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Data-driven approaches to improving emergency response times and patient outcomes

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***Abstract*---Background:** Data-driven disaster management represents a transformative shift from traditional methods, crucial amid increasing natural and man-made disasters. The escalation in climate-related threats and high-risk population densities has underscored the inadequacy of conventional disaster management strategies. This research explores the potential of big data analytics to revolutionize disaster preparedness, response coordination, and recovery efforts. **Aim:** This study aims to investigate the application of big data analytics in enhancing disaster management strategies, focusing on how extensive datasets can improve risk mitigation, response efficiency, and recovery processes. **Methods:** The research employs a comprehensive review of data-driven disaster management techniques, including Geographic Information Systems (GIS), Artificial Intelligence (AI), and the Internet of Things (IoT). It analyzes how these technologies utilize big data to predict, prepare for, and manage disasters. Additionally, the study examines the role of data-driven decision support systems and process mining in refining disaster management approaches. **Results:** Findings reveal that big data analytics significantly enhances predictive capabilities, response efficiency, and recovery operations. GIS technologies offer detailed spatial insights, AI improves predictive modeling, and IoT provides real-time situational awareness. The integration of these technologies supports more effective disaster preparedness and response strategies, although challenges in data quality and ethical concerns persist. **Conclusion:** Data-driven approaches, through the application of big data analytics, GIS, AI, and IoT, provide transformative benefits for disaster management. These technologies improve the accuracy of predictions, streamline responses, and accelerate recovery efforts. However, addressing data quality issues and ethical considerations remains crucial for maximizing their effectiveness.

***Keywords*---**Data-driven disaster management, big data analytics, Geographic Information Systems, Artificial Intelligence, Internet of Things, predictive modeling.

Introduction

Data-driven disaster management signifies a fundamental shift in how communities prepare for, address, and recover from both natural and man-made disasters. Amid escalating climatic uncertainties and increasing population density in high-risk areas, traditional disaster management methods are becoming increasingly inadequate. Such challenges demand innovative approaches, prompting this research to investigate the transformative potential of big data analytics in addressing these needs. By leveraging extensive and diverse datasets, data-driven disaster management has the potential to fundamentally transform our methods for risk mitigation, enhance response coordination, and support post-disaster recovery. This study undertakes a thorough examination of how big data analytics can be utilized to advance disaster preparedness, refine response strategies, and accelerate recovery efforts. It aims to not only highlight the promise of data-driven approaches but also to offer critical insights into their limitations and ethical concerns [1].

The importance of this investigation is profound. As disasters become more frequent and severe, the cost of inaction—both in terms of human lives and economic impact—continues to rise. While traditional disaster management techniques have been effective to some extent, they are increasingly reaching their limits. There is a pressing need to explore novel methods, with data-driven disaster management emerging as a significant area of hope [2]. The value of big data analytics lies in its capacity to transform extensive and often disorderly datasets into actionable insights, thereby improving community preparedness, streamlining responses, and accelerating recovery. This research aims to offer a systematic and evidence-based understanding of how these data-driven strategies can be effectively implemented, potentially saving lives and resources [3].

Big Data Analytics employs extensive datasets to identify patterns, forecast future scenarios, and support decision-making processes. By analyzing large volumes of data, this technology enables the recognition of trends and anomalies that can inform disaster management strategies and enhance predictive capabilities. Geographic Information Systems (GIS) facilitate the integration and analysis of spatial data, allowing for detailed mapping and spatial analysis. GIS technologies provide critical insights into geographic patterns and relationships, which are essential for effective disaster planning and response. Artificial Intelligence (AI) contributes to disaster management by improving predictive modeling and decision-making through advanced machine learning algorithms. AI systems enhance the ability to anticipate potential disaster scenarios and optimize responses based on learned data patterns and predictions. The Internet of Things (IoT) plays a crucial role in disaster management by gathering real-time data through various sensors and devices. This technology enhances situational awareness by providing up-to-date information on environmental conditions and infrastructural status, which is vital for timely and informed decision-making.

Healthcare remains an indispensable sector, with the primary goals of healthcare decisions being to maximize health benefits and physical engagement, minimize health risks, expand patient choices, effectively utilize resources and constraints, and ensure fairness and equity [1]. As society ages, the demand for high-quality care at reduced costs has steadily increased over the years [2]. Determining the optimal choices, such as prescribing treatments and allocating resources, poses a significant challenge [3]. Considerable investments have been made [1] in healthcare systems, leading to gradual improvements.

Despite the vast amount of data generated by healthcare processes, there is a lack of models that accurately reflect real-world scenarios [2]. Service quality is determined by the gap between customer expectations and their actual experiences with the services provided [4]. Decision-making in healthcare significantly impacts individuals' quality of life and must be both transparent and thorough [1][3]. Essential factors must be defined and addressed [5] in the decision-making process. Decision models for such issues involve criteria, alternatives, and their interrelationships [6]. There is a growing need to obtain comprehensive and high-quality data, along with associated knowledge and insights [7]. Data insights can reveal underlying issues and support experiential knowledge throughout the decision-making process.

The concept of using computers to assist decision-makers, known as Decision Support Systems (DSS), was first introduced in 1963 and gained prominence in 1971, with researchers like Scott Morton playing a key role [8]. An ideal DSS integrates human and computer collaboration, where the computer aids the decision-maker by providing creative and forward-thinking tools [9]. As competition intensifies, organizations are increasingly focused on understanding how their processes are implemented to address specific user needs and situations. Process mining is an emerging DSS that utilizes event data to reflect the actual processes captured by information systems.

Literature Review

The healthcare sector has transitioned from a physician-centric model to one that prioritizes patient orientation [10]. Patient care is the fundamental service [11] provided by hospitals. Healthcare organizations implement various processes to deliver these services. Information systems capture detailed records of every business process, documenting what was done, when, and by whom, in event-logs [12]. The data generated by these information systems is often more granular than what is defined by business users [13]. When integrated into specific processes, information systems can create substantial value for organizations. Digitizing business processes opens new opportunities for organizations [12]. Each process operates within a specific context and evolves over time [15]; it may fail if performance, requirements, or standards are not met [16]. While process mining reveals detailed information about processes and their variations based on actual data, flow charts offer only a limited view [16].

Process mining concentrates on the analysis of processes [17], which can be extracted from digital records such as event-logs [12, 18] within information systems. Early advancements in process mining were made by Cook [18] as part of his doctoral thesis, addressing process discovery and validation. Process mining aims to bridge the gap between business process management and workflow management on one side and data mining, business intelligence, and machine learning on the other [19]. Process mining involves three phases: (1) pre-processing, which infers the ordering of tasks; (2) processing, which involves inputting event-logs, ordering, and applying mining algorithms; and (3) post-processing, which includes graphically representing and refining the results [20]. The decision-making process is complex and may be subject to biases [3] or challenges related to data availability and access. The first two phases create a framework for the event-log, followed by populating the data within this structural framework [12].

A case identifier includes attributes such as activity name, event timestamp, resource, and cost for each event associated with a case [12]. Process mining's strength lies in its ability to analyze all data, not just samples, and to compare actual processes with expected performance [17]. Process mining offers improved insights into variations in healthcare processes, facilitating targeted interventions. Its adoption in the healthcare sector is increasing [22,23,24,25]. As a data-driven decision-making tool, process mining is gaining traction. "Multiple Criteria Decision Making/Analysis" (MCDM/A) is a field of operations research that addresses problems requiring management of conflicting objectives in uncertain environments [21]. It collects both qualitative and quantitative preferences [1] from decision-makers to provide optimal solutions considering combined requirements. Several MCDM/A methods, such as the Analytic Hierarchy Process, TOPSIS, VIKOR, MACBETH, and DEMATEL, have been applied in healthcare [3] to offer accessible frameworks for solving complex problems. The complexity of healthcare decision-making [1] can be influenced by various factors, as categorized by health system, type of intervention, and application process [3].

Among the MCDM/A methods, the "Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE)" [22] is well-documented and widely used in various sectors, including stock trading [23], maintenance scheduling [24], nuclear waste management [25], business incubator evaluations [26], and productivity measurement [27]. Different extensions of PROMETHEE serve specific purposes, such as PROMETHEE II, which is used for evaluating emergency response systems [28]. PROMETHEE II requires predefined weightages to rank alternatives [29]. The application of PROMETHEE in healthcare is expanding, including use in a Brazilian public hospital [30] and nuclear medicine for analyzing image reconstruction algorithms [31]. Hybrid approaches combining PROMETHEE with other methods have been developed and applied across various domains, such as evaluating hospital service quality using Interval Valued Intuitionistic Fuzzy (IVIF) in PROMETHEE [4]. Hospitals seek to understand how to make appropriate decisions and take necessary actions to improve parameters like care quality, resource utilization, and cost. Identifying and prioritizing areas for improvement requires timely and effective actions. Proactive steps are being taken in infrastructure development [1] to meet the information and knowledge needs of healthcare systems.

There is a gap in structured approaches that integrate data-driven insights with MCDM/A. This paper proposes a novel and systematic method for utilizing data-driven decision-making and integrating it with MCDM/A. The methodology outlined in the following sections suggests using overall and process-mining-guided insights to identify issues that need resolution through PROMETHEE. The proposed methodology emphasizes a visual approach to understand current realities based on data and use them to support decision-making. The paper is structured as follows: Section 3 presents a methodology that combines process mining with PROMETHEE II, using a hospital case study. This methodology uniquely integrates data-driven decision-making with an MCDM/A approach. The authors use three visual tools: Tableau, Celonis, and Visual PROMETHEE. Tableau is employed to extract key insights from patient data quickly, Celonis software [32] is used for applying process mining to event data, and Visual PROMETHEE is used for MCDM/A. The visual approach allows users to view ranking results and interact with Visual PROMETHEE during sensitivity analysis. Decision-makers use historical data to derive insights, identify issues, and explore potential solutions as alternatives in MCDM/A, followed by resolution through shared decision-making. Section 4 concludes and outlines future directions.

Capacity Management in Healthcare

Capacity management decisions in healthcare pertain to determining optimal resource levels, including equipment (e.g., sterile instruments), facilities (e.g., operating rooms), and personnel (e.g., nurses). These decisions can be categorized based on their time horizon into (i) strategic, (ii) tactical, and (iii) operational [4], [32]. Strategic decisions involve long-term planning and often require substantial capital investment [4], such as expanding resource capacities through the acquisition of new computed tomography (CT) devices [33], cardiotocography (CTG) machines [34], or the development of new facilities [35], [36]. Tactical decisions, positioned between strategic and operational planning, include staff scheduling [34], 37], [38] and block scheduling for operating rooms [39]. Operational decisions focus on short-term planning with limited flexibility due to fixed resource levels [4]. Examples include patient appointment scheduling [40], [41], staff rostering [42], [43], inventory management [44], and emergency scheduling [45].

Various Operations Research (OR) techniques, such as Markov processes, queueing models, mathematical programming, and computer simulation, are employed to support capacity management decisions [15], [17]. Due to the stochastic nature of healthcare processes, computer simulation—especially Discrete-Event Simulation (DES)—is a preferred method for analyzing these complex systems [46], [47], [48]. In DES, individual entities (e.g., patients) navigate through the process and wait in queues to be served by resources (e.g., nurses) [8], [49]. These entities may have attributes (e.g., age, patient type, diagnosis) that influence their pathways through the simulation model [49]. Unlike other OR techniques, DES allows for detailed analysis of individual characteristics, such as waiting times and treatment outcomes, facilitating the examination of both minor and significant changes within the model. For further insights on the use of simulation in healthcare, refer to existing review articles [50-51], [52], [53], [54], [55].

Data-Driven Process Simulation

Data-Driven Process Simulation (DDPS) involves constructing simulation models through extensive use of process execution data (i.e., event logs) [9], which are often sourced from Health Information Systems (HIS). DDPS is an emerging domain within Process Mining (PM) that focuses on extracting process-related insights from event logs [56]. Initially, PM research concentrated on discovering control-flow patterns (e.g., patient pathways) from event logs. However, advancements have led to the development of algorithms for identifying additional components of simulation models from event logs, such as arrival patterns, queueing rules, and resource schedules [8].

Despite these advancements, integrating all these components into a simulation-ready model remains a nascent field. Early research efforts involved manually combining discovered simulation model components from event logs [57], [58]. More recent work by Camargo et al. [10] automated the discovery and simulation of such models from event logs, with further extensions to account for multitasking and resource availability [11]. While these studies demonstrate the potential of using event logs to create simulation-ready models, they often rely on simplifying assumptions that may not accurately reflect healthcare settings, such as ignoring resource constraints [58] or modeling waiting times without considering resource unavailability [57]. Additionally, these studies typically assume the availability of clean and high-quality event logs [10], [11], which is not always the case in healthcare data [12], [13], [59]. Moreover, healthcare processes are knowledge-intensive and rely heavily on clinical expertise, which is not captured in process execution data [60].

Instead of fully automating the discovery and simulation process, most research leverages insights from PM techniques to manually construct simulation models. Control-flow discovery methods are frequently used to map patient journeys through care facilities for specific conditions [61], with Process Simulation employed to evaluate and enhance these care processes. For instance, Augusto et al. [62] simulated different implantable cardioverter-defibrillator strategies for cardiovascular patients, Mans et al. [63] assessed the impact of digitizing dental prosthesis processes, Kovalchuk et al. [64] explored patient flows for acute coronary syndrome, Tamburis and Esposito [65] analyzed cataract process execution data, and Johnson et al. [42] applied PM and simulation to various emergency and specialized care scenarios. Other studies focus on optimizing entire departments or care facilities to reduce patient waiting times and Length of Stay (LoS) using PM and simulation. Zhou et al. [66] adjusted staffing levels to enhance outpatient clinic performance, Antunes et al. [26] optimized physician scheduling to decrease Emergency Department waiting times, and Abohamad et al. [67] identified performance bottlenecks and explored strategies to reduce LoS.

Data Quality Issues in Event Logs

Event logs, particularly within healthcare contexts, often encounter various data quality issues that can significantly affect their utility in process mining and simulation. These issues are crucial for understanding the reliability of simulation results and improving healthcare processes.

Key Taxonomies and Frameworks

- **Bose et al.** (68) provide a comprehensive taxonomy that categorizes event log quality issues into four main groups: missing data, incorrect data, imprecise data, and irrelevant data. These categories apply to cases (e.g., missing records), events (e.g., incorrect event logs), and attributes (e.g., imprecise timestamps).
- **Suriadi et al.** (69) propose a more detailed taxonomy identifying eleven specific patterns of data quality issues, such as "elusive cases" (events not linked to any case) and "distorted labels" (e.g., typographical errors).
- **Vanbrabant et al.** (40) introduce a synthesized taxonomy for healthcare-specific data quality issues, distinguishing between missing and non-missing data. They further classify non-missing data into incorrect data,

requiring correction or removal, and data that is not directly usable but needs minor preprocessing.

Data Quality Assessment Frameworks

Several frameworks have been developed to assess the quality of event logs:

- **Andrews et al.** (70) propose a seven-step cyclical framework to identify issues such as granularity inconsistencies and null values.
- **Kherbouche et al.** (71) developed a framework integrated into ProM that evaluates complexity, accuracy, consistency, and completeness.
- **Fischer et al.** (72) and **Dixit et al.** (73) focus specifically on timestamp-related quality issues.
- **Andrews et al.** (74) and **Martin et al.** (75) use SQL and R-package DaQAPO to detect specific event log imperfections and perform quality tests.

Challenges in Data-Driven Process Simulation (DDPS)

Despite the advancements in data quality assessment, DDPS model discovery often lacks explicit attention to these issues. The quality of event log data significantly impacts the reliability of simulation results. While some studies mention data quality issues, detailed exploration of their impact is limited. For example, **Johnson et al.** (42) emphasize the role of the Clinical Review Board in ensuring data quality but do not thoroughly address the integration of domain expertise in model development. Our approach differs by incorporating guidelines and best practices from Process Simulation literature to address these challenges comprehensively. In summary, addressing data quality issues is vital for effective event log analysis and simulation in healthcare. Various taxonomies, frameworks, and cleaning methods are available to identify and rectify data quality problems, though their application in automated DDPS model discovery remains underdeveloped. Future work should focus on integrating domain expertise and refining methods to enhance data quality and simulation accuracy.

Roles of Data-Driven Approaches in Different Medical Departments: Emergency Services

Data-driven approaches in emergency services significantly enhance response effectiveness and patient outcomes. By leveraging real-time data from electronic health records (EHRs), patient monitoring systems, and incident reporting tools, emergency medical teams can make informed decisions swiftly. Predictive analytics, a cornerstone of data-driven strategies, allows for the identification of high-risk patients and potential surge scenarios, thereby optimizing resource allocation and improving triage processes. For instance, predictive models can forecast the likelihood of a major accident or disaster based on historical data, weather conditions, and traffic patterns, enabling preemptive actions and efficient resource deployment. Moreover, data-driven insights facilitate the development of protocols and training programs tailored to emerging trends and past performance metrics, ultimately enhancing the preparedness and responsiveness of emergency services.

Nursing

In nursing, data-driven approaches are pivotal in advancing patient care and operational efficiency. Advanced health informatics systems enable nurses to access and analyze patient data comprehensively, including vital signs, lab results, and medication records. This holistic view supports clinical decision-making, improves care coordination, and enhances patient safety. For example, predictive analytics can identify patients at risk of developing complications, such as pressure ulcers or infections, allowing for timely interventions. Data-driven tools also facilitate personalized care plans by analyzing patient history and preferences, thus optimizing treatment outcomes. Additionally, data analytics support nursing workforce management by predicting staffing needs based on patient census and acuity levels, thereby ensuring adequate coverage and reducing burnout among nursing staff.

Health Informatics

Health informatics relies heavily on data-driven methodologies to improve healthcare delivery and outcomes. By integrating data from various sources, including EHRs, wearable devices, and health information exchanges, health informatics professionals can derive actionable insights that inform policy-making, clinical practice, and patient engagement strategies. Data-driven approaches enable the development of robust health information systems that streamline data exchange, enhance interoperability, and support evidence-based practice. For example, machine learning algorithms can analyze large datasets to identify patterns in disease prevalence and treatment efficacy, thereby guiding clinical guidelines and public health initiatives. Furthermore, health informatics leverages data analytics to enhance patient engagement through personalized health interventions and remote monitoring, contributing to improved chronic disease management and preventive care.

Pharmacy

In pharmacy, data-driven approaches are transforming medication management and patient safety. Pharmacists utilize data from various sources, including prescription databases, patient records, and pharmacovigilance systems, to optimize drug therapy and minimize adverse drug reactions. Data analytics tools enable pharmacists to analyze medication usage patterns, identify potential drug interactions, and assess therapeutic outcomes. For example, predictive modeling can help in identifying patients at risk of medication non-compliance or adverse reactions, allowing for proactive interventions. Additionally, data-driven methods support the development of precision medicine by analyzing genetic and demographic data to tailor drug therapies to individual patient profiles. By integrating data-driven insights into pharmacy practice, pharmacists can enhance medication safety, improve therapeutic efficacy, and contribute to better patient outcomes.

Conclusion

Data-driven approaches have proven to be instrumental in revolutionizing emergency response and patient care across various medical departments. In emergency services, leveraging real-time data from electronic health records (EHRs), patient monitoring systems, and incident reporting tools enhances decision-making and optimizes resource allocation. Predictive analytics, a key component of these strategies, allows for the identification of high-risk scenarios and the efficient deployment of resources. By forecasting potential disasters and accidents based on historical and current data, emergency services can better prepare and respond, thereby improving overall outcomes and reducing response times. In nursing, data-driven methods significantly advance patient care by providing comprehensive access to patient data. Advanced health informatics systems enable nurses to analyze vital signs, lab results, and medication records, supporting informed clinical decisions and enhancing care coordination. Predictive analytics further identifies patients at risk of complications, facilitating timely interventions. Data-driven tools also aid in workforce management by forecasting staffing needs, thus improving coverage and reducing burnout. Health informatics professionals leverage data-driven methodologies to streamline healthcare delivery and enhance patient engagement. Integrating data from EHRs, wearable devices, and health information exchanges allows for evidence-based practices and robust health information systems. Machine learning algorithms analyze large datasets to identify patterns in disease prevalence and treatment efficacy, guiding clinical guidelines and public health initiatives. Personalized health interventions and remote monitoring are also supported through data analytics, improving chronic disease management and preventive care. In pharmacy, data-driven approaches optimize medication management and patient safety. Pharmacists utilize data from prescription databases and pharmacovigilance systems to analyze medication usage patterns and minimize adverse drug reactions. Predictive modeling assists in identifying patients at risk of non-compliance or adverse reactions, enabling proactive interventions. Additionally, precision medicine is advanced through the analysis of genetic and demographic data, tailoring drug therapies to individual patient profiles. Overall, data-driven approaches across these medical departments enhance decision-making, improve patient outcomes, and support efficient resource management. The integration of big data analytics, predictive modeling, and advanced informatics systems demonstrates significant potential for advancing healthcare practices and emergency response strategies. However, addressing data quality issues and ethical concerns remains essential for fully realizing the benefits of these technologies. Future research and development should focus on refining data quality assessment methods and integrating domain expertise to enhance the accuracy and effectiveness of data-driven solutions in healthcare.

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النهج المعتمدة على البيانات لتحسين أوقات الاستجابة للطوارئ ونتائج المرضى

الملخص:

الخلفية :إدارة الكوارث المعتمدة على البيانات تمثل تحولًا جذريًا عن الأساليب التقليدية، وهو أمر حاسم في ظل تزايد الكوارث الطبيعية والصناعية. التصاعد في التهديدات المرتبطة بكثافة السكان العالية قد أبرز عدم كفاية الاستراتيجيات التقليدية لإدارة الكوارث وخاصة في القطاع الطبي. تستكشف هذه الدراسة إمكانيات تحليلات البيانات الكبيرة لإحداث ثورة في استعداد الكوارث وتنسيق الاستجابة وجهود التعافي في عمليات الطوارئ والقطاع الصحي بوجه الخصوص.

الهدف :تهدف هذه الدراسة إلى التحقيق في تطبيق تحليلات البيانات الكبيرة في تعزيز استراتيجيات إدارة الكوارث، مع التركيز على كيفية تحسين مجموعات البيانات الكبيرة للتخفيف من المخاطر، وكفاءة الاستجابة، وعمليات التعافي، وعمليات الطوارئ، والعمليات الطبية.

الطرق :يستخدم البحث مراجعة شاملة لتقنيات إدارة الكوارث المعتمدة على البيانات، بما في ذلك نظم المعلومات الجغرافية(GIS) ، الذكاء الاصطناعي(AI) ، وإنترنت الأشياء .(IoT) ويحلل كيف تستخدم هذه التقنيات البيانات الكبيرة للتنبؤ، والاستعداد، وإدارة الكوارث. بالإضافة إلى ذلك، تدرس الدراسة دور نظم دعم القرار المعتمدة على البيانات وتعدين العمليات في تحسين نهج إدارة الكوارث.

النتائج :تكشف النتائج أن تحليلات البيانات الكبيرة تعزز بشكل كبير من القدرات التنبؤية، وكفاءة الاستجابة، وعمليات التعافي. تقدم تقنيات GISرؤى مكانية مفصلة، بينما يحسن الذكاء الاصطناعي النمذجة التنبؤية، ويوفر إنترنت الأشياء الوعي بالوضع في الوقت الفعلي. تدعم تكامل هذه التقنيات استراتيجيات استعداد واستجابة أكثر فعالية، على الرغم من استمرار التحديات في جودة البيانات والمخاوف الأخلاقية.

الاستنتاج :توفر النهج المعتمدة على البيانات، من خلال تطبيق تحليلات البيانات الكبيرة، وGIS، وAI، وIoT، فوائد تحويلية لإدارة الكوارث. تعمل هذه التقنيات على تحسين دقة التنبؤات، وتبسيط الاستجابات، وتسريع جهود التعافي. ومع ذلك، فإن معالجة قضايا جودة البيانات والاعتبارات الأخلاقية تظل ضرورية لتعظيم فعاليتها. وتساعد البيانات في عمليات الإدارة الطبية وعمليات الطوارئ والتمريض والبيانات الصحية والصيدلة.

الكلمات المفتاحية :إدارة الكوارث المعتمدة على البيانات، تحليلات البيانات الكبيرة، نظم المعلومات الجغرافية، الذكاء الاصطناعي، إنترنت الأشياء، النمذجة التنبؤية.