Instituto Superior de Gestão e Administração de Santarém

Mestrado em Gestão de Empresas

Dissertação

Edge Intelligence in Healthcare - Systematic Literature Review

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Abstract

This dissertation explores the integration of Edge Intelligence (EI) in healthcare through a comprehensive two-part analysis. Chapter I conducts a Systematic Literature Review to examine how EI—by combining artificial intelligence with edge computing—enhances healthcare delivery. The review, based on PRISMA guidelines, evaluates 24 high-quality articles, identifying how EI reduces latency, supports real-time decision-making, and strengthens data privacy. It also highlights technical limitations such as device resource constraints, lack of standardization, and security risks. The chapter culminates in a conceptual model that illustrates how EI, IoMT (Internet of Medical Things), and supporting technologies interact to create more efficient and personalized healthcare systems. Chapter II expands the scope by specifically focusing on the integration of EI and IoMT for real-time healthcare analytics. Using another systematic review, this chapter analyzes 32 peer-reviewed studies to assess how IoMT devices—such as sensors and wearables—work with edge computing to enable continuous patient monitoring and early intervention. It examines key enablers like Federated Learning and blockchain, which address privacy and data sharing challenges. The analysis also underscores the importance of interoperability, communication protocols, and data synchronization in heterogeneous healthcare systems. Together, the chapters offer a holistic view of EI's potential and practical impact on smart healthcare. The dissertation concludes by recommending future research into lightweight AI models, ethical governance, and secure, interoperable architectures to fully leverage EI in healthcare innovation.
Keywords: *Edge Intelligence, Edge Computing; Healthcare Systems Integration, Internet of Medical Things; Real-time Analytics; Systematic Literature Review.*

Resumo

Esta dissertação explora a integração da *Edge Intelligence* (EI) nos cuidados de saúde através de uma análise abrangente em duas partes. O Capítulo I efetua uma revisão sistemática da literatura para analisar a forma como a EI - ao combinar a inteligência artificial com a computação de ponta - melhora a prestação de cuidados de saúde. A revisão, baseada nas diretrizes PRISMA, avalia 24 artigos de elevada qualidade, identificando a forma como a EI reduz a latência, apoia a tomada de decisões em tempo real e reforça a privacidade dos dados. Destaca também as limitações técnicas, como as restrições de recursos dos dispositivos, a falta de normalização e os riscos de segurança. O capítulo I culmina com um modelo concetual que ilustra a forma como a EI, a IoMT (Internet das Coisas Médicas) e as tecnologias de apoio interagem para criar sistemas de cuidados de saúde mais eficientes e personalizados. O Capítulo II alarga o âmbito, centrando-se especificamente na integração da EI e da IoMT para a análise dos cuidados de saúde em tempo real. Recorrendo a outra revisão sistemática, este capítulo analisa 32 estudos revistos por pares para avaliar a forma como os dispositivos IoMT - tais como sensores e *wearables* - trabalham com a computação periférica para permitir a monitorização contínua dos doentes e a intervenção precoce. Examina os principais facilitadores, como a aprendizagem federada e a cadeia de blocos, que abordam os desafios da privacidade e da partilha de dados. A análise também sublinha a importância da interoperabilidade, dos protocolos de comunicação e da sincronização de dados em sistemas de saúde heterogéneos. Em conjunto, os capítulos oferecem uma visão holística do potencial e do impacto prático da IE nos cuidados de saúde inteligentes. A dissertação conclui recomendando investigação futura sobre modelos de IA leves, governação ética e arquiteturas seguras e interoperáveis para tirar o máximo partido da EI na inovação dos cuidados de saúde.
Palavras-chave*: Edge Intelligence, Edge Computing; Integração de Sistemas de Saúde, Internet of Medical Things; Análise em tempo real; Revisão Sistemática da Literatura.*

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INTRODUTION

Contextualization

External factors such as globalization and technological advances create a need to manage uncertainties that force organizations, such as the health sector, to take a proactive role in management and innovation in order to respond to external demands and meet daily objectives and future prospects (Sanches et al., 2021).

Digital innovation brings edge intelligence to the technology market, integrating artificial intelligence and edge computing to deliver continuous improvements in healthcare resource management (Badidi, 2023).

The integration of IoMT (Internet of Medical Things) devices, such as sensors and applications, has significantly altered the approach to and delivery of services. This is due to the potential for increasing the efficiency-effectiveness ratio in decision-making and enhancing the quality of life by focusing on the individual (Amin & Hossain, 2021).

With the constant demand to achieve results in the shortest possible time, using innovative intelligence services can be the answer to meeting the challenges. For this reason, edge computing technology contributes to reducing latent energy consumption, since data is decentralized. With the advent of automated intelligence systems, artificial intelligence enables early detection and action to be taken in the event of a health hazard (Islam et al., 2024).

In the area of smart intelligence in healthcare, due to the costs and limitations of mobile cloud architectures, the adoption of mobile edge computing architectures using edge machine learning is emerging. This allows systems to be more reliable than cloud-based models, thus eliminating the problem of coverage area and reducing latency compared to the traditional model (Douch et al., 2022).

Organizations, such as those in the health sector, are not indifferent to this new paradigm and are betting on digital innovation as a lever for managing resources and providing care.

Researches Questions

As healthcare systems increasingly adopt digital innovation, technologies such as Edge Intelligence (EI) and the Internet of Medical Things (IoMT) have emerged as transformative tools for enhancing service delivery, efficiency, and patient care. However, the integration of these technologies presents both opportunities and significant challenges. To better understand the implications and potential of EI in healthcare, this study addresses the following key research questions:

(1) What are the key benefits, challenges, and limitations of implementing Edge Intelligence in smart healthcare systems?

(2) How does the integration of EI and IoMT enhance real-time healthcare analytics and decision-making?

General and specific goals

This study conducts a systematic literature review to examine the role, benefits, challenges, and prospects of EI within the healthcare sector. It focuses explicitly on EI's integration with innovative technologies, such as the IoMT and real-time analytics.

<u>General goals</u>

(1) Describe the opportunities and challenges of digital innovation in healthcare management;

(2) Understand how EI works in smart intelligence healthcare services;

(3) Understand the impact of implementing edge intelligence in smart intelligence healthcare services;

(4) Describe the opportunities and future research into EI.

<u>Specific goals</u>

(1) To understand how Edge Intelligence operates in innovative healthcare systems, including its architecture, components, and key enablers like AI, federated learning, and edge computing;

(2) To evaluate the practical impact of Edge Intelligence on real-time healthcare analytics, including improvements in latency, decision-making, data privacy, and system responsiveness;

(3) To explore the integration of Edge Intelligence with IoMT devices and services, and assess how this synergy enhances patient monitoring and personalized care;

(4) To identify current limitations and propose future research directions for advancing Edge Intelligence in clinical and operational healthcare environments.

This master's thesis consists of two chapters. It also includes a brief introduction, in which a brief contextualization, research questions and objectives are presented, a conclusion, in which the main findings, conclusions and suggestions for future research are reported, and an appendix presenting an article carried out in collaboration with other researchers.

CHAPTER I

Edge Intelligence in Healthcare: A Systematic Literature Review

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Abstract. Healthcare has gained a new traction to personalized care with the introduction of technological monitoring devices. These systems enable non-invasive recording of physiological parameters such as blood pressure, glucose levels, sleep patterns, heart rate, and water levels. Furthermore, with the innovation of biomaterials, it is possible now to measure bioelectric signals with high precision and accuracy, which, through machine learning algorithms, allows irregular patterns to be identified. However, this type of technology lacks data/information storage infrastructures, whose architecture has shortcomings such as response time and privacy. Hence, new paradigm has emerged based on peripheral computing technology and on-device artificial intelligence-edge Intelligence (EI) to resolve some of these issues. This type of architecture improves the efficiency-effectiveness ratio in healthcare provision. Through ultra-thin, skin-compatible, flexible, and high-precision devices and sensors, low-cost communication technology, on-device intelligence, edge intelligence, and edge computing technology enable a personalized application of services. To deepen the discussion, this article followed a Systematic Literature Review using the PRISMA protocol (Preferred Reporting Items for Systematic Review and Meta-Analysis Protocol). The Scopus database was selected to explain the concept and assess the benefits and challenges of EI in healthcare today. As a result, this article presents a conceptual theoretical model for EI in the health sector and discusses the most important topics such as its capabilities and limitations.

Keywords: Edge Intelligence, Edge Computing, Healthcare, IoT, IoMT, Systematic Literature Review.

I.1. Introduction

The growing demand for applications with high data storage capacity and the rapid proliferation of Internet of Things (IoT) devices has driven the emergence of decentralized data analysis and processing (Hafeez et al., 2021; Islam et al., 2024).

Edge Intelligence (EI) has arisen as a promising solution, since it brings the advantages of computational training to user-friendly tools, which enables secure and efficient real-time decision-making (Mondal et al., 2023; Rocha et al., 2024). Other concepts followed, such as the Internet of Medical Things (IoMT) that enables remote patient monitoring, artificial intelligence-assisted, diagnosis and predictive symptom analysis (Hayyolalam et al., 2021; Shumba et al., 2023).

However, such devices demand low latency and high bandwidth, as data communication, processing, and analysis supposedly need to be operating in real time (Hafeez et al., 2021). To solve this issue, EI has emerged as a technical solution, as it allows data processing to take place on edge. Hence, EI has better capabilities when compared with the cloud, since it significantly reduces latency and guarantees operation of applications to work efficiently. This is a pattern shift from centralized cloud computing to a distributed architecture (Mondal et al., 2023).

However, some challenges are to be considered again, such as the need for edge computing (EC) to provide the necessary infrastructure for EI. Also, wireless communications, 6G, promises unprecedented speed and reliability, helping to boost EI capacity (Aiosa et al., 2021; Bhat & Alqahtani, 2021). Moreover, model compression allows complex machine learning (ML) models to be implemented on IoT devices with limited resources (Joshi et al., 2023). On the other side, federated learning (FL) enables training models collaboratively on EI devices without compromising data privacy (Manocha et al., 2024).

Overall, this article aims to explain the concept and assess the benefits and challenges of EI in healthcare today, responding to the question "What are the main challenges and limitations of implementing EI, given the resource constraints of the IoT devices?" This article is divided into several sections: the fundamental concepts of this topic; the methodology, which consists of a Systematic Literature Review; the results and their discussion, which will answer the research questions; and the conclusions with suggestions for future research.

I.2. Fundamental Concepts

I.2.1. Edge Intelligence and Edge Computing

EI and EC are two interconnected concepts that transform how data is processed and used. In other words, they are complementary technologies that contribute to creating more efficient systems (Douch et al., 2022). EI refers to integrating AI capabilities into environments at the edge, while EC is the underlying foundation that facilitates data processing close to the source (Islam et al., 2024).

EI consists of the convergence of AI and edge computing. A major focus is the study of optimization methods that allow AI models to be executed efficiently at the edge, with the aim of analyzing the various methods that contribute to the adaptation and application of AI in the other direction (Liu et al., 2020).

One of the main advantages of EI is the ability to process data in real time close to the data source. This reduces latency and allows systems to respond quickly to changing environmental conditions. This is particularly important in areas such as healthcare, where immediate decision-making is relevant (Xu et al., 2022).

The International Electrotechnical Commission (IEC) defines EI as acquiring, storing, and processing data using EC with deep learning (DL) and advanced net-working. In general terms, EI has six categories (Table 1) based on where the DL training and inference take place, e.g., cloud server, edge server, and end devices (Joshi et al., 2023).

Table 1 *The six levels of EI (Joshi et al., 2023)*

Level 0	DL training and inference are performed on the cloud server. This level is the most traditional form of DL processing.
Level 1	Training is carried out on the cloud server, and the trained DL model is implemented on end devices for inference. This level is suitable for applications where the data is generated on the end devices and inference needs to be done locally, e.g., virtual smartphone assistants.
Level 2	Training is carried out on the cloud server, but inference is carried out collaboratively between the servers and the end devices. This level is a hybrid between levels 1 and 3.

Level 3	Training is carried out in the cloud, and the trained DL model is implemented on the edge servers for inference. This level is suitable for applications that require low latency and high bandwidth, e.g., autonomous cars.
Level 4	The cloud and edge servers collaborate on training, and the trained DL model is implemented on the edge servers for inference. This level is a hybrid between levels 3 and 5.
Level 5	The edge servers exclusively carry out DL training and inference (implementation). This level is called "everything at the edge."

I.2.2 Federated Learning (FL)

A new approach, known as federated learning, enables the high-quality training of AI models by transforming edge and fog intelligence architectures while ensuring data protection. In fact, this training method distributes information without sharing raw data with external servers, allowing devices to collaborate with a data aggregator, or edge server (Nguyen et al., 2022).

This technique allows several institutions to train machine learning models collaboratively without compromising data privacy and security, making it a valuable asset in healthcare. This advantage stems from the capacity to share the benefits of the global model, which is particularly useful for frequent small-scale or one-off sampling (Manocha et al., 2024).

I.2.3 Internet of Medical Things (IoMT)

The Internet of Medical Things (IoMT) is an interconnected system of medical devices, software applications, and healthcare networks that allows medical data to be collected, shared and analyzed in real time (Shumba et al., 2023).

When it comes to computing resources and storage IoMT devices such as wearables, sensors and monitoring devices have their limitations, so EI is changing this paradigm by providing local processing capacity, in real time and without the need to send data to the cloud [3,4]. Not that the cloud is completely re-placed, but EI works as a complement, filtering that only relevant information goes to it (Joshi et al., 2023).

I.3. Metodology

We chose an SLR for this article because we needed a systematic, transparent, and reproducible synthesis. This research method stands out from traditional reviews because it can be reproduced, following the same steps, so that other researchers can arrive at the same results, thus providing a clear and objective view of its applicability in different areas of health (Davis et al., 2014). The main objective of this RSL is to identify all the empirical evidence that fits the prerequisites in response to the inclusion criteria to answer the research question (Snyder, 2019). By using this systematic method to review articles and scientific evidence, the room for doubt is minimized, so the conclusions are reliable and can be the basis for robust decision-making (Liberati, 2009).

To guarantee the quality of the study, the SLR will follow the guidelines of the PRISMA protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). These guidelines make it possible to identify, select, evaluate and synthesize studies (Page et al., 2021). It consists of a 3-phase diagram and 27 essential items in order to produce impartial work with rigor and quality (Aczel et al., 2019).

The database chosen was from Elsevier-Scopus database as this is one of the world's largest databases with a relevant number of peer-reviewed scientific articles. It is worth noting that, in relation to academic engines such as Google Scholar, Scopus is more credible given that it includes peer-reviewed manuscripts (Martín-Martín et al., 2018). Only one database was used so that the results presented are more transparent, reliable and reproducible by other researchers (Moher et al., 2009).

The search was carried out on November 11, 2024 in the Scopus database in a first step with the following filters applied: Article title, Abstract, Keywords "Edge Intelligence" AND "Healthcare", resulting in 154 documents found. The second step was to apply the filter articles in English, which resulted in 153 articles found. The third step was to apply the filter Articles from Journals, thus reducing the number of documents found to 69.

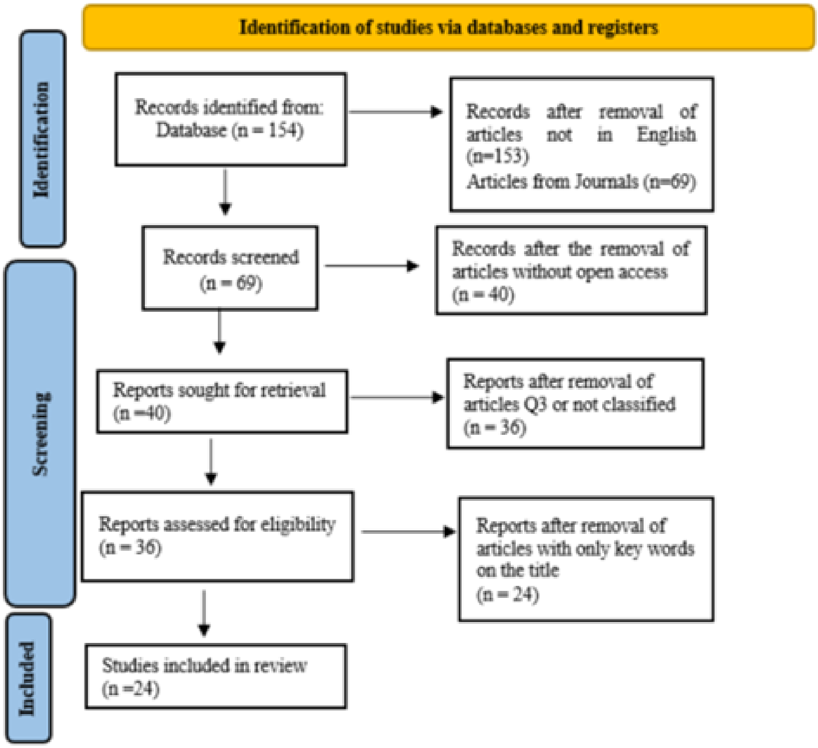

Figure 1. *PRISMA statement: Edge Intelligence in Healthcare (2020 PRISMA diagram, adapted from Page et al. 2021)*

Figure 1 illustrates the study selection process that follows the 2020 PRISMA statement. This SLR specifically centered on peer-reviewed scientific articles, which are regarded as the most trustworthy sources in academic research due to the evaluation processes they undergo. Furthermore, we restricted our selection to publications written in English, as this language serves as the predominant medium for scientific discourse. Focusing on studies from the last 4 years enables a thorough analysis of the evolution of key concepts by including recent articles that ensure the research remains relevant to current trends.

Out of an initial pool of 69 articles, only 40 scientific papers' full articles could be accessed. Four articles were excluded since they were scores Q3. We also excluded 12 articles that only had the keywords in the title, leaving a final result of 24 articles under study.

The findings from the study of these 24 articles are detailed in the following section, which sheds light on the significant concept of EI is benefits and challenges in the healthcare sector.

I.4. Results and Discussion

We analyzed the articles qualitatively and quantitatively, including the year of publication, the country of origin, the specific research area, the journal in which each article was published, the quality determined by quartile ranking, and citation metrics recorded in Scopus [15]. Through this analysis, we aim to show the knowledge developed regarding contemporary trends within the field.

I.4.1Qualitative Analysis of the Results

Table 2 summarizes each of the 24 articles under study of research on EI and healthcare. During the selection period, one of the exclusion criteria was to re-move articles that did not have at least one of the following words in their key-words: edge intelligence, edge computing, fog computing, health, IoT/IoMT.

We found that 15 out of 24 articles had at least the word edge intelligence; 10 out of 24 had at least the word IoT or internet of things; 7 out of 24 had at least the word edge computing; 2 out of 24 had at least the word IoMT or internet of medical things; 9 out of 24 had edge intelligence, edge computing and IoT or internet of things simultaneously. From this overview, we can see that all the articles under study contribute to a good sample of results to answer the aim of this article, which is to explain the concept and assess the benefits and challenges of EI in healthcare today.

Reading the articles' titles makes it easy to see the interconnection between the keywords, giving evidences as to the topic under study and the objective to be achieved. On a macro level, it is easy to see that several concepts are needed to understand the subject of EI. On a micro level, it may seem that some articles don not fit in, even if they have one of the requested keywords, but this is only be-cause of the complexity involved in this topic.

Therefore, throughout this presentation and discussion of results, different areas culminate in the concept of EI.

Table 2. *Articles on Edge Intelligence and Health.*

Authors	Date	Title and keywords	Objective
Bhat and Alqahtani.	2021	6G Ecosystem: Current Status and Future Perspective	6G promises advances in automation, as well as aligning with

		Keywords: 6G, artificial intelligence; cloud computing; sustainability goals; digital divide; healthcare; machine learning; terahertz communication; cellular network; 6G architecture.	sustainability, EI and ML goals.
Nguyen et al.	2021	6G Internet of Things: A Comprehensive Survey Keywords: 6G; internet of things; network intelligence; wireless communications.	This article explores the emerging opportunities of 6G technologies in IoT
Mondal et al.	2023	A hybrid deep neural network compression approach enabling edge intelligence for data anomaly detection in smart structural health monitoring systems Keywords: data anomaly detection; deep neural network compression; edge intelligence; network pruning; structural health monitoring	The study explores an alternative to the existing centralized process for detecting data anomalies in modern IoT-based structural health monitoring systems.
Priyadarshini et al.	2021	A survey of fog computing-based healthcare big data analytics and its security Keywords: cloud computing; e-healthcare systems; fog computing; healthcare security; latency; machine learning.	The research explores the architecture of fog computing, focusing on the physical, fog and cloud layers, and investigates the role of ML in data processing on EI devices.
Ghosh et al.	2022	CASE: A Context-Aware Security Scheme for Preserving Data Privacy in IoT-Enabled Society 5.0 Keywords: context-aware security; IoT security; contextual information;	This scientific article looks at security in the IoT context and its contributions to the security and privacy of IoT devices.

		authentication; smart home applications; user-centric security.	
Aiosa et al.	2021	Coknoweme: An edge evaluation scheme for QoS of IoMT micro-services in 6G scenario Keywords: 6G networks; QoS; evaluation systems; internet of medical things; edge intelligence; microservices	The study highlights the importance of EI for evaluating IoMT services in 6G networks, exploring concepts of complex systems.
Hazra et al.	2024	Deep reinforcement learning in edge networks: Challenges and future directions Keywords: cloud computing; resource scheduling; review; deep reinforcement learning.	The article analyzes Deep reinforcement learning methods for improving resource management in cloud computing.
Hayyolalam et al.	2022	Dynamic QoS/QoE-aware reliable service composition framework for edge intelligence Keywords: artificial intelligence; connected healthcare; COVID 19; fault prevention; meta-heuristics; IoT.	This scientific article presents a new framework for dynamic and reliable composition of AI subtasks in edge computing devices, focusing on IoMT.
Rocha et al.	2024	Edge AI for Internet of Medical Things: A Literature Review Keywords: edge intelligence; edge computing; artificial intelligence; machine learning operation; internet of medical things; smart health.	This literature review article explores the potential of EI for the IoMT.
Douch et al.	2022	Edge Computing Technology Enablers: A Systematic Lecture Study	This comprehensive review article explores edge computing, detailing its evolution.

		Keywords: Edge computing; cloud computing; fog computing; multi-access; edge intelligence; 5G: containerization.	
Amin and Hossain	2021	Edge Intelligence and Internet of Things in Healthcare: A Survey Keywords: internet of things; smart healthcare; artificial intelligence; edge computing; fog computing.	This review article analyzes the use of EI and IoT in healthcare.
Hafeez et al.	2021	Edge intelligence for data handling and predictive maintenance in IIoT Keywords: data reduction & analysis at the edge; machine learning for IoT; predictive maintenance in IIoT; edge computing.	This article analyzes the use of CE for data processing and predictive maintenance.
Manocha et al.	2024	Edge intelligence-assisted smart healthcare solution for health pandemic: a federated environment approach Keywords: edge intelligence; smart healthcare; federated environment; data; privacy; healthcare analytics	To investigate and demonstrate the ways in which EI can enhance and support various aspects of smart health applications.
Joshi et al.	2023	Enabling All In-Edge Deep Learning: A Literature Review Keywords: artificial intelligence; all in-edge; deep learning; distributed systems; decentralized systems; edge intelligence.	This review article analyzes "all in-edge" computing, an emerging paradigm that performs the training and inference of deep learning models exclusively on edge servers.
Islam et al.	2024	Healthiness and Safety of Smart Environments through Edge Intelligence and Internet of Things Technologies	This scientific article describes an IoT system based on EI to

		Keywords: smart environment; edge intelligence; air quality monitoring; air sanitization; internet of things	monitor and control indoor air quality.
Chen et al.	2023	Implementing ultra-lightweight co-inference model in ubiquitous edge device for atrial fibrillation detection Keywords: edge intelligence; parameter quantitation; lightweight model; atrial fibrillation.	This article deals with the implementation of an ultra-light co-inference model in ubiquitous EI devices for the detection of arterial fibrillation.
Shumba, et al.	2022	Leveraging IoT-Aware Technologies and AI Techniques for Real-Time Critical Healthcare Applications Keywords: internet of things; edge intelligence; healthcare and wellness; piezoelectric sensors; multi-sensor; anomaly detection	This scientific article analyzes IoT-based healthcare system architectures, focusing on the use of IoT devices.
Abdullatif et al.	2023	Reinforcement Learning for Intelligent Healthcare Systems: A Review of Challenges, Applications, and Open Research Issues Keywords: deep learning; distributed machine learning edge computing (EC); Internet of Things (IoT); remote monitoring.	The scientific article presents a comprehensive analysis of the use of reinforcement learning (RL) in intelligent healthcare systems.
Kumar et al.	2021	Security and privacy-aware Artificial Intrusion Detection System using Federated Machine Learning Keywords: beyond 5G; edge intelligence; differential privacy; artificial immune system; intrusion detection system.	This scientific article describes an IS security system for 5G networks, focusing on privacy preservation.

Tashako**ri et al**.	2023	SemiPFL: Personalized Semi-Supervised Feder-ated Learning Frame-work for Edge Intelligence Keywords: edge computing; edge heterogeneity; personalized federated learning; federated learning; edge intelligence.	The scientific article presents SemiPFL, a new semi-supervised and personalized federated learning framework for EI.
Liu et al.	2020	Toward Edge Intelligence: Multiaccess Edge Computing for 5G and Internet of Things Keywords: sustainable smart cities; blocchain technology, edge intelligence; IoT (internet of things);	This article analyzes the synergy between blockchain technology and EI in building sustainable smart cities.
Qu et al.	2023	Towards Privacy-Aware and Trustworthy Data Sharing Using Blockchain for Edge Intelligence Keywords: edge intelligence; blockchain; personalized privacy preservation; differential privacy; Smart Healthcare Networks (SHNs)	This scientific article proposes a model for sharing health data in smart health networks (SHNs)
Springer et al.	2022	Towards QoS-Based Embedded Machine Learning Keywords: embedded machine-learning; edge intelligence; runtime resource management and allocation; quality-of-service; feedback control	The scientific article presents a new runtime resource allocation structure for embedded machine learning.
Chen et al.	2024	Vehicle as a Service (VaaS): Leverage Vehicles to Build Service Networks and Capabili-ties for Smart Cities Keywords: internet of things (IoT); internet of vehicles (IoV); smart city;	This scientific article proposes a new paradigm for smart cities, called "Vehicle as a Service" (VaaS). The article proposes the use of technologies such as

	edge computing; edge intelligence; cognitive; radio networks.	edge computing, cognitive radio and blockchain to make the solution viable.

The articles were divided into different clusters to simplify the presentation of the results and their discussion. In this way, the articles are organized by similar themes, allowing for a clearer and more comprehensive understanding of the topic.

A first cluster focuses on communication networks, particularly the role of 6G as a driver of IoT. The articles explore the 6G ecosystem, highlighting its ability to overcome the limitations of 5G and meet the growing demand for immersive experiences and applications with intense use of mobile data (Bhat & Alqahtani, 2021; Nguyen et al., 2022).

Situations of pandemic brought a new reality with an increase in the frequency of virtual meetings and real-time interactions. The emerging opportunities brought by 6G technologies in IoT networks and applications highlight key technologies such as IoT, reconfigurable smart surfaces, and Terahertz communications to meet the demands of more immersive experiences (Amin & Hossain, 2021; Aslam et al., 2020).

The articles also shows that EC are expected to be crucial for reducing latency and increasing service reliability, scalability, and privacy. Recent advances in FL and IoT are key requirements for 6G-IoT integration, which includes EI, THz communications, and blockchain (Aiosa et al., 2021). Regarding healthcare data protection, a personalized differential privacy model has emerged based on levels of trust between users, using blockchain to mitigate data protection failures (Qu et al., 2023).

A second cluster comes with EC and security, with a detailed analysis of EC technology and its main pillars, such as resource management, computing offloading, data management, and security. AI-assisted data analysis usually takes place in cloud infrastructures, but this presents limitations such as data privacy and high latency, which EC solves by moving AI services and data storage to AI devices (Hayyolalam et al., 2022). EC and FC offer promising solutions to increase reliability and responsiveness in IoMT applications, since mobile EC architectures have lower latency and greater coverage than cloud-based models (Amin & Hossain, 2021).

We also find out that most Internet technologies and communication protocols are not designed to support IoT security and privacy, and common IoT attacks include: unauthorized access; physical capture of devices; corruption of information; and code execution (Ghosh et al., 2022; Mondal et al., 2023).

The third cluster explores the importance of ML for predicting failures, related to EC and FL as an approach to forming DL models. Machine learning operations (MLOps) are essential for rapidly developing and managing ML systems on the periphery, guaranteeing real-time analysis of user data (Rocha et al., 2024). Deep reinforcement learning (DRL) has emerged as a solution for better resource management in the cloud. DRL shows superior performance in problems of scale in cloud computing, due to its flexibility and adaptability (Joshi et al., 2023).

Also, integrating ML models into systems that evaluate quality of service (QoS) and IoMT microservices on limited hardware platforms offers benefits such as lower latency, energy consumption, and greater security (Aiosa et al., 2021; X. Chen et al., 2024). In addition, hardware heterogeneity is a significant challenge in IoT applications, requiring customized models for different processing capabilities. So the integration of blockchain and EI is highlighted as a capable approach to improving sustainability and resilience (Liu et al., 2020; Qu et al., 2023).

The last cluster consists of articles that focus on IoMT devices. Smart healthcare uses IT to speed up diagnosis and treatment, reducing costs and improving the quality of patient care. IoT sensors and health applications have significantly changed the approach, with more than 162 billion IoT devices in use globally in 2020 (Amin & Hossain, 2021).

Moreover IoT-based healthcare systems using IoT devices can be applied in many scenarios, including assisted living, where continuous monitoring and early warnings can provide independence for the elderly and chronically ill (Shumba et al., 2022).

The main challenges are security and the limitations of EI devices, such as power and low memory. Another aspect to highlight is the use of ML to extract the data to make predictions, classifications and groupings based on local data (J. Chen et al., 2023).The use of a network training and inference framework with model compression makes it possible to improve performance comparable to that of a computer.

I.4.2.Quantitative Analysis of the Results

EI is a topic that has been discussed in the academic community, so the selected articles were analyzed according to their distribution by journal, quality (quartile), and the citations reported in the Scopus database.

Table 3. *Distribution by journal, its quality (quartile) and citations*

Magazines	Citations	Quartile (Q)	% de 24
IEEE Access	242	Q1	21%
IEEE Internet of Things Journal	179	Q1	21%
Smart Structures and Systems	64	Q2	4%
International Journal of Ambient Computing and Intelligence	26	Q2	4%
Sensors	245	Q1	4%
Physical Communication	49	Q2	4%
Cluster Computing	69	Q2	8%
Computers and Electrical Engineering	94	Q1	8%
Expert Systems with Applications	271	Q1	4%
Future Internet	60	Q2	4%
Big Data Mining and Analytics	38	Q1	4%
Electronics	83	Q2	4%
IEEE Communications Surveys and Tutorials	264	Q1	4%

Table 1 shows the list of scientific journals, indicating the number of citations received, the classification quartile (Q) and the percentage they represent in the total number of citations. The information allows an analysis of scientific production regarding the impact and relevance of publications. The journals exhibit a strong tendency towards the fields of electrical engineering and computer science, with a particular emphasis on networks, IoT, sensors, and data analysis. They show a distribution of citations across several renowned journals: Q1 accounts for 70% of citations, comprising 8 journals, while Q2 accounts for the remaining 30%, totaling 6 journals. The presence of journals only in Q1 and Q2 indicates that the sources for scientific evidence are reliable.

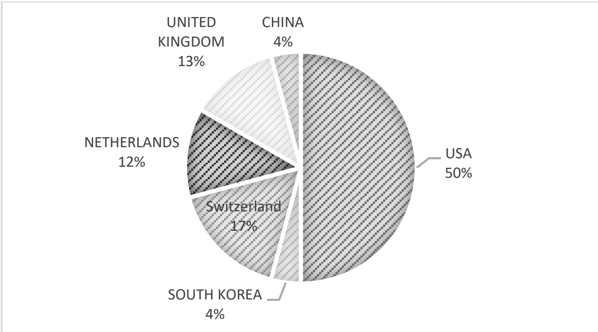

Figure 2. *Distribution according to county*

The distribution of journals by country was also analyzed, as shown in Figure 2. The predominance of journals from the USA (50%) can be explained by the fact that this country is one of the global leaders in research and development, with significant investment in technology and engineering. The strong European presence, with reviews from the UK, the Netherlands and Switzerland, indicates that Europe also plays an important role in research and development in these areas.

The presence, albeit smaller, of journals from China (4%) and South Korea (4%), indicates the growing investment and relevance of Asia in technological research. These countries are becoming increasingly important in the engineering and IT research landscape, with a growing focus on areas such as sensing and electronics, as indicated by the themes of some of the journals.

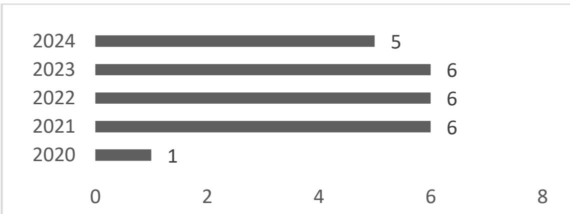

Figure 3. *Distribution of the articles analyzed according to the year of publication.*

According to the year of publication and as shown in figure 3, there is a consistency in the number of articles published in these areas after 2020. According to the sample, 2021, 2022 and 2023 are the years with the highest number of publications (18/24). This may be related to the topic being current in such an emerging area as AI, EI, IoT/IoMT and communication networks. It should also be noted that according to the figure 4 the topic under study is published in approximately 92% of computer science journals and according to figure 5 the categories with the highest number are computer networks and communications and computer science (miscellaneous).

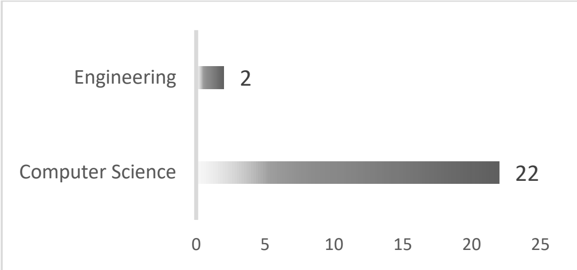

Figure 4. *Distribution of the articles analyzed according to the type of journal.*

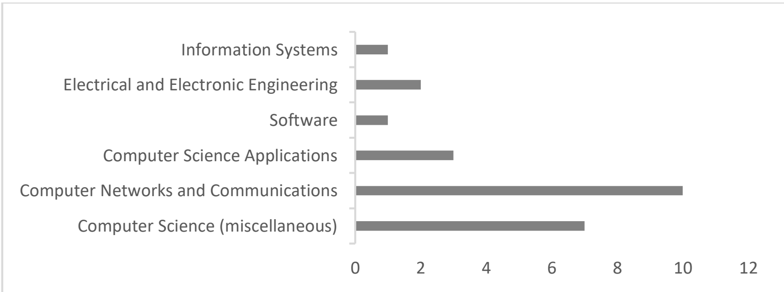

Figure 5. *Distribution of the articles analyzed according to category.*

I.4.3. Discussion

Based on our results, it is our understanding that the 24 articles under study offer a comprehensive view of EI, its applications and its enabling technologies, particularly in the context of 6G networks and AI in healthcare. They highlight the shift from traditional cloud-centric computing to decentralized architectures in which data is processed closer to the source.

The studies in this research aim to present the complexity and the numerous ways that EI involves integrating AI, ML and EC architectures with processing at the source, which in the context of healthcare includes IoMT devices (Amin & Hossain, 2021; Rocha et al., 2024). This approach allows data to be processed in real-time, reducing latency and ensuring data protection (J. Chen et al., 2023; Joshi et al., 2023; Shumba et al., 2023). The high capacity of EC allows a large number of sensor devices to operate without overloading the underlying network and creates more efficient and economical intelligent environments because limited amounts of data are transmitted to the cloud (Islam et al., 2024).

Furthermore, EI is a key technology for future healthcare systems that require low latency, high reliability, and strong privacy protection (Aiosa et al., 2021). On the one hand, minimizing the amount of data sent over networks through pre-processing and analysis at the edge reduces network congestion, bandwidth consumption, and costs (J. Chen et al., 2023; Douch et al., 2022; Islam et al., 2024; Shumba et al., 2023). On the other hand, processing data locally reduces the need to transfer sensitive health information to the cloud, thus minimizing the risk of data breaches and ensuring greater privacy (Nguyen et al., 2022).

Moreover, EI devices often have limited computing power, memory, and energy resources, which is a challenge for implementing complex AI models [9]. Another challenge lies in the diversity of peripheral devices and network conditions, which makes it difficult to develop universal EI solutions (Abdellatif et al., 2023).

Regarding the developing and implementing AI models at the edge, specialized knowledge and complex methodologies are required. Also processing and managing large amounts of data from various sources at the edge can be challenging due to limited resources and the variability of data quality (Aslam et al., 2020). Although IoT provides greater privacy, IoT devices can be susceptible to security attacks, requiring robust security mechanisms to protect sensitive data (Priyadarshini et al., 2021; Qu et al., 2023).

Two major cons relate to the difficulties in updating AI models on edge devices with limited resources and interoperability problems, due to the heterogeneous nature of healthcare systems and the need to integrate various devices and applications (Liu et al., 2020). Ensuring the reliability and stability of EI systems under varying conditions is essential for critical healthcare applications (Manocha et al., 2024).

In short, EI is a transformative approach that brings AI capabilities closer to the data source. While it offers numerous advantages, such as reduced latency, increased privacy, and real-time analysis, it also presents resource constraints, heterogeneity, and security challenges. However, the scientific community and technological advances are continually addressing these challenges and expanding the potential of AI in healthcare.

Having said this, and according to all the information collected, analyzed, and discussed, it is possible to arrive at a conceptual theoretical model. This representation in Figure 6 aims to describe reality simply by visualizing the topic's relationship, processes, and structures.

This model demonstrates how technologies work together to create an intelligent, efficient, safe healthcare system, using EI as a key component. The interaction between these layers makes healthcare systems more adaptable, personalized, and effective.

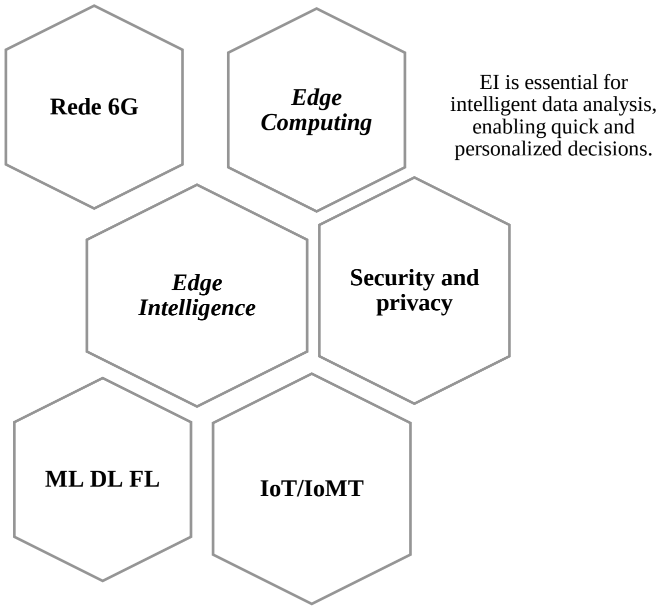

Figure 6. *Representation of the conceptual theoretical model*

I.5. Conclusion

Overall, this article examines how EI has emerged as a fundamental concept in the healthcare sector, potentially transforming how care is provided and data is processed. In our view, EI means integrating AI directly into portable devices, allowing data to be processed on the device, resulting in better response times and energy conservation.

In terms of applicability, EI enables applications to provide highly personalized healthcare, adapting to individual needs. That is, by remote monitoring and the efficient use of resources, EI is helping to reduce the costs associated with traditional healthcare systems and can even reduce the need for frequent doctor visits. Although the lack of standardization might be hindering the widespread adoption of EI in healthcare, the tools and the technical requirements will be needed for its integration into existing architectures.

Future directions is pointing out that FL has been seen as a promising approach to training ML models on distributed data, while preserving privacy. Also, RL techniques are being used to optimize healthcare systems and dynamic treatment regimes. As well as blockchain technology can improve the security and privacy of data sharing in healthcare systems and enables secure data exchange and remote monitoring.

I.6. Appreciation

We would like to thank ISLA-Santarém for supporting and funding our participation in the WorldCEM'25 - The 2025 World Conference on Economics and Management.

CHAPTER II

Edge Intelligence and IoMT for Real-Time Healthcare Analytics: A Systematic Literature Review

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Abstract. Integrating Edge Intelligence and the Internet of Medical Things (IoMT) has emerged as a transformative approach to real-time healthcare analytics. IoMT devices, including wearable sensors and connected medical equipment, generate substantial volumes of real-time health data and, thus, can significantly enhance patient care. However, the processing and analysis of such data require efficient solutions that address the challenges of data volume, latency, and privacy issues. Edge Intelligence, which involves processing data at or near the source of generation, provides a promising solution by enabling faster data processing and reducing dependency on centralized cloud systems. This systematic literature review explores the synergy be-tween Edge Intelligence and IoMT in enabling real-time healthcare analytics. By promoting edge computing, healthcare systems can gain immediate in-sights from patient data, facilitating quicker decision-making and more personalized treatment. Additionally, this review highlights the advantages of reducing latency, enhancing data privacy, and optimizing resource usage through distributed processing at the edge. It also discusses the challenges involved, including the need for robust security measures, data synchronisation, and seamless integration across heterogeneous devices and systems. Ultimately, this review aims to shed light on the potential of Edge Intelligence and IoMT in revolutionizing healthcare by improving the efficiency, responsiveness, and quality of care while addressing key technical and ethical concerns associated with real-time healthcare analytics.

Keywords: *Edge intelligence; IoMT; Real-time Healthcare Analytics; Healthcare Systems Integration.*

II.1. Introduction

Within healthcare, advanced Internet of Things (IoT) devices can now collect vital parameters to feed Edge Intelligence (EI) processes, providing relevant information and assistance to healthcare professionals (Rancea et al., 2024). However, some challenges in adopting EI persists, as it includes data confidentiality and safety, as well as the tuning of artificial intelligence (AI) and computation offloading at the edge (Zhou et al., 2019).

On the other side Internet of Medical Things (IoMT) is changing the healthcare paradigm in many ways through the integration of devices and technologies that enable more continuous, personalized, and efficient monitoring of patients (Wagan et al., 2022).

Also, it is important to note that IoMT devices, such as wearable sensors, implants, and mobile applications, enable continuous monitoring of vital signs, health conditions, and other relevant parameters (El-deep et al., 2025). This remote monitoring allows early detection of health problems and faster intervention, leading to better patient outcomes and reduced hospital stays and readmissions (Gupta et al., 2023).

Other aspect to consider is that IoMT are linked to smart things, physical objects of sensors, software, and computing power which allows exchange data across different networks providing a cost-effective solution and, resulting in diagnoses and solutions to problems quickly (Ashfaq et al., 2022).

This article then explores the integration of Edge Intelligence and the Internet of Medical Things to enable real-time healthcare analytics. To conduct this review, it set out the Preferred Reporting Items for the Systematic Reviews and Meta-Analyses (PRISMA) method with meaningful objectives, specified inclusion and exclusion criteria for articles, and coverage range across key sources (Scopus). The PRISMA statement ensures that the review's conduct is consistent and transparent, while also providing readers with access to helpful information about the current state of research in the field (Page et al., 2021).

The research question is “How does the integration of EI and IoMT enhance real-time healthcare analytics?”

The paper is divided into the following parts: Chapter 2 contextualizes concepts such as edge intelligence, IoMT, edge computing and Federated learning in IoMT, real-time health data analytics, and health systems integration. Chapter 3 describes the systematic review's methodology and approach; Chapter 4 presents the findings by defining and organizing the identified articles. Also, the research results and the shortcomings highlighted in the present study will be discussed. At the same time, Chapter 5 serves as the paper's conclusion, highlighting the essential aspects for future research.

II.2. Contextualization

II.2.1. Edge Intelligence

Edge intelligence (EI), also known as edge artificial intelligence (AI), involves integrating AI functionality within edge computing appliances located near the origin of information, allowing data to be processed locally (Ometov et al., 2022). This way it enables faster decision-making and real-time responses, which are crucial for applications with low-latency requirements, such as anomaly detection (Barbuto et al., 2023).

In order to understand it, we describe in Table 4 its key points (Rancea et al., 2024).

Table 4. *Edge intelligence key points (Rancea et al., 2024)*

Local data processing	Reduced network pressure	Improved privacy and security	Inference and making decisions locally	Blockchain
The ability to perform computations and data analysis directly on the device or near the data source without relying on transmission to the cloud.	Local processing reduces the need to transmit large amounts of raw data over the network, reducing stress on network links and bandwidth consultation.	Processing sensitive data locally can increase privacy and security by avoiding the transmission of confidential information to centralized servers.	The ability to perform inference and make decisions locally, even in situations with limited or intermittent network connectivity. This ensures that critical applications can continue to operate reliably.	The possibility of being combined with other technologies, such as blockchain, to reinforce security and privacy in the management of health data, guaranteeing the integrity and immutability of records

Regarding the healthcare domain, EI has the potential to transform services. Through the dynamic implementation of AI algorithms on edge devices, in order to enable the detection, prediction, and prevention of health issues (Putra et al., 2024). For this to happen, a useful methodology emerges in a hybrid form, which combines optimized machine learning and deep learning models for faster and more accurate analysis of complex medical information (Wang et al., 2024).

However, it is known that EI faces challenges in the privacy sector due to its handling of sensitive personal information, which can lead to privacy policy issues. In terms of communication security and decentralized security management, we are dealing with security policies and data breaches (Adeniyi et al., 2021).

In addition, the lack of a standardized naming system for various devices and the complexity of managing multiple virtual functions across dispersed locations pose significant challenges, including interoperability, troubleshooting, limited scalability and portability, testing, and validation issues (Rahman et al., 2024).

II.2.2. Internet of Medical Things (IoMT)

Due to the increasing number of patients and limited resources, traditional healthcare and medical systems can't respond quickly, effectively address variations in diseases and therapies, or meet patients' needs in real time (Naghib et al., 2025). Therefore, IoT in the medical domain can overcome the above problems because patients and healthcare professionals can easily connect to IoT-based medical devices through Internet services (Pradyumna et al., 2024).

The combination of the IoT with medical devices is termed IoMT. It is a connected, extensible network of medical and wearable devices with internet connectivity, applications, hardware, and software infrastructure (Chaganti et al., 2022). In practical terms, it enables remote monitoring of patients, allows for personalized therapy regimes and care, facilitates large-scale data collection, and enhances decision-making (Khan et al., 2023).

In terms of management tools, they are mainly responsible to handle the monitoring of operations with the aid of cloud management tools. Its management process has different layers, as shown in Table 5, which contribute to a functional working framework (Wagan et al., 2022).

Table 5. *System management process of layers in the IoMT (Wagan et al., 2022).*

Layer management in IoMT			
Sensor	Network	Internet	Service
lowest layer Key elements	layer interacts with the	Data storage logically linked pools	HTTPS/HTTP, JavaScript, Restful web services

	Internet Protocol (IP)		
Sensors can be defined as electrical devices that capture signals from the body. By allowing the tracking of their health, biosensors can enable data to be interpreted automatically and diagnoses to be made more quickly and accurately.	Communicates with IP address. This involves hardware components, such as gateways, routers, and access points.	The Internet is responsible for handling and storage of data. It employs cloud storage techniques. A hosting company typically owns and manages the hardware storage, including one or more servers. The cloud offers on-demand services, including BigQuery, Cloud Datastore, Cloud Storage, Cloud SQL, and ML algorithms, as well as support for Android and JavaScript.	The service layer facilitates immediate access to data for physicians, emergency rooms, hospitals, and medication supply chains. Consequently, doctors can remotely supervise patients, access their prescription records, and provide remote assistance in emergencies.

II.2.2.1 Edge Computing in IoMT

Edge computing (EC) offers a cutting-edge distributed computing data at the edge with reduced latency and bandwidth consumption. Thereby enhancing system efficiency, scalability, privacy, and security for IoMT (Rancea et al., 2024).

Its definition focuses on providing value and processing to support the requirements mentioned above, needed for real-time and distributed systems. Even though margin processors have greater computing power and capacity, they are limited in comparison with the performance of the cloud servers (C. Chen et al., 2024; Gyamfi & Jurcut, 2022).

This role becomes increasingly significant once it is built into the IoMT concept, allowing services to be delivered efficiently and securely to the end-user. However, most requirements are not fulfilled by the end-user, to which vast amounts of information processing and memory must be migrated to the cloud, which could lead to considerable delay (Arcas et al., 2024).

II.2.2.2 Federated Learning in IoMT

Federated learning (FL), also referred to as collaborative learning, is a non-centralized training method and machine learning (ML) method that enables algorithms to be trained on several hardware devices (e.g. Edge) or software servers without sharing or transferring their respective local data (Gyamfi & Jurcut, 2022).

FL dramatically improves the privacy and efficiency of Intrusion Detection Systems (IDS) in the IoMT environment (Naghib et al., 2025). This innovative approach enables machine learning algorithms to be trained directly on IoMT devices. By performing the training locally on the devices, federated learning eliminates the need to centralize personal or sensitive data in a cloud environment, often posing security risks (Mallidi & Ramisetty, 2025).

Although FL offers transformational ways to improve confidentiality and effectiveness in IDS, it presents inherent challenge that must be addressed. The main issue is the non-Independent and Identically Distributed (non-IID) character of the aggregated data, which may compromise the model's validity, data manipulation and the guarantee of integration of standard updates (Monteiro et al., 2023).

II.2.3 Real-time Healthcare Analytics and Healthcare Systems Integration

The concepts of real-time health data analytics and health systems integration are crucial aspects in the evolution of healthcare facilitated by the IoMT. This capability allows healthcare professionals to receive alerts and intervene rapidly, significantly reducing the time spent on routine monitoring (El-deep et al., 2025).

This is possible due to technologies such as EI, IoMT, and FL that enable proactive interventions and personalized treatment plans. The continuous data stream provides invaluable insights for healthcare management (Monteiro et al., 2023).

Standardizing communication protocols and data formats is essential for ensuring seamless data exchange and compatibility between different IoMT components. By adopting common standards, healthcare providers can integrate data from multiple sources, including electronic health records (EHRs), medical devices, and patient monitoring systems, into a unified platform (Khan et al., 2023).

II.3. Methodology

Systematic literature reviews (SLRs) are a structured method for collecting, analyzing, and synthesizing existing research to answer specific investigation questions (Snyder, 2019; Wayant et al., 2019). This process provides a clear overview of findings by compiling evidence, identifying trends, and highlighting gaps in the literature (Page et al., 2021; Prins et al., 2016). By offering a synthesis, SLRs guide future research directions, helping researchers better understand fragmented studies and facilitating the integration of knowledge across fields.

This SLR offers a comprehensive and systematic overview of the existing knowledge regarding integrating Edge Intelligence and the Internet of Medical Things for real-time healthcare analytics. It provides an objective and impartial assessment of current research while identifying potential avenues for future exploration. Furthermore, the SLR establishes a solid foundation for understanding EI's benefits, challenges, and impacts and enables real-time healthcare analytics.

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement has been adopted to enhance the transparency, reproducibility, and reliability of systematic reviews and meta-analyses. This framework helps ensure that all relevant information is disclosed and facilitates the critical appraisal of research by peers and stakeholders. Adopting the PRISMA guidelines aims to improve the quality of research reporting and bolster trust in the findings of systematic reviews and meta-analyses within the scientific community (Page et al., 2021).

For our systematic search, we considered three databases: Google Scholar, Web of Science, and Elsevier Scopus. Google Scholar has more citations across different research fields than the other databases. However, a large portion—48% to 65%, depending on the field—includes dissertations, books, unpublished studies, and other documents that usually have less scientific value than peer-reviewed sources found in Elsevier Scopus or Web of Science (Martín-Martín et al., 2018; Prins et al., 2016). On the other hand, Elsevier Scopus offers broader coverage in areas like healthcare and innovation, technology, and artificial intelligence, providing a wider range of sources and better analytical tools (Reis et al., 2019).

Our search focused on scientific articles that contained the terms "Edge Intelligence" and "healthcare analytics" in their titles, abstracts, or keywords. The inclusion criteria were limited to articles peer-reviewed between the years 2020 and 2025. Excluded, those not written in English and unavailable in full text.

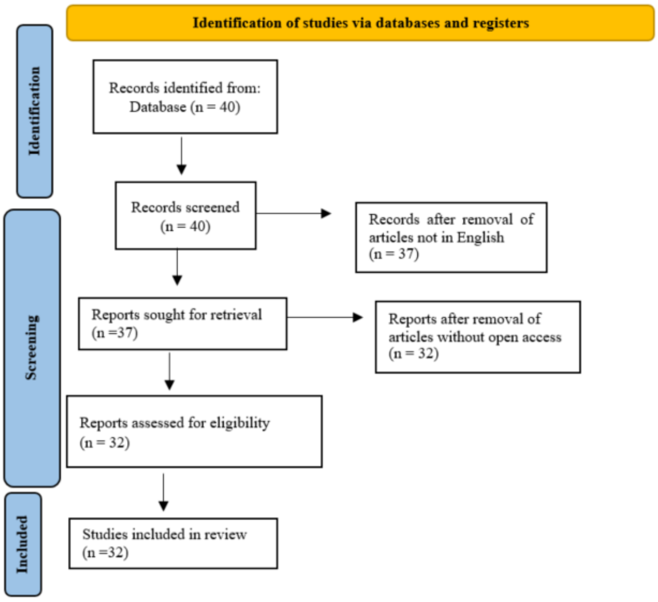

Figure 7. *PRISMA statement: Edge Intelligence and IoMT for Real-Time Healthcare Analytics (2020 PRISMA diagram adapted from Page et al. (Page et al., 2021))*

Figure 7 illustrates the study selection process that follows the 2020 PRISMA statement. This SLR specifically centered on peer-reviewed scientific articles, which are regarded as the most trustworthy sources in academic research due to the stringent evaluation processes they undergo. Furthermore, we restricted our selection to publications written in English, as this language serves as the predominant medium for scientific discourse. Focusing on studies from the last 5 years enables a thorough analysis of the evolution of key concepts by including recent articles that ensure the research remains relevant to current trends.

Out of an initial pool of 40 articles, 32 were selected for detailed analysis based on the inclusion criteria. The findings from the study of these 32 articles are detailed in the following section, which sheds light on the significant integration of EI and the IoMT for real-time healthcare analytics.

II.4. Results and Discussion

II. 4.1. General Analysis of Results

Table 6 presents a summary of five years of research on EI and healthcare analytics. The overall articles were reviewed to assert the research question. We analyzed the articles in a multidimensional way, including the year of publication, the country of origin, the specific research area, the journal in which each article was published, the quality determined by quartile ranking, and citation metrics recorded in Scopus. Through this analysis, we aim to show the knowledge that has been developed regarding contemporary trends within the field.

Table 6. *Articles on Edge Intelligence and Healthcare Analytics.*

Authors	Date	Title	Objective
Choi and Lee.	2024	Secure and Scalable Internet of Things Model Using Post-Quantum MACsec	To present a new IoT network platform that effectively uses post-quantum cryptography (PQC) for IoT devices with limited computing power.
Gong et al.	2024	RSMS: Towards Reliable and Secure Metaverse Service Provision	To examine the deployment of Metaverse services within a cloud-edge resource architecture.
Naser et al.	2024	A Review of Machine Learning's Role in Cardiovascular Disease Prediction: Recent Advances and Future Challenges	To provide a focused exploration of machine learning models in cardiovascular disease prediction.
Tomer et al	2024	Resilience in the Internet of Medical Things: A Review and Case Study	To examine remote patient monitoring (RPM) for a heart patient within IoMT networks
Wu et al. (Wu et al., 2022)	2022	Real-Time Anomaly Detection for an ADMM-Based Optimal Transmission Frequency	To explore various scenarios of anomaly detection in decentralized IoT applications, and focus on leveraging edge AI for real-time anomaly detection.

		Management System for IoT Devices.	
Hwang and Majeed .	2024	Analysis of Federated Learning Paradigm in Medical Domain: Taking COVID-19 as an Application Use Case	To explore the fundamental concepts of federated learning (FL), including its differences from centralized learning, the roles of clients and servers, workflows, and data characteristics.
Shinde et al	2024	A comprehensive survey on recommender systems techniques and challenges in big data analytics with IoT applications	To explore recommended system techniques in Big Data Analytics.
El-deep et al.	2025	A comprehensive survey on the impact of applying various technologies on the Internet Of Medical Things	To provide a concise review of the IoT and the IoMT about EI smart healthcare.
Oliveira et al.	2024	Internet of Intelligent Things: A convergence of embedded systems, edge computing, and machine learning	To explore the emerging concept of the Internet of Intelligent Things (IoIT), highlighting the connections between embedded systems, edge computing, and machine learning.
Ratre et al.	2024	Smart carbon-based sensors for the detection of non-coding RNAs	To explore advanced, smart carbon-based nano-biosensors. Highlights the use of AI tools in designing and optimizing these

		associated with exposure to micro(nano)plastics: an artificial intelligence perspective	innovative carbon nanomaterials, showcasing their potential to transform biosensing.
Putra et al.	2024	A Review on the Application of Internet of Medical Things in Wearable Personal Health Monitoring: A Cloud-Edge Artificial Intelligence Approach	To analyze recent trends in the academic literature on wearable health monitoring via the IoMT.
Acosta et al.	2022	Multimodal biomedical AI	To highlight key applications of multimodal AI in healthcare.
Majeed and Hwang.	2024	A Multifaceted Survey on Federated Learning: Fundamentals, Paradigm Shifts, Practical Issues, Recent Developments, Partnerships, Trade-Offs, Trustworthiness, and Ways Forward	To present a concise survey of FL, covering its foundational concepts and the paradigm shifts from centralized to decentralized learning.
Manocha et al.	2024	Edge intelligence-assisted smart healthcare solution for health pandemic: a federated	To investigate and demonstrate the ways in which EI can enhance and support various aspects of smart health applications.

		environment approach.	
Khatun et al.	2023	Machine Learning for Healthcare-IoT Security: A Review and Risk Mitigation	To explore the foundational concepts of healthcare IoT while examining the intricate privacy and data security challenges
Kollu et al.	2023	Cloud-Based Smart Contract Analysis in FinTech Using IoT-Integrated Federated Learning in Intrusion Detection	To develop an advanced cloud-based intrusion detection system using IoT federated learning and smart contract analysis.
Hoang et al.	2024	Evaluating Dimensionality Reduction Methods for the Detection of Industrial IoT Attacks in Edge Computing	To introduce a new IDS for edge devices that employs a lightweight deep neural network to detect IIoT attacks.
Baranitharan et al.	2023	A collaborative and adaptive cyber defense strategic assessment for healthcare networks using edge computing	To offer a comprehensive overview of the various technologies and protocols that underpin the foundation IoT.
Bhalgaonkar et al.	2024	Model compression of deep neural network architectures for visual pattern recognition: Current	To explore various compression techniques for sequential, non-sequential, and advanced deep neural network (DNN) architectures in Visual Pattern Recognition (VPR).

		status and future directions	
Javaid et al.	2022	Significance of machine learning in healthcare: Features, pillars and applications	To explore the critical role of ML in healthcare.
Arora et al.	2022	Evolution and Adoption of Next Generation IoT-Driven Health Care 4.0 Systems	To provide an overview of essential emerging technologies revolutionizing Healthcare 4.0 systems.
Shafi et al.	2024	Safeguarding the Internet of Health Things: advancements, challenges, and trust-based solution	To emphasizes the critical importance of safeguarding the Internet of Health Things (IoHT), which connects various medical devices and health-related applications.
Ahmad et al.	2023	Leveraging 6G, extended reality, and IoT big data analytics for healthcare: A review	To address the gap in the existing literature by reviewing how the convergence of 6G, extended reality (XR), and IoT big data analytics will influence the future of healthcare systems.
Majeed and Zhang.	2023	On the Adoption of Modern Technologies to Fight the COVID-19 Pandemic: A Technical Synthesis	To analyze digital technologies that benefited communities during the COVID-19 pandemic.

		of Latest Developments	
Aledhari et al.	2020	Federated Learning: A Survey on Enabling Technologies, Protocols, and Applications	To comprehensively summarize FL's most important protocols, platforms, and real-world use cases
Tariq et al.	2024	Trustworthy Federated Learning: A Comprehensive Review, Architecture, Key Challenges, and Future Research Prospects	To propose a straightforward framework for Trustworthy FL that checks in terms of interpretability and explainability, transparency, privacy and robustness, fairness, and accountability.
Jha et al.	2020	Multiobjective Deployment of Data Analysis Operations in Heterogeneous IoT Infrastructure	To present a significant extension of the PATH2iot framework, which aims to address the challenges of distributing computations for IoT applications.
Junaid et al.	2022	Recent Advancements in Emerging Technologies for Healthcare Management Systems: A Survey	To evaluate the application of emerging technologies—such as Smart Sensors, IoT, AI, and Blockchain—in Healthcare.
Chatterjee and Ahmed.	2022	IoT anomaly detection methods and applications: A survey	To summarize detection methods and their applications, followed by a discussion on the

			classification of IoT anomaly detection algorithms.
Dunai et al.	2025	Prosthetic Hand Based on Human Hand Anatomy Controlled by Surface Electromyography and Artificial Neural Network	To present a real-time hand gesture recognition method using surface electromyography (sEMG) and a multilayer neural network. It employs TinyML, which combines embedded systems with machine learning, to deploy models on devices with limited processing power.
Kadam and Kim.	2024	Knowledge-Aware Semantic Communication System Design and Data Allocation	To present a knowledge-aware semantic communication system (SemCom) and its application to a data allocation problem.
Shakor and Khaleel	2024	Recent Advances in Big Medical Image Data Analysis Through Deep Learning and Cloud Computing	To focus on integrating cloud computing and deep learning technologies in analyzing medical data and their impacts on the healthcare sector.

The above studies examine various innovative technologies and their applications in the healthcare industry. Although it may seem at first that the different articles are not entirely related, in the end, we will see that their coaction will achieve the goal of this study.

In this regard Acosta et al. (2022) shows prospers of the development of multimodal AI solution, while using the availability of data provident from different medical sources. Such as EHRs, medical imaging, wearable and ambient biosensors, and the lower cost of genome and microbiome.

Considering the development of nanobiosensors, Ratre et al. (2024) provide views into the articulation of AI and ML within public healthcare concerning nanoplastics in the human body system. By presenting smart carbon-based nanobiosensors it can revolutionize methods for capturing non-coding RNAs. In terms of neural network it also can be an articulation of AI and ML for real time application as Dunai et al. (2025) show by involving training the system with signals.

Ahmad et al. (2023), Shinde et al. (2024), Arora et al. (2022), Putra et al. 2024), Kadam et al. (2024) and Jha et al. [53] enhance the advantages of healthcare analytics management by adopting and integrating 6G communication, extended reality (XR), and IoT/IoMT big data analytics. Also widen this issue Junaid et al. (2022) and El-deep et al. (2025) highlights the need of IoMT AI and Blockchain in healthcare systems integration. In a way this results present the improvement given within the use of innovation technology although healthcare has been slowly adopt them. Additionally, this improves reliability, reduces data rates and latency, and enhances mobile connectivity.

On the matter of big medical image data analysis, Shakor et al. (2024), Oliveira et al. (2024), Khatun et al. (2023), Kollu et al. (2023), and Javaid et al. (2022) enhance the combination of cloud and edge computing and ML at various healthcare delivery and outcomes. Hwang and Majeed (2024), Manocha et al. (2024), Tariq et al. (2024), Aledhari et al. (2020) in terms of data analysis and data sharing they address the challenge with collaborative model training – FL ecosystem in order to attend protection data regulations as well as real-life applications and use-cases. Overall, relying on ML techniques is crucial for the early detection of indicators for an epidemic or pandemic.

With regard to remote patient management, Tomer et al. (2024) provided a comprehensive insight into how IoMT applications can work through a network, combining software, ML and microservices architectures.

In terms of security issues within IoT and IoMT Choi and Lee (2024), Baranitharan et al. (2023), Hoang et al. (2024), Gong et al. (2024), Shafi et al. (2024), Bhalgaonkar et al. (2024), Chatterjee and Ahmed (2022) and Wu et al. (2022) secure networks are crucial to provide scalability, viability and efficiency in protection data from digital threats. Overall it’s said that combining deep learning, ML EC and EI contributes to anomaly detection on decentralized systems, bringing tailored platforms and devices.

The distribution of the analyzed articles is represented in Figure 8 according to their year of publication. The line chart plots document creation or processing trends over time. The chart highlights a dip in activity in 2021 (0 documents), gradual growth from 2022 to 2023, a sharp peak in 2024 (17 documents), and a significant drop in 2025 (2 documents). This provides numerical and graphical insights into document activity trends over the years.

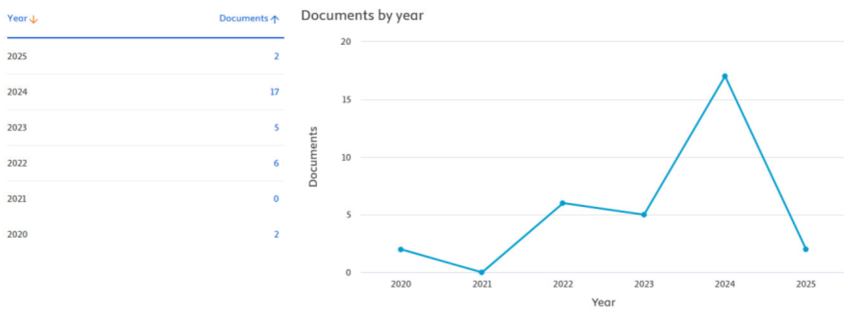

Figure 8. *Distribution by year of publication (in Scopus)*

Figure 9 illustrates the distribution of articles by country. India leads in document counts, indicating high activity in this region; South Korea and Canada show significant numbers, while other countries, such as the United States, UAE, and Ireland, have moderate levels, reflecting diverse operational and regulatory environments.

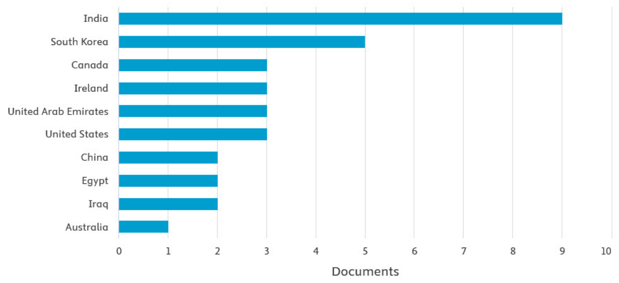

Figure 9. *Distribution by country (in Scopus)*

Figure 10 shows a breakdown of documents by subject area. Analyzing these data, it is clear that Computer Science has the most significant number of documents (25) and the highest percentage representation (34.2%). The second most relevant area is engineering, with 17 papers (23.3%). This distribution shows the multidisciplinary approach to research in emerging health technologies, highlighting the essential roles of computing and engineering. While there are fewer documents in Medicine, their inclusion emphasizes the application of these technologies in health and their potential benefits.

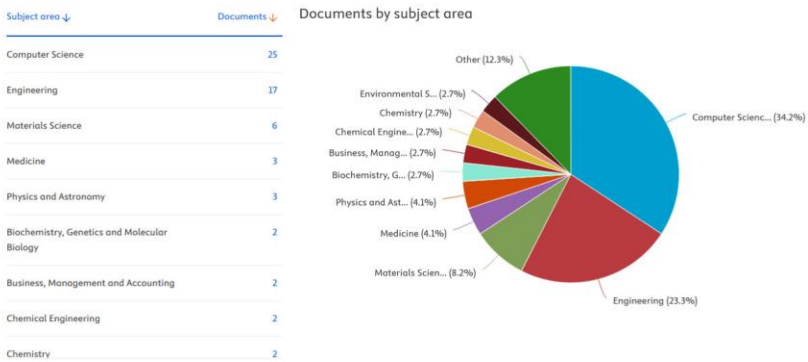

Figure 10. *Distribution by area of research (in Scopus).*

As shown in Table 7, the distribution of articles across scientific journals and their citation quartiles, meaningful information about the quality and impact of research on the sources can be obtained.

Overall, the presence of articles in Q1 and Q2 journals (12 journals in total, including IEEE Access with the highest number of articles) suggests that a considerable part of the research analyzed is of good quality and has the potential for significant impact in their respective fields. The increase in the number of publications over the years that we observed previously, together with the presence of articles in high-impact journals, reinforces the idea of growing interest in applying emerging technologies in the health sector.

Table 7. *Distribution of the most relevant Journals, their quality (quartile), and citations*

Articles	Citations	Quartile
IEEE Access	4	Q1
Applied Sciences Switzerland	2	Q2
EEE Transactions On Vehicular Technology	2	Q2
Algorithms	1	Q2
Artificial Intelligence Review	1	Q1
Cluster Computing	1	Q2
Computer Science Review	1	Q2
Computers And Electrical Engineering	1	Q2
Covid	1	Q3
Data	1	Q3
Electronics Switzerland	1	Q2
Environmental Science And Pollution Research	1	Q2

Future Internet	1	Q3
Healthcare Analytics	1	Q3
Healthcare Switzerland	1	Q2
IEEE Open Journal Of The Communications Society	1	Q2
IEEE Transactions On Industrial Informatics	1	Q1
International Journal Of Computers Communications And Control,	1	Q3
International Journal Of Intelligent Networks	1	Q3
Nature Medicine	1	Q1
Revista De Gestao Social E Ambiental	1	Q3
Sensors	1	Q1
Technologies	1	Q3
Telecommunication Systems	1	Q2
Wireless Personal Communications	1	Q3

II. 4.2 Further Discussion: Integration of EI, IoMT and Healthcare Analytic

Based on our results, it is our understanding that the great potential behind the technology of EI in IoMT has the utmost contribution in the healthcare domain.

The studies in this research aim to present the complexity and the numerous ways that such prospective integration can be possible and transform real-time data analysis.

Various studies have assessed that IoMT, powered by wearable sensors, wireless communication technology, and real-time monitoring of patients (Putra et al., 2024; Tomer et al., 2024). Due to their benefits, proactive management of chronic conditions, diagnostics, and treatment plans is a reality. Nevertheless, from what we learn from the articles, its complexity can hinder effective control over the devices and the applications they support, making it essential to develop streamlined processes for their oversight and management.

In addition, EI, in collaboration with ML, FL, and EC, improves the efficiency of decision-making processes by facilitating faster data analysis within network nodes and offering notable advantages by being physically closer to end users. This strategic positioning enables swift data handling, significantly reducing latency and facilitating near-instantaneous responses (El-deep et al., 2025; Junaid et al., 2022). On the other hand, it allows organizations to implement effective internal firewalls by processing data locally, ensuring that sensitive information is accessible solely within their secure network.

We also acknowledge the significant limitations and challenges that arise, such as the absence of standardized protocols, which can create barriers to efficient data sharing and collaborative efforts (Majeed & Hwang, 2024; Manocha et al., 2024). Another issue is the lack of cooperation between edge devices, cloud resources, and network safety, and unfortunately, executing complex ML algorithms effectively can also be a barrier, which are essential for advanced analysis and decision-making (Aledhari et al., 2020; Kollu et al., 2023; Tariq et al., 2024)

Regarding the preservation of data privacy and a secure network, we are aware of their crucial role. Despite the fact that the real challenges lie in the complex architecture structures required to address the need to process, store, and transmit data across multiple layers (devices, edge networks, cloud), this increases the attack surface and privacy risks.

II.5. Conclusions

This article examines how integrating EI with the IoMT offers advantages for real-time healthcare data analysis. We identified that EI reduces latency by processing data closer to its source, which enables faster feedback and decision-making. This is therefore important for healthcare applications. Local processing also minimizes bandwidth consumption, thereby relieving pressure on healthcare networks and reducing the costs associated with transmitting large volumes of data to the cloud.

As EI-based IoMT networks expand, we believe that security and privacy concerns become increasingly significant. The risk of compromised sensitive health data necessitates robust security models at edge nodes. Additionally, vulnerabilities to cyberattacks also poses threats to data integrity and device functionality. This ensures security within IoMT systems, which is essential to protect data and maintain the reliability of healthcare services.

However, implementing this integration is not straightforward. Resource constraints on edge devices, interoperability issues, and a lack of standardization need further attention. That is, the need for distributed collaboration, and the complexity of managing edge devices, are significant limitations to consider.

In conclusion, the integration of EI and IoMT holds potential to transform real-time health data analytics, but it is crucial to recognize and address the above-mentioned concerns and challenges.

Moreover, when we search for IoMT, the articles that appear are more related to IoT devices than to IoMT, which make it difficult to encounter reliable information solely on IoMT without considering all the themes discussed above. Proving that IoMT still has plenty of room to develop before it can achieve widespread application. Lastly, we hope this study also provides a foundation for further research in this field, particularly the application (viability) of implementing IoMT on the national health system.

II.6. Appreciation

We would like to thank ISLA-Santarém for supporting and funding our participation in the 6th International Conference on Quality, Innovation and Sustainability (ICQIS 2025).

CONCLUSIONS

First of all, we would like to highlight that this master thesis had always the aim of filling a gap in the topic concerning the integration of Edge Intelligence (EI) in healthcare. Such matter represents a transformative shift from traditional centralized computing to decentralized, real-time processing at the edge of networks. This shift has enabled improvements in data privacy, reduced latency, faster clinical decision-making, and cost-effective resource management.

This research highlights a significant opportunity for the integration of AI, EC, and the IoMT in healthcare. By offering personalized, real-time services, this combination not only enhances patient care but also safeguards patient privacy and reduces reliance on cloud infrastructure. Furthermore, the systematic literature review conducted in this study unveils a notable surge in interest and development in this field, particularly in the wake of the COVID-19 pandemic, which revealed an urgent demand for remote, responsive, and secure healthcare solutions.

The integration of advanced technologies, particularly EI in conjunction with the IoMT, is transforming how healthcare data is processed and utilized. Through enabling real-time analysis and decision-making, these advancements are not only improving patient outcomes but also enhancing the overall efficiency of healthcare systems.

Despite these advantages, the adoption of EI still faces technical, ethical, and infrastructural challenges such as hardware limitations, security vulnerabilities, and lack of interoperability. However, ongoing advances in FL, reinforcement learning, 6G networks, and blockchain technologies are gradually addressing these barriers.

Moreover, allowing data to be processed locally, edge intelligence reduces the time required to analyze and act on critical health information. This is especially important for applications like continuous patient monitoring, early detection of medical emergencies, and personalized treatment plans. The use of edge computing, combined with federated learning and the IoMT, allows healthcare providers to deliver more responsive and individualized care while minimizing the risks associated with transmitting sensitive patient data over long distances or to centralized servers.

The systematic literature review conducted in this master thesis highlights that EI not only improves the efficiency and effectiveness of healthcare delivery but also enhances the reliability and scalability of health information systems. Innovations such as ultra-thin, skin-compatible sensors and on-device AI algorithms have made it possible to collect and analyze physiological data—like blood pressure, glucose levels, and heart rate—with unprecedented accuracy and immediacy. These advancements support proactive health management and facilitate the early identification of irregular patterns that could indicate health risks.

Despite these clear benefits, the implementation of EI in healthcare is not without obstacles. Technological challenges remain, such as the need for robust and secure infrastructures, standardization of data formats, and seamless interoperability between diverse devices and platforms. There are also significant concerns around data security, privacy, and compliance with regulatory frameworks, which must be addressed to build trust among patients and providers.

Additionally, this master's thesis highlights a gap in the large-scale, real-world deployment of EI solutions. Most current applications are still in experimental or pilot phases, indicating a need for further research and investment to move from theory to practice. Future studies should focus on developing standardized protocols, enhancing integration with existing healthcare systems, and exploring the ethical implications of decentralized data processing.

In summary, EI represents a promising path for digital innovation in healthcare, offering the potential to transform patient care, resource management, and health system efficiency. However, to realize its full potential, we must overcome technical, organizational, and regulatory challenges through ongoing research, cross-sector collaboration, and a commitment to patient-centered innovation.

An interesting future research will be to study the potential of develop lightweight and energy-efficient AI models suitable for deployment on edge devices with limited processing power. In light of this master thesis results, it will be relevant to investigate ethical and governance frameworks to guide the deployment of EI systems in healthcare while ensuring fairness, accountability, and transparency. These directions are essential to overcome current limitations and expand the safe and effective use of EI in clinical and operational healthcare settings.

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APPENDIX 1

Edge Intelligence in Logistics: Transforming Supply Chains for a Sustainable and Resilient Future

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Abstract: The combination of edge computing and artificial intelligence, known as edge intelligence, is driving innovation in the logistics sector. This technology transforms operational processes by enabling real-time data processing, in-creasing efficiency and meeting sustainability goals. By decentralizing processing, edge intelligence reduces delays, improves information security and provides localized decision-making. This study explores how this approach is being applied in key areas of logistics, including cold chain monitoring, last-mile deliveries, smart warehouse management, supply chain sustainability and logistics network security. Through a detailed literature review and case studies, the benefits, challenges and barriers to implement this technology are highlighted. Moreover, strategies to facilitate its large-scale adoption, as well as future trends, such as 6G and digital twins, are presented.

Keywords: *Edge Intelligence, Logistics, Supply Chain..*

1 Introduction

The Circular Economy (CE) emerges as an alternative to the linear economic model, proposing the maintenance of materials and products in continuous cycles, with a focus on reuse, recycling, and remanufacturing, thus reducing dependence on new resources and minimizing environmental impacts (Geissdoerfer et. al., 2017). On the other hand, Lean Management (LM) focuses on eliminating waste within production processes, promoting operational efficiency and value creation (Womack, 2007). The integration of these approaches offers a promising path for companies wishing to align economic efficiency with sustainable practices, responding to regulatory pressures and growing demands from conscious consumers.

The logistics sector has long faced persistent challenges, including inefficiencies in cold chain monitoring, high costs of last-mile deliveries, complexities of managing warehouse operations and increasing concerns over supply chain (SC) security. These challenges have been magnified by the increasing demand for real-time data, the rapid expansion of e-commerce, the global emphasis on sustainability, and intensified expectations for delivery and accuracy (Gani, 2017; Lv & Shang, 2023; Montanari, 2008). Traditional logistics systems often struggle with delays in data processing, security vulnerabilities, the agility required to adapt to dynamic supply chain environments, and the inefficiency of integrating emerging technologies with legacy systems (Shi et al., 2016; Villar-Rodriguez et al., 2023).

Edge Intelligence (EI), which combines edge computing (EC) and artificial intelligence (AI), offers a transformative approach to addressing these issues. By decentralizing data processing and enabling localized decision-making, EI reduces latency, enhances operational efficiency, and improves data security (Singh & Gill, 2023). For example, EI enables real-time monitoring of temperature-sensitive goods in cold chains (Chaudhuri et al., 2018; Montanari, 2008), supports route optimization in last-mile logistics (Peng et al., 2024; Raj et al., 2024), and enhances inventory management through intelligent warehouse automation (Acharya et al., 2024; Bormann et al., 2019). Additionally, its alignment with sustainability objectives makes it a critical tool for reducing waste, improving energy efficiency, promoting environmentally responsible practices, and optimizing resource utilization across SC operations. (Akbari, 2024; Bhattacharya et al., 2024).

This study explores the potential of EI in logistics by focusing on five key areas: cold chains, last-mile deliveries, warehouse automation, sustainability, and security. Through a systematic review of 28 peer-reviewed articles published between 2008 and 2024, the study identifies the benefits, challenges, and main opportunities associated with EI. By synthesizing insights from diverse sources, this article provides actionable recommendations for advancing the adoption and impact of EI in modern logistics operations.

Integrating CE and LM allows companies to improve their internal processes and extend the useful life of materials. This helps reduce the extraction of natural resources and waste generation. This alignment is facilitated by the advance of Industry 4.0 technologies, such as the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI), which enable real-time monitoring and dynamic adjustments to production flows (Ciliberto et. al., 2021). These technologies allow a more agile transition to circular and lean practices, increasing the overall efficiency of operations.

This study explores how integrating CE and LM can promote sustainable business models. Firstly, the fundamentals of these approaches and their relevance to the current context are analyzed. Next, successful examples in sectors such as automotive and consumer goods are presented to illustrate the practical benefits of this combination. Finally, the cultural and structural barriers that companies face when adopting these practices are discussed, as well as proposed strategies for overcoming these challenges. The relevance of the topic is evident in a scenario where sustainability is not only an environmental responsibility, but also a competitive advantage and a global market requirement (Kirchherr et. al., 2023; Kirchherr et. al., 2017).

Based on the examples presented and the analysis of the barriers faced, this study also proposes a theoretical framework that can guide companies from different sectors in the efficient implementation of these practices. This work therefore seeks to contribute to the construction of business models that reconcile economic growth and environmental responsibility, providing practical insights and strategies for facing new challenges.

2 Literature Review

EI has emerged as a transformative technology in logistics, addressing critical challenges across cold chains, last-mile deliveries, warehouse automation, sustainability, and security. This section synthesizes findings from the literature, highlighting key applications, benefits, opportunities and persistent challenges.

2.1 Cold Chains

EI has played a crucial role in optimizing cold chains, facilitating real-time monitoring, ensuring compliance with temperature regulations, and waste reduction. Montanari (2008) introduced a managerial vision for cold chain tracking, high-lighting the importance of using

IoT-based sensors to minimize losses and im-prove temperature monitoring [2]. Chaudhuri et al. (2018) broadened this discus-sion by addressing the use of big data (BD) and IoT to improve decision-making and reduce operating costs [7]. Recently, Lv & Shang (2023) investigated how intelligent transport systems (ITS) can optimize energy consumption in cold chains, contributing to lower emissions, however, high deployment costs remain a significant obstacle (Lv & Shang, 2023). Da Costa et al. (2022) complemented the discussion by exploring how real-time monitoring technologies can minimize food waste (Da Costa et al., 2022). Beyond temperature-sensitive goods, EI's capacity for real-time monitoring ex-tends into last-mile delivery, where it addresses logistical inefficiencies and delays.

2.2 Last-Mile Deliveries

Last-mile deliveries remain a high-impact area for IoT due to their complexity and costs. Raj et al. (2024) discussed the specific challenges of e-commerce, highlighting how IoT can mitigate hidden risks associated with these operations (Raj et al., 2024). Sawik (2024) presented an optimized approach to deliveries, using smart lockers and crowd shipping to increase efficiency. Peng et al. (2024) introduced EI to optimize delivery routes in dynamic scenarios, addressing complex route optimization challenges and demonstrating cost savings in e-commerce deliveries through edge-enabled route optimization. In addition, De Maio et al. (2024) investigated the use of autonomous robots in public transport net-works, providing more sustainable logistics solutions.

2.3 Warehouse Automation

Warehouse automation has been widely explored as a key application of EI and AI. Bormann et al. (2019) highlighted the use of robots powered by AI to increase productivity and reduce operational errors, though with high initial implementation costs. Van Geest et al. (2021) explored how AI can optimize storage and inventory management in smart warehouses. Acharya et al. (2024) advanced the discussion by introducing digital twins (DT) as tools to improve process control and real-time forecasting, while Andriulo et al. (2024) evaluated edge-cloud architectures to provide scalable IoT solutions. However, latency and system integration challenges still persist (Novák et al., 2015).

2.4 Sustainability

Sustainability is a cross-cutting theme in EI applications. Akbari (2024) demonstrated how edge architectures support circular economy (CE) objectives, high-lighting scalability as a critical barrier in applying EI to CE initiatives, while Bhattacharya et al. (2024) emphasized the role of AI in reducing waste and in-creasing traceability . Guo et al. (2024) presented the impact of AI on SC resilience, promoting operational flexibility, but pointed to high operational costs as a significant barrier. Olawade et al. (2024) discussed how AI can support green logistics goals, emphasizing sustainability metrics.

2.5 Security

Security is another critical component in the adoption of EI. Villar-Rodriguez et al. (2023) introduced frameworks to improve security in edge devices, while Rupanetti & Kaabouch (2024) explored the use of AI to prevent cyber-attacks. Ergen et al. (2024) highlighted how 6G networks can expand connectivity in logistics systems, but warned of security and standardization challenges [23]. Finally, Rodrigues & Marques (2023) and Shamsan Saleh (2024) investigated the role of blockchain in improving transparency and traceability in logistics operations, facing challenges such as scalability and the need for investment in infra-structure.

2.6 General Insights

In addition to specific areas, the literature points to general benefits of EI in logistics. Shi et al. (2016) provided an initial framework for EC, highlighting its ability to increase operational efficiency and reduce delays. Arena et al. (2024) explored a selection of algorithms for predictive maintenance, while Tafakkori et al. (2023) demonstrated the applicability of stochastic planning to deal with logistical uncertainties. These studies reflect the potential of in-formation systems to transform logistics operations holistically but also point to barriers such as initial costs and modelling complexity.

3 Methodology

This study employs an exploratory and qualitative approach to analyze the bene-fits, and challenges of EI in logistics. The research is based on a pre-selected set of 28 peer-reviewed articles, chosen for their relevance to the topic and their contribution to the understanding of key logistics domains: cold chains, last-mile deliveries, warehouse automation, sustainability, and security. (see Fig. 1).

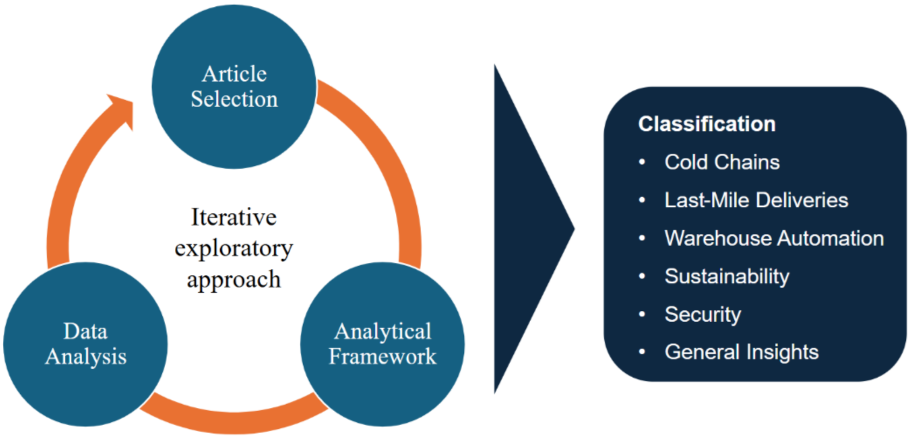

Fig. 1. *Methodology's exploratory and qualitative approach.*

3.1 Article Selection

The articles were identified through prior expert-driven selection, leveraging the Scopus database as the primary source. The criteria for inclusion were:

1. Relevance: the articles address applications of EI or closely related technologies in logistics;

2. Focus: emphasis on practical implementations and challenges within logistics, including domains like IoT, AI, EC, and sustainability;

3. Publication quality: articles published in recognized journals or conference proceedings between 2008 and 2024.

The selection process was guided by a thematic alignment with the study's objectives, ensuring that each article contributes with unique insights into the applications of EI in logistics.

3.2 Analytical Framework

The study adopts a thematic synthesis approach, categorizing the articles into five primary logistics domains:

1. Cold chains: monitoring and optimization of refrigerated SC;
2. Last-mile deliveries: efficiency improvements in the final stage of delivery;
3. Warehouse automation: automation and optimization within storage facilities;

4. Sustainability: contributions to environmentally friendly logistics practices including reverse logistics (RL);

5. Security: enhancements in data and operational security.

Thematic analysis was used to extract and synthesize:

- The technologies employed (e.g., IoT, AI, blockchain, edge architectures);
- The benefits highlighted (e.g., cost reduction, real-time monitoring);
- The challenges identified (e.g., interoperability, scalability, security risks).

3.3 Data Analysis

The analysis process included the following steps:

1. Categorization: each article was assigned to one or more logistics do-mains based on its primary focus;

2. Content extraction: key findings were extracted from each article, including methodologies and technologies used;

3. Cross-comparative analysis: findings across domains were compared to identify synergies, trends, and gaps in the application of EI in logistics.

This approach ensures a targeted and meaningful analysis by focusing on a carefully curated dataset that directly addresses the objectives of the study. The pre-selection of articles reflects an intentional effort to balance thematic scope with analytical depth, allowing for comprehensive insights into the evolving role of EI in logistics.

The following Table 1 categorizes the selected articles into thematic areas, de-tailing their focus, the technologies used, and the key benefits and challenges presented. It serves as a synthesis of the reviewed literature, facilitating an understanding of the state-of-the-art in EI applications within logistics. While this study offers a focused review, reliance on Scopus may have excluded relevant studies from other databases, and the absence of grey literature may limit insights from practical implementations.

Table 1. *Synthesis of applications, benefits and challenges of EI in Logistics.*

Category	Article Reference	Focus Area	Technology Used	Benefits Highlighted	Challenges Identified
Cold Chains	Montanari (2008)	Cold chain management	IoT sensors with EC	Real-time monitoring, reduced losses	Integration of IoT with logistics
	Chaudhuri et al. (2018)	Cold chain data analytics	BD and IoT	Enhanced decision-making, cost savings	High investment in data systems
	Lv & Shang (2023)	Cold chain energy optimization	ITS for energy conservation	Lower emissions, energy savings	High deployment costs
	Gani (2017)	Logistics performance in international trade	Global Logistics and IoT	Strengthening of logistics competitiveness	International regulatory barriers
	Da Costa et al. (2022)	Monitoring food waste	IoT and real-time technologies	Reducing losses and increasing efficiency	Reliance on robust sensors
Last-Mile Deliveries	Raj et al. (2024)	Last-Mile E-commerce Logistics	IoT for Last-Mile Efficiency	Reduced risks in e-commerce logistics	Hidden risks in e-commerce logistics
	Sawik (2024)	Last-Mile Delivery Optimization	Smart Lockers and Crowdshipping	Improved delivery efficiency	Scalability of smart locker networks
	Peng et al. (2024)	Dynamic Route Optimization	Edge AI for Route Planning	Efficient delivery route management	Complex route optimization

	De Maio et al. (2024)	Autonomous robots in public transport	Robotics and integrated transport	More sustainable logistics	Infrastructure for robot support
Warehouse Automation	Bormann et al. (2019)	Warehouse Robotics	AI-Powered Robots	Enhanced productivity, error reduction	High upfront investment
	Van Geest et al. (2021)	Smart Warehousing	AI in Warehousing	Optimized storage and inventory	Compatibility of warehouse systems
	Acharya et al. (2024)	Interoperability in Digital Twins	Digital Twins and EC	Better process control and prediction	Lack of standardization and interoperability
	Andriulo et al. (2024)	Edge-Cloud Architectures for Warehousing	Edge-Cloud Architectures	Scalable IoT solutions	Latency in edge-cloud frameworks
	Novák et al. (2015)	Integration of Engineering Knowledge	Simulation and Modeling Tools	Efficient support for industrial modeling	Challenges in the integration of diverse systems
Sustainability	Akbari (2024)	Edge in Circular Economy	Edge Architectures	Support for circular economy goals	Scalability in circular economy applications
	Bhattacharya et al. (2024)	AI in Closed Chains	AI	Waste reduction and greater traceability	Technological barriers

	Olawade et al. (2024)	AI for Net Zero Logistics	AI for Sustainability Metrics	Support for green logistics goals	Data accuracy in sustainability metrics
	Guo et al. (2024)	Supply chain resilience	AI for sustainability	Operational robustness and flexibility	High operating costs
Security	Villar-Rodriguez et al. (2023)	Security in Edge Computing	Edge Security Frameworks	Enhanced security for edge devices	Security risks in decentralized systems
	Shamsan Saleh (2024)	Blockchain in AI Security	Blockchain Scalability Challenges	Enhanced trust in AI systems	Blockchain scalability challenges
	Rodriges & Marques (2023))	Blockchain for Logistics Optimization	Blockchain in Logistics Networks	Transparency and traceability	Need for infrastructure investments
	Ergen et al. (2024)	Future netwoks with EC	IoT and 6G	Expanded connectivity and new capabilities	Security and standardization in 6G networks
	Rupanetti & Kaabouch (2024)	Safety with AI and EC	IoT and Edge AI	Prevention of cyber attacks	Dependency on device integration
	Singh & Gill (2023)	Edge AI and safety	EI frameworks	Better management of security risks	Implementation barriers in global networks
General insights	Shi et al. (2016)	General Framework for Edge Computing	Edge Computing and IoT	Quick response and increased operational efficiency	Initial adoption barriers

Arena et al. (2024)	Algorithm Selection for Predictive Maintenance	AI and Machine Learning	Optimization of maintenance processes	High initial costs
Habibi et al. (2023)	Resilience of Logistics Networks	Disruption Modeling	Improved responsiveness to interruptions	Complexity in modeling
Tafakkori et al. (2023)	Robust Planning in Supply Chains	Stochastic Planning	Ability to handle uncertainties	Scalability barriers

4 Discussion

EI is increasingly recognized as a transformative solution in logistics, addressing inefficiencies and enabling sustainable practices. By synthesizing the findings from the literature review, this discussion explores how EI supports key logistics domains—cold chains, last-mile deliveries, warehouse automation, sustainability, and security—while identifying the challenges that must be overcome to enable its widespread adoption.

4.1 Applications and Benefits of EI

EI has shown significant promise in cold chain management, addressing the critical need for real-time monitoring of perishable goods. Technologies such as IoT sensors and edge computing have improved decision-making and reduced losses in refrigerated (Chaudhuri et al., 2018; Montanari, 2008). However, the high cost of integrating IoT with existing systems remains an obstacle. Recent studies suggest that leveraging intelligent transportation systems (ITS) can enhance energy efficiency not only by reducing waste but also in aligning with broader sustainability goals by minimizing energy consumption (Lv & Shang, 2023). Yet, the deployment costs associated with such technologies may delay broader adoption.

In last-mile logistics, EI has the potential to revolutionize last-mile logistics by optimizing delivery routes and addressing hidden risks in e-commerce supply chains (Peng et al., 2024; Raj et al., 2024). For example, EI technologies like dynamic route optimization have shown potential to reduce delivery times, as demonstrated in studies by Peng et al. (2024). Dynamic route optimization using edge AI has demonstrated in-creased efficiency, while innovations such as smart lockers and autonomous robots are improving sustainability and customer satisfaction (De Maio et al., 2024; Sawik, 2024). Despite these advancements, challenges such as scalability and the complexity of route planning systems need to be resolved to ensure widespread implementation.

Warehouse automation is another area where EI has shown remarkable potential. The integration of EI in warehouse automation has resulted in enhanced inventory management and process optimization. AI-driven robotics and edge-cloud architectures have been pivotal in increasing productivity and reducing operational errors (Bormann et al., 2019; Van Geest et al., 2021). However, barriers such as the high upfront costs of automation and the lack of standardization in digital twin (DT) technologies persist(Acharya et al., 2024). Addressing these issues will require collaboration between technology providers and logistics operators to establish scalable and interoperable solutions.

Sustainability goals are closely aligned with EI's capabilities. Studies have demonstrated the role of edge technologies in promoting green logistics through waste reduction, improved traceability, energy efficiency, and the adoption of renewable energy solutions (Akbari, 2024; Bhattacharya et al., 2024). However, achieving scalability in CE applications and ensuring data accuracy in sustainability metrics remain significant challenges(Guo et al., 2025; Olawade et al., 2024). Future research should focus on creating cost-effective solutions that align with global environmental goals.

Finally, security continues to be a critical factor in the adoption of EI. Advances in edge security frameworks and blockchain technologies have enhanced trust and transparency in logistics operations (Shamsan Saleh, 2024; Villar-Rodriguez et al., 2023). However, risks such as cyberattacks and interoperability challenges with DT highlight the need for robust and decentralized solutions [22, 24]. Emerging technologies like 6G could expand the capabilities of EI but also introduce new challenges related to standardization and network security (Ergen et al., 2024).

4.2 Challenges and Future Directions

Despite its clear benefits, several barriers impede the broader implementation of EI in logistics. Interoperability is a recurring issue, as many legacy systems lack compatibility with modern EC architectures (Acharya et al., 2024). High implementation costs and the technical expertise required to deploy EI solutions also ask for significant challenges

(Andriulo et al., 2024) . Furthermore, data security and privacy concerns must be ad-dressed, particularly in decentralized systems where vulnerabilities can propagate rapidly (Villar-Rodriguez et al., 2023).

Future research should focus on addressing these challenges through the development of interoperable standards, cost-effective deployment strategies, and robust security protocols and advanced training programs for workforce adaptation. The integration of emerging technologies such as DT and 6G networks with EI presents exciting opportunities for further enhancing logistics operations (Acharya et al., 2024; Ergen et al., 2024). Additionally, cross-industry collaboration between academia, industry, policymakers and providers of technology is crucial to overcoming regulatory barriers and promoting the widespread adoption of EI.

5 Conclusion

EI is transforming the logistics sector by addressing persistent challenges and introducing innovative solutions across cold chains, last-mile deliveries, warehouse automation, sustainability, and security. By decentralizing data processing, EI enhances real-time decision-making, reduces latency, improves operational efficiency, and strengthens data security across decentralized systems, positioning itself as a critical enabler of resilient and sustainable SC.

The findings from this study highlight EI's capacity to optimize logistics operations, such as real-time monitoring in cold chains (Chaudhuri et al., 2018; Montanari, 2008), dynamic route optimization for last-mile deliveries (Peng et al., 2024; Raj et al., 2024), and intelligent inventory management in ware-houses through robotics and digital twins (Acharya et al., 2024; Bormann et al., 2019). Furthermore, EI aligns with sustainability objectives by supporting CE practices and reducing waste (Akbari, 2024; Bhattacharya et al., 2024). Security frameworks leveraging EI and blockchain technologies further reinforce its role in safeguarding logistics networks (Shamsan Saleh, 2024; Villar-Rodriguez et al., 2023).
Despite these benefits, the study also identifies significant challenges that de-lay the broader adoption of EI. Interoperability issues and security concerns re-main critical barriers. Additionally, reliance on Scopus for article selection and the exclusion of grey literature limits the scope of this study. Future research should address these limitations by expanding data sources, incorporating quantitative methods, analyzing the scalability of EI solution and

exploring the integration of emerging technologies such as 6G and digital twins (Acharya et al., 2024; Ergen et al., 2024).

Collaborative efforts among peers are essential to overcome these barriers and promote the widespread implementation of EI. By developing standardized protocols, cost-effective deployment strategies, robust security measures, advanced workforce training programs, and enhanced interoperability frameworks, the logistics sector can unlock the full potential of EI paving the way for more efficient, resilient, digitally integrated, and environmentally conscious global supply chains.

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