safety. The National Coordinating Council for Medication Error Reporting and Prevention (NCC MERP) [28] developed a comprehensive Taxonomy of Medication Errors which defines terms with high granularity in all dimensions of medication errors. These medication error reporting tools serve as trustworthy resources for the determination of necessary data elements and the construction of the model for narrative reports.

Similar to the role of the International Classification of Diseases (ICD) in EHR systems, a taxonomy for event reporting plays an important role in terms of event analysis, data integration, data quality assessment, data quality improvement, and shared learning. In our preliminary project, we reference to the prevailing patient safety taxonomies that support event reporting in broad scopes:

- The National Coordinating Council for Medication Error Reporting and Prevention (NCC MERP) [28];
- The Joint Commission on Accreditation of Healthcare Organizations (JCAHO) Patient Safety Event Taxonomy (PSET) [29];
- a Preliminary Taxonomy of medical errors in Family Practice (PTFP) [30];
- Cognitive Taxonomy of Medical Errors (COG) [31];

- Taxonomy of Medical Errors for Neonatal Intensive Care (NIC) [32];
- Pediatric Patient Safety taxonomy (PED) [33];
- Taxonomy of Nursing Errors (TNE) [34];
- The FDA Safety Information and Adverse Event Reporting Program the FDA's medical product safety reporting program for health professionals, patients and consumers (MedWatch) [35];
- International Classification for Patient Safety (ICPS) [27];
- AHRQ Common Formats [6].

The creation and development of the taxonomies can be guided by the strategies of top-down, adopting focus groups, expert panel discussion, or Delphi method, etc., and by the strategies of bottom-up, employing case analysis, inductive reasoning[29] which can be assisted by natural language processing and machine learning technologies.

A variety of taxonomies have been employed in homegrown or commercialized e-reporting systems. The taxonomies have the advantageous features for offering categorical information on reporter interface, prioritizing or trending events per pre-defined categories. Over the years, issues of taxonomy application in e-reporting systems have drawn the attention of researchers.

- Low utilization of taxonomies from reporters who often choose "other" or "miscellaneous" as a confident classification;
- Lack of unified taxonomy to cover various domains and aspects of patient safety events in large healthcare organizations, which leads to poor interoperability;
- Appending categories or subcategories to an established taxonomy per unsystematic approach often resulted in overlaps between categories, redundant subcategories, and reporters' confusion that can exacerbate the low utilization of taxonomies;
- Taxonomies are not well integrated with e-reporting systems and analysis, upgrading homegrown e-reporting systems poses challenges in adopting a new taxonomy without losing connection to the old one, merging entire events for trending and learning purposes.

Therefore, a compatible taxonomy could help solve the problems that currently pose barriers to data integration, system interoperability, and transition from data repositories to intelligent systems [36]. To overcome the barriers and improve the quality of reports, researchers have developed an ontology for e-reporting based on the WHO ICPS and AHRQ Common Formats, which helps user-centered design by providing data entry support as well as feedback upon reporting to ensure data quality [37].

3.1. Evolution of Patient Safety Taxonomies

There is a long-standing need for controlled language for patient safety. The Australian Patient Safety Foundation (APSF) originally reported the Australian Incident Monitoring System in 1987. Later, in 1993 and 2000, respectively, APSF expanded the system twice [38]. As shown in figure 1, a cognitive taxonomy was developed in 2004 to categorize major types of human error contributing to medical errors [31]. Other taxonomies or standards such as JACHO patient safety event taxonomy [29], national coordinating council for medication error reporting and prevention (NCC MERP)'s taxonomy of medication errors [28], neonatal intensive care system (NIC) [39], pediatric patient safety taxonomy (PED) [33], preliminary taxonomy of medical errors in family practice (PTFP)[30], a taxonomy of nursing errors (TNE) [34], adverse event reporting ontology

(AERO) [40], and the ontology of adverse events (OAE) [41] shared insights in several specific domains.

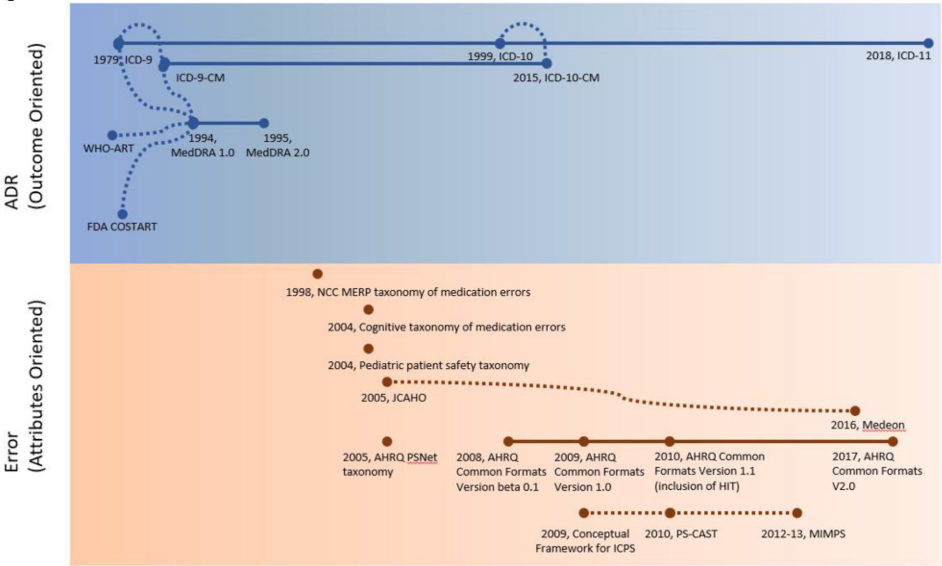

Figure 1. Evolution of taxonomies for patient safety.
Solid lines: updates of the same taxonomy;
Dotted lines: new taxonomies developed based on existing taxonomies.

These vocabularies have been recognized as a necessary element for facilitating communication, health data collection, knowledge representation, and exchange, etc. [42,43]. Nevertheless, research interest in the development of these vocabularies has been primarily focusing on whether sufficient vocabulary terms are employed to cover the intended domain. In recent years, the emerging need for nationwide incident reporting, the adoption of e-reporting systems, large-scale error analysis, and the ever-growing knowledge of patient safety problems call for a highly competent method to represent the vocabulary for patient safety.

3.2. Patient Safety Ontology Supporting Intelligent e-Reporting Systems

Ontologies were explored to enable a number of needed functions of controlled vocabulary for patient safety, including computerized linguistic representation, semantic reasoning, and advanced data analysis, such as biomedical Natural Language Processing (NLP). A publication reported the development of an ontology for medical errors by using refined concepts and semantic relations stemmed from UMLS Metathesaurus and Semantic Network [44]. The other ontological approach is reported to model patient safety incidents knowledge from the ICPS [45–47]. Recent progress has been reported to develop a patient safety ontology to underpin incident reporting regulated by the AHRQ Common Formats [37,48] and incident analysis using NLP [49,50].

In addition to meeting the fundamental information need for patient safety reporting and analysis, ontologies also serve as a cornerstone for developing patient safety intelligent systems. Although the application of intelligent systems in health care is not recent, such an application in patient safety is still at the conceptual stage. The global or national strategies for patient safety improvement require large-scale incident reporting and timely analysis. To meet these requirements, a specialized intelligent e-reporting system is indispensable for providing timely information service and decision support during incident reporting and analysis. A uniformed patient safety ontology is regarded as the key requirement for building such a system for the following reasons [51].

First, ontology is a promising approach to enhancing knowledge requirements for various communication gaps, especially in the patient safety domain. For example, communication in health care requires commonly shared knowledge [52]. Such knowledge consists of different medical terminologies, persons, locations, temporal information, and intricate relations and constraints among entities. Ontologies written by highly expressive languages, e.g., Web Ontology Language (OWL), allow the formal representation of various entities and relations.

Second, the 'ontology language' is computer understandable [53]. This feature largely improves the automation of patient safety knowledge management, particularly tasks involving narrative medical incident data [37].

Third, ontologies hold the potential to inform new knowledge from retrospective data. One approach is to perform semantic reasoning tasks based on predefined entities and relations [54]. Another approach is to perform various machine learning tasks where the ontology can provide rich linguistic features to improve the feature space in machine learning tasks.

In sum, the development of ontologies to support e-reporting would promote the revolution from the data repository of patient safety events to intelligent systems in e-reporting.

4. Medication Events

Medication event is one of the most significant threats to patient safety in hospitals[45], it could cause severe patient harm even death. The Institute for Safe Medication Practices (ISMP) has defined high-alert medications as drugs that have higher risks of causing [56]significant patient harm in the medication events [57]. The ISMP's high-alert medications list contains 19 categories of drugs, which are updated based on the opinions of patient safety experts, the error reports submitted to ISMP, and related literature [57]. Among all categories of drugs, the Institute for Healthcare Improvement (IHI) identified four types of drugs that may cause the greatest harm to patients and have great opportunities for improvement[58]. The four types of drugs include narcotics and opiates, anticoagulants, insulins, and sedatives, which are associated with adverse drug reactions such as hypotension, bleeding, hypoglycemia, delirium, lethargy, and oversedation [56]. Opiates are identified as the most common specific cause of adverse drug event outcomes, which account for 5.6% of all inpatient events [59].

Medication error reporting is an essential way of controlling the occurrence of medication errors and developing strategies for error prevention. The Joint Commission in the USA has been collecting and analyzing error reports from accredited hospitals, and issuing alerts and recommendations based on the results of integrated data analysis [29]. Also, the Food and Drug Administration (FDA) has launched the FDA Adverse Event Reporting System (FAERS) since 1997 to collect medication error reports. Many Patient Safety Organizations (PSO) in the USA and individual healthcare facilities also established their reporting programs to manage medication errors. These error reporting programs hold the potential to improve the quality of patient care and to further understand the nature of medication errors [50,60,61].

4.1. Challenges in Reporting Medication Events

Several factors make the reporting of medication events a challenging task in clinical settings. The medication event has one of the highest rates among all patient safety events [62]. The relationship between medication errors and adverse drug events [63–65] could cost a large amount of time to report all the events. Medication event is an umbrella concept that clinicians may have a different understanding of it. Thus, clinicians may have biases when reporting the medication events. There are several concepts related to medication events, such as medication error, adverse drug event (ADE), adverse drug reaction (ADR), etc. According to the NCC MERP, a medication error is defined as any preventable event that may cause inappropriate medication use or patient harm while the medication is in the control of the healthcare professional, patient, or consumer [66]. It may happen at any stage of the medication distribution process in hospitals, starting from a clinician who prescribes a medication to the end the patient takes the medication. An ADE is an injury caused by the use of any medication. The medication error and ADE have some overlaps. Only a portion of medication errors could result in ADEs, and not all ADEs are caused by medication errors. The ADEs that are not caused by medication errors are called non-preventable ADEs. Non-preventable ADEs do not have any errors until the medications are taken and related harm identified [67], it is usually due to the patient's pathophysiological factors. The near-misses, a subset of medication errors, refer to those identified before they reach the patients. However, the near misses hold similar learning values compared to other medication errors. Among all the medication error reports, those describe the medication errors, including the near misses, are key for healthcare facilities to identify error causes and create processes to reduce the risk of errors [68]. At the current stage, the ADEs and medication errors are usually not differentiated, and all regarded as medication events in many reporting systems.

Moreover, multiple personnel are likely to be involved in medication events, such as physicians, nurses, which could make the events complicated. The various types of medication events also make it challenging to report. Since the patient needs to receive the right drug, in the right dose, at the right time, and in the right way [69], any compromise during the procedure will lead to different types of errors. And for a certain type of error, there may be different causes. For example, if a patient receives a wrong dose of a drug, it may be due to a wrong prescription by a physician, or due to wrong administration by a nurse. Thus, during medication error reporting, the events may need more elaborated narratives to restore the key information in the events.

4.2. Related Taxonomies of Medical Errors

In order to systematically study the medication errors, guide the medication error reporting and promote the safe use of medications, it is important to build a taxonomy for medication error. The NCC MERP has developed a comprehensive medication error taxonomy that aims to record, track, categorize, and analyze medication errors [66]. The effectiveness of medication error reporting and the resulting analysis of the error reports are highly dependent on the amount and the quality of the data collected by medication error reports. Thus, how to design and build the medication error reporting mechanism within healthcare facilities remains a challenging problem. The NCC MERP taxonomy provides healthcare facilities with a framework to collect adequate information for recording medication errors. The taxonomy is in a tree structure and contains 454 items organized in 5 levels, which covers detailed information about the patient involved in the error, the medication involved in the error, the context of the error, the type, cause, and contributing factors of the error, and the patient outcome. And it still has the potential to be expanded. Considering the complexity of medication error and the information needed for its reporting, the taxonomy has great potential to improve the efficiency and efficacy of medication error reporting if it is integrated into the error reporting system. In order to maximize the application of the taxonomy, the reporting system should collect as much information as the taxonomy required (NCC MERP). In most cases, if the error is reported under the framework of the taxonomy, it could avoid using the time to conduct retrospective audits to collect the needed information. The taxonomy also suggests that the information related to the medication error should be collected and reported as soon as possible, the reporting mechanisms within healthcare facilities should set regulations to keep the timeliness of the information.

The NCC MERP Medication Error Index was proposed in 1996 and revised in 2001. Several authors advocate that it is the most adequate method. However, more data from different institutions needs to be collected in a methodologically similar fashion so that comparisons can be made with the data presently available [70][71].

4.3. Medication Events Often Involved with HIT Components

In recent years, the implementations of health information technology (HIT) in healthcare facilities have increased rapidly. It has been proved that HITs, such as EHR, CPOE, and CDSS, are playing important roles in preventing medication errors and improving patient safety [72]. However, the use of HIT to improve patient safety has led to new and unexpected types of errors [73]. According to the statistics from the Joint Commission, the typical medication errors related to HIT were attributed to the human-computer interface, workflow and communication in healthcare settings, and clinical content [74]. The HIT-related errors could happen during every step of the medication-use process, especially during the prescribing, transcribing, and administering stage[73].

And among all HIT components, the computerized physician order entry (CPOE) system, pharmacy system, and the electronic medication administration record (eMAR) are the top contributing factors to medication errors. Other components, including the clinical documentation system and clinical decision support system (CDSS), are also often involved. These HIT components could increase the complexity of medication errors. The users, such as physicians, nurses, and pharmacists, have to frequently interact with the HIT components during the medication distribution process, which may result in errors due to the design flaws of the systems, user errors, communication errors, etc. Accordingly, it will also increase the difficulty of reporting the medication events. The HIT factor has not received enough attention in medication events reporting. For instance, the AHRQ Common Format for medication events only contains one question about HIT, it cannot reflect the role of HIT factor in a medication event.

5. Patient Falls

Patient falls have been listed as one of the top patient safety events in hospitals [75]. Fall events have serious consequences: physical injuries, lowering the quality of life, or even death, which are common causes of psychological stress and extending hospitalization and costs incurred [76]. For example, a fall with injury adds on average 6.3 days to the hospital stay and costs around $14,000 [77]. Different from diseases, which could be effectively controlled per clinical procedures, patient falls are difficult to control due to multiple inputs, including healthcare providers, systems, or even patients [78]. Theoretically, fall events are preventable in hospitals as most fall-related contributing factors are detectable, such as frailty, fatigue, insomnia, and functional degradation due to therapies and medications [79]. However, lacking publicly accessible fall event resources hinders the development of a fall risk detection model toward patient safety improvement. Besides, falls always appear simultaneously with other patient safety event types (e.g., medication) in the same cases, which increases the difficulty of factor identification.

Multiple fall risk assessment tools have been developed to reduce patient falls. The Pennsylvania Patient Safety Authority developed patient safety tools for risk factor measurement and post-fall investigation [80]. Centers for Disease Control and Prevention, The National Institute for Occupational Safety and Health (CDC-NIOSH) developed a tool that listed top risk factors for patient falls, including indoor and outdoor environmental conditions and improper use of equipment [81]. AHRQ WebM&M provides peer-reviewed patient safety cases and expert analysis, which can serve as a resource of patient safety event solutions. AHRQ also developed a toolkit for improving the quality of care, called Preventing Falls in Hospitals [82]. This toolkit focuses on overcoming the challenges associated with developing, implementing, and sustaining a fall prevention program. The validity of fall risk assessment tools was verified in some hospitals[83,84], however, current tools are still far away from an integrated system that could fully support the information flow within the patient fall management circle, i.e., event reporting, retrospective analysis, and prospective analysis, etc. A knowledge base is expected to provide the foundation for knowledge-based interventions if one could be developed and integrated into the routine workflow of patient risk management [85]. In such a knowledge base, the solutions for patient fall should be included, and their logical connections to the specific cases should be well established to support learning and clinical decision making.

In our previous study [66,67], we proposed a hierarchical list of contributing factors for fall event reports based on the contributing factor infrastructure released by AHRQ Common Formats 2.0. Based on the factor list, a rule-based contributing factor identification model was developed through an expert review on one-year narrative PSO fall reports to automatically identify the fall-related contributing factors from PSO reports. We identified solutions for patient falls from multiple authoritative resources, such as the AHRQ WebM&M, Joint Commission Center for Transforming Health Care's Targeted Solutions Tool, Pennsylvania Patient Safety Authority, National Safety Council, and National Patient Safety Agency's Patient Safety Observatory report, and synthesized them by building a connection between the entry-based solutions and the AHRQ Common Format. These solutions were summarized and grouped into two types: general solutions (for all fall event reporters) and specific solutions (customized according to the reporting contents). We also surveyed a PSO institute to evaluate and extend our solution entries. 20 general and 102 specific solution entries were determined through the survey[24]. All solutions were also labeled with our contributing factors of fall events, which finalized the connection between fall reports and solutions. Applying fall events as a trial, a novel patient safety event reporting and learning system was prototyped based on a knowledge-based strategy. In this system, a user can launch a learning session after determining a query that could be either an existing or a new report in any reporting format. According to the analysis of the query and the reporter role (e.g., manager, physician, nurse, and patient), the system can provide customized learning materials, including similar historical reports and recommended solutions. The user preference may vary due to different learning purposes. Therefore, the system allows the user to provide feedback about whether he/she likes or dislikes a certain similar report or solution. All feedback returns to the algorithm implementation step in order to update the weights of similarity matrices and dynamically upgrade the system performance. This mechanism can gradually stabilize the similarity matrices and make them more convincing as the feedback increases.

Lacking management and analysis resources are the main challenges of the establishment of a knowledge-based system. The first step of future study may need to focus on identifying fall data from multiple resources to support the application of advanced information retrieval methods. Moreover, developing a knowledge-based fall reporting and learning system is only the beginning of achieving improved public health. Asking practitioners to change their ways of work to include the skillful uses of knowledge-based fall prevention interventions and asking organization leaders to change the roles, functions, and structures to more fully support the work of practitioners sends ripples throughout the public health system.

6. Application of Informatics in Patient Safety Research

Since the implementation of national reporting systems to better understand patient safety events, many countries across the world have developed a large repository of patient safety events. For example, the National Reporting and Learning System in England and Wales has accumulated over 40,000 safe events [88]. It has been a key challenge to systematically analyze and to learn from the data, which is largely represented in unstructured, free-text formats. Current analysis of patient event reports is inefficient, which often requires manual reviews at a variety of frequencies, ranging from weekly to monthly review workload for clinicians. An automated pipeline was proposed to help clinicians handle the accumulated reports, extract valuable information, and generate timely feedback from the reports [50].

Analyzing patient safety reports helps understand how and why incidents occur, which can inform policy and practice for quality improvement. Unfortunately, our capacity to monitor and respond to incident reports promptly is limited by the sheer volumes of data collected. To prioritize the incidents, one critical task of reporting analysis is to identify the severity level of the patient, which is essential for triggering risk management, identifying preventability of medical incidents, and investigating the causes and preventable actions of the harm.

It is essential to analyze the reports based on reliable and accurate assessments. A number of harm scales developed by national and international organizations are available for such purposes, including but not limited to WHO's five-level harm scale classification [27], NCC MERP's index for identifying levels of harm [66], IHI's 'Global Trigger Tools' [89], and AHRQ's five-category Harm Scale implemented within the Common Formats [90].

In a study using multiclass classification to automate the identification of incident reports via type and severity [91,92], the researchers evaluated the feasibility of regularized logistic regression, linear support vector machine (SVM), and SVM with a radial basis function (RBF) kernel to automate the identification of 10 incident types and 4 severity levels.

In United States, the harm scale from the Common Formats is suggested and widely used in hospitals. Recent studies have reported considerable deviation among clinician's judgment on patient harm when using the Common Formats harm scale, suggesting moderate to poor reliability of the tool[93,94]. Such a negative result may be related to multiple factors: (1) diverse knowledge and training of the clinician who reports incidents and submits harm scores; (2) possible equivocal definitions and descriptions of neighboring levels of harm.

One recent advance to mitigate the problem is to provide a secondary prediction of harm scores by leveraging machine learning classification and the semantic information from the description of events (free text). The best-performed classifier has achieved 0.89 on the F measure [49]. A future direction is suggested to include both human judgment and machine-learning aided prediction in the decision making.

7. Intelligent User-Centered Design Features

7.1. Intelligent Features to Promote Analysis, Aggregate, and Trending of Patient Safety Events

When reporting a patient safety event, reporters often meet the challenges of competing priorities. Clinicians would spend more time being with patients and arrive at a high probability of proper diagnosis and treatment if data entry in reporting systems can be completed efficiently and effectively. Structured data entry is usually combined with free-text that pervades computerized patient safety event reporting systems. As a primary attempt to investigate the effectiveness of text prediction in healthcare, study findings validated the necessity of text prediction to structured data entry and laid the ground for further research improving the effectiveness of text prediction in clinical settings [16,26]. The most important knowledge in the field of patient safety is regarding the prevention and reduction of patient safety events (PSE) during treatment and care.

The similarities and patterns among patient safety events serve as a mainstay in analyzing, aggregating, and trending the events. There is an urgent need to develop an intelligent reporting system that can dynamically measure the similarities of the events and thus promote event analysis and learning effect. The similarity algorithms and scores integrated into an intelligent reporting system resulted in a high consistency with the experts' review than those randomly assigned [87]. The algorithms enable a mechanism to keep updating based on event similarity [87] and promote learning from previous events and offering timely knowledge support to the reporters.

With the knowledge base driven by similarities in the patient safety domain, the intelligent reporting system holds promise in preventing the recurrence and serious consequences of patient safety events. Further, the knowledge base in patient safety holds promise in providing personalized knowledge support based on user inputs. The learning materials (contributory factors, solutions, available toolkits, etc.) can be organized by similarities instead of merely contributing factors. Further perspectives based on the similarity will be added for developing a grouping mechanism, such as role-based, location-based, and response priority. Moreover, the user feedback module will share data with the review priority module in order to dynamically optimize the grouping mechanism to further incorporate user preferences.

7.2. User-Centered Features for Improving Completeness, Accuracy, Timeliness

Narrative data entry pervades computerized health information systems and serves as a key component in collecting patient-related information in electronic health records and patient safety event reporting systems. The quality and efficiency of clinical data entry are critical in arriving at an optimal diagnosis and treatment. In patient safety event reporting, the application of text prediction has been tested effective for enhancing the human performance of data entry in reporting patient safety events [26]. The two functions of text prediction, tested via a two-group randomized design, were proven for increasing efficiency and data quality of text data entry reporting patient safety events [16,26].

While both groups of participants exhibited a good capacity for accomplishing the assigned task of reporting patient falls, the results from the treatment group showed an overall increase of 70.5% in text generation rate, an increase of 34.1% in reporting comprehensiveness score, and a reduction of 14.5% in the non-adherence of the comment fields. The treatment group also showed an increasing text generation rate over time, whereas no such an effect was observed in the control group.

As an attempt to investigate the effectiveness of text prediction functions in reporting patient safety events, the study findings proved an effective strategy for assisting reporters in generating complementary free text when reporting a patient safety event [16].

8. Learning Support

Current patient safety event reporting systems present defects that may influence the efficacy and usability of the systems. One major defect is that the systems usually do not give any feedback to users, they just collect the data about the patient safety events. Other major defects are related to the lack of learning-oriented design in the systems. The Kirkpatrick model has the potential to systematically guide the design and development of reporting and learning systems. The Kirkpatrick model is frequently used for training and performance evaluation in many areas, such as business companies, universities, and government agencies [95]. The model, comprised of four levels, could be applied to evaluate whether a training program meets the expected outcomes of both organizations and the staff[96]. The model enables the participants of the training program not only to learn what they need to know, but also to react favorably to the program. No matter in the business area or the healthcare setting, the training activities have a commonality regarding their core challenge, which is how to reach the expected outcomes through improving the staff's learning effect and applying what they have learned in daily work. Thus, the Kirkpatrick model has great potential to help improve the patient safety event reporting systems [97].

The Joint Commission Center for Transforming Healthcare has developed an online patient safety events management system, the Targeted Solutions Tool (TST), which covers four major patient safety events, i.e. patient falls, surgery, hand hygiene, and hand-off communications in hospitals. The TST tool uses a fact-based, systematic, and data-driven problem-solving approach to facilitate the hospitals to build long-term training programs to reduce patient safety events. To achieve the goal, it first defines the scope of the program and sets up plans for patient safety event management. And it provides the pragmatic reporting tool for an individual event, which could collect detailed information about event data. Compared to other existing event reporting systems, the TST collects data describing the events and integrates the data analysis module in the tool to facilitate the process of understanding why and how the events happened. Moreover, the TST contains a knowledge base that can provide suggestions to healthcare facilities based on the analysis. Overall, the TST sets a good example of how the patient safety event reporting system can guide the healthcare facilities to identify the root causes of patient safety events and provide them with authoritative solutions that are based on specific root causes [98].

It is imperative that collecting patient safety events through reporting systems that should provide intelligent features to support the creation of accurate, complete, and timely reports. The reports are invaluable assets for us to understand, mitigate and reduce the occurrence of patient safety events and improve the safety of care.

Over the years, effects have been made in improving health information systems mainly focusing on electronic health records, yet the potential impact of event reporting systems has not been fully created. More collaborative efforts are needed for patient safety event reporting systems to deliver the expected benefits in terms of offering timely feedback, shared learning, and sustainable reduction of risks and safety events. Healthcare systems and organizations around the world have sought to create databases of patient safety events, which has paved the path toward an intelligent system supported by knowledgebase for extracting and refining actionable knowledge on patient safety events.

In addition to event reporting, the applications of the event triggering tools and machine learning approaches are complementary to e-reporting for enriching the learning experiences and to detect risk signals, prioritize safety concerns, and enhance healthcare quality.

9. E-reporting and Global Roadmap of Patient Safety

Improving and ensuring patient safety has been recognized as a growing challenge for health service delivery globally. Since the very first World Patient Safety Day in 2019, the WHO has been urging healthcare leaders to understand the purpose, strengths, and limitations of patient safety event reporting, which remarks a global campaign to create an awareness of patient safety and to make healthcare safer. The initiatives include the design of event reporting and learning systems on an international classification [99].

It is a long-term and worldwide effort to meet the challenges and opportunities of patient safety event reporting. Recently, a global patient safety action plan has been formulated in consultation with WHO member states, a wide range of partners, and other organizations. The global action prioritizes patient safety as an essential foundational step in designing, developing, operating, and evaluating the performance of all health care systems. The adoption of such a plan represents a remarkable milestone in global efforts to take concerted action on patient safety to reduce the burden of patient harm because of unsafe health care. It is expected that the global collaboration will facilitate the implementation of strategic patient safety interventions at all levels of health systems over the next ten years (2021-2030) [100].

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On Appropriate Evaluation Methodologies in the Context of Using Both Accident and Health Record Data

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Abstract. Accident and emergency informatics has become a new approach to accident research in the era of digitization, where it has become realistic to integrate data recorded at accident sites with data in electronic health records of patients. This chapter deals with the question on whether the existing and well-established evaluation methodologies used in accident-centered research as well as in patient-centered research within clinical medicine are sufficient and should also be used for such integrated data or whether they have to be modified or extended. Based on the Gaus-Muche-Nomenclature on studies in clinical medicine, it will be outlined which types of studies are appropriate here. In addition to observational studies and registers, controlled trials using randomization are also be regarded as an important approach for gaining new knowledge. In order to appropriately access data from health records and from accidents, standards for representing and communicating data for such studies will be of importance. Another criterion is referential integrity. Here and with respect to accidents the International Standard Accident Number (ISAN) may be of importance.

Keywords. accident research, injury research, electronic health records, health information systems, study design, data analysis, accident informatics, emergency informatics, medical informatics

1. Introduction

1.1. On the Relevance of Accident Research

Accident research remains an important topic for health coverage and health care worldwide. E.g. “Road injuries killed 1.4 million people in 2016” and are still among the 10 leading causes of death in the world [1].

Traditional accident research is based on individual accidents having occurred in reality ([2], p. 1). As outlined in [3] evaluation methodologies there focus on “In-Depth-Analyzes of accident statistics and accident analyzes. Special focus is placed on research on the basis of … data collections at the sites of the accidents …, which are characterized by extensive documentations of the sites of the accidents, of the vehicles as well as of the injuries …”.

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1.2. Accident and Emergency Informatics: A New Approach to Accident Research in the Era of Digitization

In the era of digitization, it has become realistic to integrate data recorded at accident sites with data in electronic health records of persons being involved in such accidents [4]-[6]. It is assumed that including both data sources, i.e. accident and health record data, will lead to better support and curation.

Although not in the focus here, it has to be mentioned that such opportunities in the era of digitization can be regarded as part of an even more comprehensive development, transforming and, hopefully, improving health care. In addition to traditional health care settings like hospitals, medical offices and nursing homes, we can now much better include personal living environments like homes or vehicles in health care processes (e.g. [7]-[14]).

Based on these now existing opportunities of using both accident and health record data, a novel discipline was formed, called accident and emergency informatics [15]. This "trans-disciplinary science of systematic collecting and managing medical data (e.g., electronic health records) as well as sensor data from the human environment (e.g., acceleration sensors in the vehicle)" [15] aims at integrating such data of accident sites with health records data of persons being involved in such accidents. Research in this discipline has started. International collaboration has been established at IMIA, the International Medical Informatics Association, where in 2018 a Working Group on Accident and Emergency Informatics was formed [16].

1.3. Question and Objective

In this new situation, where it has become realistic to integrate data recorded at accident sites with data in health records, we have to raise the question on whether the existing and well-established evaluation methodologies used in accident-centered research as well as in patient-centered research within clinical medicine are sufficient and should also be used for such integrated data or whether they have to be modified or extended.

The objective of this chapter is to outline, which types of research questions are asked in this context, which types of study may fit in order to provide answers, and what deserves special consideration in the context of information system architectures and infrastructures in order to be able to combine such data.

1.4. References and Approach

As reference for evaluation methodologies in traditional accident research, the reader is referred to [2] and to the proceedings of the Expert Symposia on Accident Research Conferences (e.g. [3]). As reference for evaluation methodologies in clinical medicine the reader is referred to textbooks in medical statistics / biostatistics, such as [17], [18], and [19].

Please note that, as mentioned in the beginning, traditional accident research is based on recording and analyzing individual accidents, including modeling and simulation of accidents. Empirically analyzing patient data in the context of health care is usually done in empirical studies, where sets of patients are included.

In the following, this will be introduced in some more detail. Section 2, highlighting a specific evaluation approach in clinical medicine, is strongly based on parts of two manuscripts in German language [20] and [21]. In particular, in [21] further details as well as examples for studies can be found. In section 3 proposals will be made on applying and, to some extent, extending evaluation methodologies of clinical medicine. This will be done with respect to considering data from health information systems (based on [22], [23]) and from accidents ([2], [3]), taking into account the visions and activities proposed in accidents [4]-[6] and in [15], [16]. Section 4 will be used for briefly discussing the contents of the previous sections of this chapter, which will close with a call for research on accident and emergency informatics evaluation methodologies in section 5.

2. Evaluation Methodologies in Clinical Medicine

2.1. Introduction

In patient-centered and health-care-oriented 'clinical medicine', the approach to assess health care has developed considerably over the past decades. This has led to specific evaluation methodologies, which can today be assigned to the field of (bio-) medical biometry or (bio-) medical statistics. Evaluation in clinical medicine is focused on humans, especially on patients.

As a medical informatician with close ties to medical statistics, the author would like to use therapy research as an example to describe an important, if not currently, the most important evaluation approach in clinical medicine. This is particularly so because this could and should also play an important role in accident and emergency informatics.

In order to explain this in more detail, this section will report on clinical medicine, on therapy research, and on evaluation methods in therapy research. Their significance for the evaluation in the context of accident and emergency informatics, and there in particular when including accident as well as health record data, will be outlined in the next section.

Let us first of all recall that in clinical medicine, empirical evaluation approaches play an important role due to the complexity of the human being. The reason therefore, which is still valid today, is a quite simple one ([19], p. 5, translated from German): "Every human being is unique ... Therefore, we cannot expect that diagnostic procedures will always provide correct results and that therapies will always work in the same way".

2.2. Controlled Clinical Trials as Gold Standard for Assessing Therapies

In the 20th century, clinical research based on empirical approaches gained further importance. The reason was that because of the mentioned uniqueness of patients, a purely subjective assessment based on the diagnostic or therapeutic outcomes of one patient or of few patients was viewed critically and classified as unscientific. In Germany, such empirical approaches were and still are closely associated with Paul Martini (1932-1959) and his methodology for clinical medicine [24]. It is not without reason that the first article in the journal 'Methods of Information in Medicine', the oldest journal devoted to information in biomedicine and health care [25], was written by Paul Martini and dealt with the "methodology of therapeutic assessment" [26]. In his statement "The basic rule for every therapeutic-clinical trial must involve a comparison of therapeutic approaches" an important finding is summarized: Due to the complexity of the human being, knowledge about how health care can be shaped in the best possible way and, in particular, which therapeutic measures are best suited for patients, can best be gained by a fair comparison of several therapies.

In the second half of the 20th century, therapy research based on such fair comparisons was established by means of controlled clinical trials, which contributed significantly to progress in medicine and in health care as we know it today. The basic prerequisite for fair comparison is so-called structural equality: With the exception of therapies under investigation, all other characteristics of patients that could influence the success of therapies, whether known or unknown, should be distributed as equal as possible in the respective therapy groups [27]. Randomization, the strictly random allocation of patients to therapies, resulted for good reasons in being the best method for this fair comparison. Systematic study design, formal analysis methods (especially statistical hypothesis testing) and computer-based data analysis systems contributed to this progress.

In this context and with a special emphasis on scientific developments in Germany, reference should be made to the textbook on medical statistics by Herbert Immich, published in 1974 [28], to the "memorandum on the planning and conduct of controlled clinical trials" [29], written under the leadership of Hans Joachim Jesdinsky in 1978 [29], and to the book on therapeutic studies published in 1981 under the leadership of Norbert Victor [30].

The essay by Karl Überla on "therapeutic studies: indication, knowledge and challenge", contained in [30], further explains this matter: "The essential component of empirical knowledge acquisition is the repetition of the same events under the same conditions" as well as "In biological comparison, the events do not occur with the same regularity as the rising of the sun. ... Therapeutic studies are the attempt to deal rationally with this variability, which leaves one helpless." ([31], p. 10, translated from German).

In a recently published article on the "development of clinical studies from Paul Martini to the present" Martin Schumacher wrote about this development: "Over the last 40 years randomized clinical trials have become the 'gold standard' in clinical therapy research worldwide and also in Germany." ([32], translated from German).

Ultimately, the aim of these evaluation approaches was to make decisions on a scientific basis in clinical medicine, despite the uniqueness of each individual ([19], p. 5), for the benefit of the patient. Criteria for this scientific basis, including reproducibility, are further discussed in [33], where also additional literature on this topic can also be found there.

2.3. A Nomenclature for Study Types

A scheme for the various study types in clinical medicine based on three criteria, as proposed by Gaus and Muche in [19], is shown in Figure 1. This scheme will be denoted here as the Gaus-Muche-Nomenclature on studies. It describes studies by indices on three axes. Controlled clinical trials are indexed there under diagnostic or therapeutic interventions as intervention studies assessing therapies.

2.4. Ethics and Admission Procedures for Studies in Clinical Medicine

Strict ethical criteria, for which the Declaration of Helsinki [34] forms an important basis, apply to the design, conduct and analysis of such studies, which are experiments on humans, especially in clinical trials.

Before such studies are conducted, ethics committees established for this purpose must approve their study plans. In the case of studies with medications, clinical trials must first have successfully completed phases I (pharmacokinetics, dose-response relationship) and II (tolerability, principal efficacy) before proof of efficacy can be tested in a larger number of patients in phase III controlled clinical trials [19]. Only after approval of phase III, medications will be admitted in Germany and in many other countries. Phase IV studies, after admission, then serve, among others, for drug monitoring.

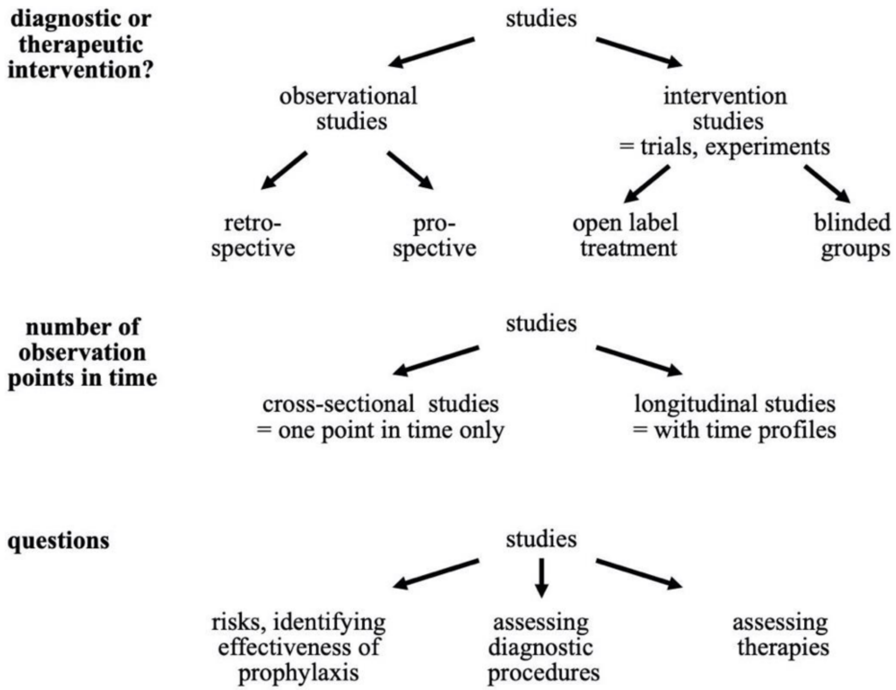

Figure 1. The Gaus-Muche Nomenclature for Studies: Indexing of clinical studies is based on three criteria or axis ([19], p. 38, translated from German). Controlled clinical trials are indexed there at 'diagnostic or therapeutic intervention?' as 'intervention studies' and, at 'questions', as 'assessing therapies'.

Authorities established for this purpose are., e.g., the Federal Institute for Drugs and Medical Devices (BfArM) in Germany and the European Medicines Agency (EMA) in the European Union.

3. Evaluation Methodologies in Accident and Emergency Informatics

3.1. Introduction

Also when discussing appropriate evaluation methodologies in the context of accident and emergency informatics and there in particular when both accident and health record data shall be used, we should first ask, which research questions have to be treated. In addition, in finding answers to such questions by empiric investigations, the use of studies with appropriately planning, conducting and analysis of them, will remain to be a scientific standard. The Gaus-Muche Nomenclature on studies, presented in figure 1, may be of help here.

3.2. Types of Questions and Respective Study Types

Identifying risks in the health of persons as well as preventing risks – i.e. the first index in the question-axis, the third axis of the Gaus-Muche-Nomenclature – is certainly given in accident research. The same holds for assessing therapies, where the term therapy might better be replaced by broader terms, such as activities or procedures.

When patient data are involved, we can assume for the second axis of the Gaus-Muche-Nomenclature that there will usually be several observations in time, in particular when long-term effects of accidents on patients are regarded.

In the first axis, it is suggested to differentiate on whether the intention is to treat questions of prevention or assessment primarily in recording data and in finding correlations. Then observational studies, usually longitudinal ones, are appropriate. Such empirical research may be done in dedicated studies or in registers (see e.g. [27], pp. 71-72).

Being aware that for causal relationships we can hardly find answers through observational studies, the concept of intervention studies, in particular through randomized trials, is also here the most appropriate study type. The reasons are the same as outlined in section 2. The research questions may, however, vary. In accident and emergency informatics questions may, e.g., be on whether a certain treatment of patients after an accident is better than another one, or on whether autonomous vehicles will lead to more risks for humans than vehicles being driven by humans themselves.

3.3. Patient-centered or Accident-centered Studies?

Another question which has to be raised here is on whether such studies should be centered on (a certain group of) accidents or on (a certain group of) humans, respectively patients. As an author coming from medical informatics with, as mentioned, close ties to medical statistics, my first reaction was that also such studies have to center on humans / patients. As accidents are, fortunately, rare events, accident-centered studies may however also be an option.

3.4. On the Use of Data from Health Information Systems for Such Studies

In the context of accident and emergency informatics and in particular when both accident and health record data shall be used, then, of course, using data from health information systems should be considered. An extensive introduction to health information systems, their architectures and their information management strategies can be found in [23]. Here, only some aspects with respect to evaluation methods can briefly be touched.

The most important data sources of health records can be found in hospitals, in medical practices and, maybe, in inpatient or outpatient nursing institutions. In such institutions these data can now often be found in electronic patient records. This eases the access to and the use of such data compared to former times, when records have primarily been paper-based. Data of patients in the mentioned settings are mostly routine data, being primarily recorded and used for patient care. As mentioned in [6] accessing and using these data would most probably improve our understanding of injury events, in particular of long-term effects, and facilitate identification of targets for prevention.

With respect to information system architectures, the efforts in using such data is strongly correlated with the use of standards in representing and communicating such data. If internationally available standards are used (see e.g. [6])), then accessing these data is easier. Existing national infrastructures for patient data are also helpful as well as so-called eHealth strategies, which usually include such standards (e.g. [35], [36]). Finally, referential integrity, here with respect to patients, is of importance (details in [6], p. 145).

Unfortunately, until today, information processing within health care institutions (e.g. in hospitals) is much better implemented than patient-centered information processing beyond single institutions [37], [38], [39]. Insofar, including such data is clearly possible, and much better possible than in the past. However, efforts in accessing and using these data can still be significantly improved.

For using such data in studies we also have to ask for their data quality and how they were recorded. As mentioned, such date is primarily documented for being used in patient care, and so for patient-oriented (casuistic) data analysis (details e.g. in [27], pp. 75-78). When this data will also be used in studies, among others observational equivalence must be given, too. Observational equivalence means that for each patient, data are recorded in a standardized way. Only then multiple usability of such data is possible. Details on this can be found in [27].

3.5. How to Include Data from Accidents?

From the viewpoint of medical statistics, accident data can be treated similar like diagnostic or therapeutic units, e.g. like lab data. Insofar and with respect to evaluation methodologies nothing additional has to be considered here.

The complexity of including data from accidents is mainly at a technical level. Also, here like with clinical data, it is helpful if existing international standards for representing and for analyzing data are used. As combining accident and health record data is still new, standards in both fields – accident research and clinical medicine – will differ, which will produce more workload for jointly analyzing these data.

Like for data from health information systems, another challenge also will be referential integrity of data from accidents, also comprising referential integrity of human beings, involved there. In this context, the International Standard Accident Number (ISAN), proposed in [5], may play an important role in achieving this integrity.

4. Discussion

In the age of digitization, combining accident and health record data should be encouraged as it can be assumed that with both types of data, better knowledge can be gained for prevention of accidents as well as for diagnosis and treatment of patients after accidents.

Section 2 described how empirical research in clinical medicine is done. Evaluation methodologies are based on studies, with controlled trials as ‘gold standard’.

The author strongly recommends that this evaluation approach also be applied to research questions in accident and emergency informatics. Both observational studies / registers as well as intervention studies seem to be appropriate. However, as causal relationships can best be found empirically through fair interventions also here controlled trials, using randomization are regarded as an important approach for gaining new knowledge.

Let me finally recall that, as mentioned in section 1.2, accident and emergency informatics and its evaluation methodologies may also be considered as being part of another and broader context. Health care is a continuous process in the life of humans. In the era of digitization, in addition to specialized settings like hospitals, medical offices and nursing homes, such care can also be done in further settings, may it be at homes or in vehicles, and may it be during work or in leisure times. This development is supported, among others, by the now existing health-enabling technologies. In addition, the mentioned references [7]-[14] in 1.2, further examples can be found in [41]-[43]. As oulined in section 2.4 for clinical studies, also here considering ethical constraints is of considerable relevance [44].

5. A Call for Research on Appropriate Evaluation Methodologies in the Context of Using both Accident and Health Record Data

As we are still at the start of combining such data, as visions of linking event data recorder with electronic health records, as suggested in [4], are still visions, and having in mind that in the era of digitization such combinations are possible and should be investigated for the sake of good patient care, a call for research on appropriate evaluation methodologies is proposed.

The author is convinced that the evaluation methodologies from medical statistics form a good basis for empirical research in accident and emergency informatics. He is particularly convinced that study designs like the ones, mention in figure 1, with respective methodologies on how to collect and how to analyze data, should be used as a starting point.

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