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Determination of Driving Power and Dependency of Wastes in the Healthcare Sector: A Lean and ISM-Based Approach

Abstract

Purpose: The objective of this study is to systematically identify, categorize, and assess the driving factors and interdependencies associated with various types of healthcare waste. The study specifically focuses on waste that has been managed or is recommended for treatment through the application of Lean Six Sigma (LSS) methodologies.

Design Methodology/Approach: To accomplish the study's objectives, Interpretive Structural Modeling (ISM) was utilized. This analytical tool aided in quantifying the driving power and dependencies of each form of healthcare waste, referred to as 'enablers,' as well as their related variables. As a result, these enablers were classified into four distinct categories: autonomous, dependent, linkage, and drivers or independents.

Findings: In the healthcare sector, the 'high cost' emerges as an autonomous variable, operating with substantial independence. Conversely, variables such as skills wastage, poor service quality, and low patient satisfaction are identified as dependent variables. These are distinguished by their low driving power and high dependency. On the flip side, variables related to transportation, production, processing, and defect wastes manifest strong driving forces and minimal dependencies, categorizing them as independent factors. Notably, inventory waste is highlighted as a salient issue within the healthcare domain, given its propensity to engender additional forms of waste.

Research Limitations/Implications: Employing the ISM model along with comprehensive case study analyses provides a detailed framework for examining the complex hierarchies of waste existing within the healthcare sector. This methodological approach equips healthcare leaders with the tools to accurately pinpoint and eliminate unnecessary expenditures, thereby optimizing operational efficiency and enhancing patient satisfaction. Of particular significance, the study calls attention to the key role of inventory waste, which often acts as a trigger for other forms of waste in the sector, thus identifying a crucial area requiring focused intervention and improvement.

Originality/Value: This research reveals new insights into how waste variables are structured in healthcare, offering a useful guide for managers looking to make their waste reduction strategies more efficient. These insights are highly relevant not just for healthcare providers, but also for the administrators and researchers who are helping to shape the industry. Using the classification and ranking model developed in this study, healthcare organizations can more easily spot and address common types of waste. In addition, the model serves as a useful tool for practitioners, helping them gain a deeper, more detailed understanding of how different factors are connected in efforts to reduce waste.

Keywords: Healthcare waste, Lean Six Sigma, Waste Management, Driving power and Dependency, ISM model

I. Introduction

Industrial waste has long been a major concern since the beginning of the industrial revolution (Almorsy & Khalifa, 2016). The development of industrial diversification, combined with the expansion of healthcare facilities, has led to an increased output of hazardous industrial and biomedical waste, each with its unique and potentially serious environmental consequences (Andersson & Pardillo-Baez, 2020; Yazdani et al., 2020). In the healthcare sector, a whopping 85% of waste is regarded as non-hazardous, whereas a smaller yet significant portion, comprising 15%, raises alarms due to its potentially infectious, chemically reactive, or radioactive characteristics, as highlighted by Torkayesh et al. (2021). This latter category of waste has the potential to transmit diseases to patients, healthcare workers, and the wider community (Das et al., 2021; Kumar et al., 2022F). For instance, healthcare sharps such as needles, if improperly disposed of, can pose a significant threat to those who come into contact with them. Geetha et al. (2019) point out the risk of spreading drug-resistant organisms from healthcare facilities to the surrounding environment.

Recent studies show that the majority of healthcare waste is generated from medical centers and research laboratories. However, additional areas such as storerooms, transportation logistics, and the movements of medical staff within healthcare facilities also require immediate attention (Avadhut & Uike, 2021; Iyengar et al., 2020). Effective waste management is considered a crucial component of healthcare hygiene, essential in ensuring the smooth and safe operation of healthcare services for both staff and patients (Andreamatteo et al., 2015). As a result, existing studies emphasize the importance of skillful healthcare waste management as a critical area of concern

(Ahmed et al., 2013; Das et al., 2021; Khorasani et al., 2020). Industry experts advocate for a comprehensive understanding of waste classifications, volumes, and attributes as essential building blocks for designing effective and economically sustainable waste management strategies (Al-Qatawneh et al., 2019; Hicks et al., 2015; Spagnol et al., 2013). Specifically, such a detailed understanding enables healthcare institutions to prioritize areas of intervention, allocate resources more efficiently, and tailor strategies that are both environmentally responsible and financially prudent.

The healthcare sector in India, a diverse collection that includes hospitals, medical tourism, telemedicine, and related fields, is experiencing substantial growth (Maggon & Chaudhry, 2018). This trend is propelled by broader service availability, diversified offerings, and significant investments from both public and private sectors. The hospital industry alone accounts for 80% of the market and attracts major domestic and international capital. Revenue for the healthcare market stood at US$86 billion in 2016 and is projected to swell to US$367 billion by 2023 and US$638 billion by 2025. In parallel, this boom has triggered the adoption of complex waste management methods such as recycling, radiation treatment, and incineration (Ramori et al., 2021; Raval et al., 2021). Recent years have seen a rise in specialized forms of waste like electronic waste or e-waste, encompassing discarded computers and medical equipment (Tortorella & Fettermann, 2018), as well as an increase in pharmaceutical waste, marked by surplus medications and vaccines. These evolving dynamics necessitate Lean Six Sigma (LSS)-based projects aimed at operational efficiency and waste minimization, contributing to a culture of ongoing improvement and sustainability (Bateh & Farah, 2017; Rodgers & Antony, 2019). Accordingly, scholarly works highlight the value of LSS in controlling process variability, waste elimination, and defect identification (Gaikwad & Sunnapwar, 2020; Iyede et al., 2018; McDermott et al., 2022a, b; Martin, 2021; Rejikumar et al., 2020).

LSS methodologies demonstrate their potential to aid healthcare organizations by expediting waste management initiatives and focusing more on patient-centered values (Pakdil et al., 2020). Scholars such as Park et al. (2020) advocate that healthcare organizations that embrace LSS concepts can realize substantial reductions in errors and costs and elevate overall patient satisfaction. Moreover, Gaikwad and Sunnapwar (2020) elucidate how LSS facilitates the integration of organizational strategies, structure, culture, and value-stream mapping. Paez et al. (2004) further illustrate how waste reduction can improve the dynamic process and thus increase the overall efficiency of value chain activities. The empirical research underscores that even incremental adaptations rooted in LSS principles can promote effective knowledge communication and cultivate a collaborative learning environment. Rejikumar et al. (2020) highlight how LSS concepts can foster medical operations that are adaptable to fluctuating patient needs. Adoption of LSS principles, as posited by Majava and Ojanpera (2017), could lead healthcare organizations toward overall waste reduction, cost minimization, and heightened patient satisfaction.

To encapsulate, while the LSS methodology emerges as a potent framework offering enriched value to patients via an optimized resource management strategy (Martin, 2021), current research landscapes somewhat overlook thorough explorations into the dimensions, categorizations, and hierarchical evaluations of wastes (McDermott et al., 2022a). This underscores an imperative for more nuanced inquiries to glean a comprehensive perspective on the complexities of the healthcare sector. Despite the focus of earlier studies on cost reduction and enhancing patient satisfaction, a significant gap persists in comprehensive investigations that utilize the Lean Six Sigma methodology (Panayiotou & Stergiou, 2020; Raval et al., 2021). While the healthcare domain has witnessed the initiation of LSS projects, a consolidated representation delineating their outcomes is conspicuously absent. Notably, a significant fraction of LSS case studies have their roots in sectors other than healthcare, presenting a sparse picture of its ramifications within the healthcare arena (McDermott et al., 2022b). This study aims to address these noticeable gaps in the current literature by providing an in-depth analysis of successful Lean Six Sigma projects in healthcare settings. It summarizes their effects on waste management and methodically classifies various types of waste to inform future remediation efforts.

The findings of this study will provide hospital management teams with powerful tools to rank and control waste effectively, thereby contributing to an enhanced patient satisfaction paradigm—a growing goal within the healthcare sector. In accordance with this aim, the subsequent research objectives have been established:

1. To undertake a comprehensive literature review aimed at assembling a database of healthcare wastes that have been both identified and mitigated through the implementation of Lean Six Sigma (LSS) practices within the healthcare sector.
2. To systematically categorize and critically examine the key drivers and dependencies associated with the healthcare wastes identified, with the intent of deepening the understanding of their inherent dynamics and interdependencies.

3. To prioritize and rank healthcare wastes—commonly referred to as 'enablers'—and their corresponding variables within the healthcare context. This objective seeks to clarify the underlying factors and mechanisms that govern the relationship between waste components and their respective outcomes.
4. To develop and formalize an Interpretive Structural Modeling (ISM) framework that succinctly captures the intricate relationships and complexities prevalent in healthcare waste management. This model aims to serve as both a visual guide and a decision-support tool for future waste management initiatives.

2. Literature Review on LSS Applicability in the Healthcare Sector

In this study, the literature review is divided into two parts. The first section highlights the results of some successful LSS-based projects in the healthcare industry. The second section includes a table that summarizes the relevant literature on healthcare waste according to the main principles of LSS.

2.1 Literature Review on LSS Projects in the Healthcare Sector

The following three points emerged during the initial review of pertinent literature:

1. The number of clinical research studies exploring the implementation of lean thinking in healthcare has increased in recent years.
2. Numerous studies assert the importance of prioritizing optimization by identifying value-added tasks from the patient's perspective and applying them to waste-reduction services. During the literature review, it was found that LSS has been widely employed to improve the operational efficiency of clinical procedures.
3. Various practitioners have identified effective methods for implementing LSS in the healthcare industry.

However, their findings need to be collected and presented on a centralized platform. The authors attempt to close this gap in the literature in the following paragraphs.

In 2001, the Virginia Mason Medical Center took inspiration from Toyota's waste management principles after visiting Japan. The goal was to make patient care more efficient. Using "lean thinking," they removed unnecessary steps in their process. By improving technology, reorganizing doctors' workstations, and starting team consultations at patients' bedsides, they cut down on wait times and made better use of operating room equipment (Pakdil et al., 2020; Kharub et al., 2023). They also used generic drugs instead of brand names and added automatic safety alerts, which helped reduce mistakes. Almorsy and Khalifa (2016) argued that these methods could be used by other medical institutions to find and reduce waste.

Improta et al. (2018) utilized lean thinking in the emergency department at Cardarelli Hospital in Naples, which had been notorious for its overcrowding and lengthy wait times. The delays and patient mortality were recorded as high, and resources were identified as areas where efficiency could be improved. These issues had been detrimental to both staff and patient satisfaction. However, after implementing the LSS project, researchers were able to enhance patient flow, optimize the processes that facilitate patient flow through various stages of medical treatment, and remove many bottlenecks (Olese et al., 2015)

In a parallel study, Lot et al. (2018) employed lean thinking and action research to gather data. They specifically utilized personal observations, interviews, and team brainstorming. These authors created a value stream map, identified opportunities for simplification, and eliminated non-value-added activities (Teichgraber & de Bucourt, 2012). During the assessment, they discovered severe problems and applied and evaluated solutions. The immediate remedial action indicated was a slight modification of the schedule pattern; moreover, adopting a flow chart and a surgical technologist Kanban visual guide were recommended.

By offering an online schedule option for healthcare visits, Lot et al. (2018) managed to decrease patient wait time, cutting it in half after the LSS project. Exceptional data quality also increased by 50%. Initially, procedural sequences were constructed, resulting in a culture of perpetual development. It was observed that LSS initiatives allowed processes to generate value while incurring minimal costs. Another observation was that tools like the Gemba Walk were excellent for engaging people and processes with a Kaizen mindset (Tyagi et al., 2021).

Zhuo (2019) and Ahmed et al. (2013) have emphasized the importance of tactics for dealing with dissatisfied patients, which must not be overlooked. Healthcare personnel were found to need more time with dissatisfied patients, and proactive communication with them was advised in adherence to the LSS approach to consumer engagement. Furthermore, Almorsy & Khalifa (2016) noted that to meet ever-changing patient needs, LSS helps create an environment where individuals feel empowered and motivated to contribute ideas.

The current literature frequently discusses the necessity for innovative patient care strategies (Martin et al., 2011). However, the importance of establishing a culture that enables healthcare professionals to make continuous improvements should be noted (Lizarelli et al., 2021). Factors such as the unproductive use of resources, misalignment of incentives, and lack of coordination were cited as primary reasons for the failure of healthcare improvement projects. These failures ultimately had a negative impact on healthcare quality, cost, and outcomes. Integrated delivery systems (IDS) have been specifically recommended in numerous studies to enhance healthcare service quality, outcomes, and costs, particularly for patients with complex needs (Al-Saddique, 2018; Jones et al., 2017). Researchers found that the LSS model in businesses promotes consistent training and assessment by professionals, increasing awareness about various types of waste such as transport, inventory, motion, waiting time, overproduction, overprocessing, defects, and skills (TIMWOODS; Andreamatteo et al., 2015; Narayanamurthy et al., 2018). Antony et al. (2018) compared quality models to control these wastes and found Six Sigma particularly effective in reducing medical mistakes and enhancing care delivery systems. Six Sigma has been shown to reduce medical mistakes and make care delivery systems more efficient, which means fewer patients and employees are on standby (Bharsakade et al., 2021).

Additionally, the proactive maintenance project under Six Sigma prevented equipment breakdown, enhancing care service and patient satisfaction (Robinson et al., 2012). Al-Qatawneh et al. (2019) created an inventory model indicating that excess supplies and redundant data constituted inventory waste, increasing the risk of theft or obsolescence. Employees can be trained to recognize surplus inventory and devise methods to reduce it through the LSS program (Ahmed et al., 2013). Likewise, Bharsakade et al. (2021) depicted defect waste in the healthcare sector as including system failures and medical errors. Specific examples are infections incurred during healthcare, errors in surgical procedures, avoidable allergic reactions, and incorrect medical records. The authors recommend leveraging lean principles to encourage healthcare staff to eliminate this defective waste, enhancing quality and reducing costs and errors.

In conclusion, although existing literature has explored the impact of LSS on diverse types of waste in the healthcare industry, no previous research has specifically focused on identifying and categorizing these wastes. This current study, however, embarks on the effort to arrange these wastes into the widely recognized eight types of lean waste, known colloquially as TIMWOODS. An overview of these findings is provided in Table 1.

Table 1. A Brief Summary of Waste in the Healthcare Setting.

Wastes	Description	References
Transport waste (TW)	Inefficiencies in the transportation of materials and patients invariably lead to time and resource waste. Such inefficiencies manifest when medication is transported from the pharmacy to its designated administration point, or when materials are moved from storage facilities to active care floors. Moreover, patients frequently navigate between different hospital buildings to access diverse care elements, which further exacerbates transportation inefficiencies. While transportation remains an inherent component of healthcare provision, certain transportation modes are discerned as non-value-adding and are thus earmarked for reduction. This "transportation waste" encompasses superfluous movements of patient test samples, medications, and other supplies. Given that numerous hospital infrastructures adhere to a process-oriented layout, a strategic design of these establishments can substantially curtail such nonessential movements.	Agrawal et al. (2019) and Ramori et al. (2021)
Inventory waste (IW)	Inventory waste is any supply that is either surplus or unavailable when needed. A hospital needs a wide range of equipment and supplies to do its job. Keeping excess materials creates inventory. More inventory often leads to cash shortages. Some inventory, like supplies and medications, may expire. An example of inventory waste in healthcare is that keeping patients longer than necessary can prevent another patient from using the facility. Healthcare inventory management is vital for system quality and delivery efficiency. The LSS philosophy prioritizes patient care while minimizing inventory. For example, hospitals should stock up on emergency medications in an emergency. Extensive inventories may be cheaper, but they can cause unnecessary movements, inefficient procedures, or patient injury if not properly managed. Inventory management can also help hospitals reduce other waste. Excess patient data storage is one example of inventory waste. Extra information waste can decrease efficiency, cause treatment delays, and increase healthcare complexity. More data are needed to complete the healthcare process, while abundant data necessitate more work to capture, store, search, and manage. In addition, investigations must quickly gather relevant data to be used later.	Teichgraber and de Bucourt, (2012), Olese et al. (2015), and Ahmed et al. (2013)
Motion waste (MW)	Waste of motion in the healthcare system refers to employees' excessive movements. Therefore, the healthcare process must run smoothly to avoid motion waste. Employees walking around a hospital to treat patients commit the most common form of motion waste. Despite being unable to remain stationary in a hospital, medical professionals must avoid unnecessary movements. There are frequent team member movements because the hospital's layout could be more efficient. When delivering services to a patient, employees must travel from where they are based on need. Workers might be forced to move around too much if necessary equipment is not in the right place. Motion waste must be eliminated in any healthcare setting because it adds no value. Additionally, motion waste can result in a delay in the delivery of care to the patient. A more efficient layout can reduce motion waste.	Almorsy and Khalifa (2016), Avadhut and Uike (2021), Iyengar et al. (2020), and McDermott et al. (2021)
Waiting time waste (WTW)	Waiting, in operational terminology, denotes an interval characterized by patient inactivity, precipitated by lags in subsequent stages of a procedure. This stagnation can arise due to imbalanced task allocation, causing employees to experience intervals of inactivity during certain phases of an operation. Within the healthcare milieu, it is commonplace for patients to endure waits for physician diagnoses, hospital admissions, or discharges. Patient backlogs in numerous healthcare procedures are often attributed to suboptimal scheduling practices. It is not uncommon for hospitalized individuals to await the outcomes of pathology or radiological assessments, given that such evaluations underpin the	Robinson et al. (2012) and McDermott et al. (2022b)

	majority of contemporary diagnostic decisions. The intricacy inherent in the setup of many healthcare procedures further contributes to delays. Optimizing efficiency in medical evaluations necessitates judicious resource utilization, fostering streamlined procedures.	
Overproduction (OPR)	Overproduction, within the context of operational efficiency, refers to the generation of goods in excess of what is immediately required by subsequent processes or operations, or completing tasks ahead of stipulated schedules. Consider the challenges faced by researchers attempting to discern superfluous utilization of healthcare resources: Directly identifying unnecessary procedures or an overprescription of medication proves elusive. Studies have indicated a propensity for investigators to recommend redundant tests, including surgical and imaging diagnostics. Moreover, there is an observed trend toward suggesting scheduled follow-ups, leading to the manifestation of waste stemming from overproduction. The paradigm of imposing treatments upon patients, albeit seemingly advantageous in specific scenarios, can inadvertently amplify the workload for both the healthcare provider and the patient. Another consequence of overproduction is its potential to mask other forms of waste; for instance, pharmacists may allocate extended periods to manage returned medications. Conversely, increased testing frequency might expedite patient flow within a healthcare facility, necessitating augmented personnel mobilization.	Tortorella and Fettermann (2018) and Majava and Ojanpera (2017)
Overprocessing (OVP)	Overprocessing refers to the unwarranted or excessive steps taken in a procedure that do not add value or are redundant from the outset. Often in healthcare, overprocessing emerges when medical practitioners aim for a level of quality that surpasses the patient's actual needs or expectations. A salient example of this is the mandate for repeated pathological tests, despite their redundancy. It is not uncommon for a surplus of blood tests to be prescribed beyond the actual necessities. Overprocessing can also manifest in the recurrent collection of redundant patient data, such as acquiring an exhaustive patient history during every visit, irrespective of its pertinence. Some healthcare providers might replicate specific procedures under the guise of offering thorough care, even they are superfluous. Communication gaps within the workforce can further exacerbate the prevalence of overprocessing.	Al-Qatawneh et al. (2019), Hicks et al. (2015), Spagnol et al. (2013), Rejikumar et al. (2020), and Antony et al. (2021)
Defects waste (DW)	Tasks that are completed improperly are referred to as defects. In healthcare, mistakes carry particularly grave consequences, as they can result in injury or even death. Such errors often stem from procedural missteps, communication breakdowns, or misdiagnoses. For instance, during a surgical procedure, miscommunication can lead to wrong-site surgery, while carelessness might result in foreign objects remaining inside a patient postoperation. Moreover, precise calibration of healthcare equipment is imperative. Otherwise, it could yield inaccurate results and subsequently lead to misdiagnoses. Conversely, not every error necessarily results in harm. However, procedural inconsistencies may, in some cases, necessitate revisions. In certain scenarios, a misdiagnosis could lead to patient readmission. Many errors in healthcare arise from flawed processes, potentially delaying patient treatment. Defects not only waste time and money but also contribute to patient dissatisfaction.	Yazdani et al. (2020), Torkayesh et al. (2021), Das et al. (2021), Andreamatteo et al. (2015), and Rodgers and Antony (2019)
Skills waste (SW)	The eighth form of waste pertains to the underutilization of human potential and creativity. This type of waste materializes when healthcare institutions establish rigid demarcations between the roles of technical and nontechnical personnel. For instance, in certain healthcare environments, the technical staff assumes responsibilities for designing, coordinating, managing, and refining testing facilities. Concurrently, the support staff is tasked with equipment transportation, patient reporting, and maintaining routine schedules. However, procedural enhancement becomes challenging when technical	Gaikwad and Sunnapwar (2020), Pakdil et al. (2020), and

	personnel are engaged in tasks such as inventory movement or when physicians are relegated solely to administering tests. This is predicated on the understanding that those directly involved in a task are ideally positioned to identify challenges and devise solutions. Consequently, such misallocations lead to a squandering of expertise.	Paez et al. (2004)
Impact of Waste on Resulting Variables in the Healthcare Sector		
High patient waiting time (HPWT)	Long patient waits times, stemming from excessive waste, can undermine doctor–patient trust. This is a perilous situation in an era characterized by collaboration, action, organization, and a populace that is increasingly skeptical. Though seemingly inconspicuous, the most significant wastes in hospitals often remain hidden, unacknowledged by the healthcare industry. These may include avoidable mistakes that healthcare professionals inadvertently repeat, thus creating potential inefficiencies. Fortunately, there exist tangible strategies to alleviate patient wait times. The solution lies in the implementation of task division, coupled with the integration of practice schedules and methodologies that actively engage staff insights. As a result, healthcare practices are likely to witness enhanced efficiency, culminating in increased patient satisfaction and loyalty. This strategic approach not only promotes a streamlined patient experience but also fosters a culture of continuous improvement within healthcare institutions.	Narayanamurthy et al. (2018)
Low-quality service (LQ)	There exists substantial inefficiency within the healthcare system, characterized by waste that renders processes slow and ineffective. For instance, employees endowed with crucial problem-solving skills are frequently relegated to tasks such as inventory management or superfluous transportation—inefficiencies stemming from overprocessing and overproduction that culminate in inordinate resource consumption and repetitive process execution. Conversely, unforeseen machinery and equipment malfunctions often translate into extended patient wait times, leading to significant dissatisfaction.	Spagnol et al. (2013)
High cost (HC)	Depending on the specific type of waste generated within the healthcare system, the associated costs can vary dramatically. Typically, these expenditures are categorized under three main headings: raw material, labor, and waste management. Such wastes not only prolong the overall process but also diminish service efficiency. Consequently, they escalate the total cost of the patient's bill, undermining both affordability and the effective delivery of care.	Leite et al., (2020)
High patient dissatisfaction (HPD)	Prior to implementing any modifications within healthcare services, it is imperative to ascertain whether such changes would align with patients' needs and provide the highest attainable level of quality commensurate with their expectations. The importance of addressing dissatisfaction among patients cannot be overstated. When healthcare professionals are disproportionately engaged in addressing new patient interactions, there is a propensity to neglect spending adequate time with contented clients. By employing LSS methodologies, one can strategically schedule time and delineate objectives for patient outreach, placing an emphasis on proactive engagement with satisfied clients.	Bharsakade et al. (2021)

2.2. Framework Development

Every quality improvement initiative in healthcare must commence with a well-defined objective. Utilizing structured frameworks and roadmaps is essential in maintaining control over measurements throughout this complex journey. The literature review conducted in this study identified eight predominant types of waste within the healthcare industry. A critical redefinition of the identified waste is imperative before integrating it into our conceptual framework. Within the context of the literature review, waste is delineated as any activity or step within a process that fails to impart value to the patient. In more precise terms, waste encapsulates any procedure or process for which the patient would be disinclined to incur a cost.

Taiichi Ohno, Toyota's Chief Engineer, created the first seven wastes (Muda) as part of the Toyota Production System (TPS), and they are often abbreviated as "TIMWOOD". The eighth waste of underutilized talent, or "Skills," of employees was introduced in the 1990s with the adoption of the TPS in the Western world. A framework presenting TIMWOODS wastes in the healthcare sector is provided in Figure 1. The classification of various waste streams in the healthcare sector is meant to assist academics and practitioners in creating LSS-based initiatives inside their organizations.

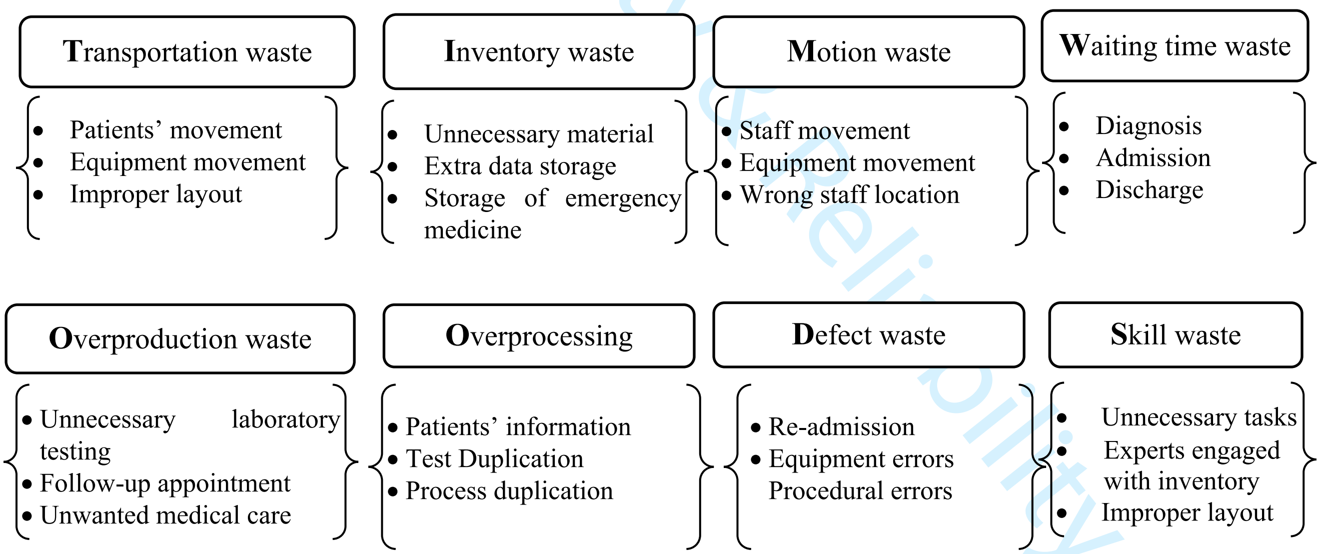

Figure 1. Healthcare Waste (TIMWOODS Model)

3. Research Methodology

This article is organized into two distinct sections. In the initial section, the ISM methodology is employed to define and scrutinize the contextual relationships among lean wastes, facilitating an examination of the hierarchical structure of waste enablers. Subsequently, in the ensuing section, the structural self-interaction matrix (SSIM) modeling technique is implemented for enabler ranking in relation to performance variables, allowing a nuanced analysis of their dominant relationships among the enablers. The procedural steps of the study are articulated as follows:

1. The identification and selection of enablers for lean wastes in healthcare organizations are carried out through an exhaustive literature survey, supplemented by insights, suggestions, and expert opinions from industry specialists.
2. The ISM method was utilized to analyze the interrelationships among enablers for lean practices in healthcare. This method also helped to identify key challenge areas by examining driver and dependence–power relationships among enablers.
3. The SSIM model was employed to develop a diagrammatic model that ranks enablers according to their impact on performance variables.

3.1 Interpretive Structure Modeling

ISM is employed when multiple variables are present, and there is a need to discern their intricate interrelationships (Poduval & Pramod, 2015). Specifically, in the context of this study, healthcare wastes, particularly the TIMWOODS wastes, constitute the variables under investigation. The examination of the interrelationships between these variables necessitates the utilization of the ISM methodology. J. N. Warfield pioneered ISM as a computer-aided technique designed to dissect complex scenarios and distill them into comprehensible structures. In the course of directed structured analysis within our study, we identified 12 distinct healthcare wastes. The ISM methodology serves as an essential tool for thoroughly evaluating and prioritizing these variables, rendering the relationships between these latent variables in an organized and accessible manner. Based on the delineation of these interrelationships, a strategic action plan can be formulated. Such a plan would aim at mitigating identified waste and aiding the healthcare sector in fulfilling its objective of delivering services with enhanced efficiency.

As elucidated by Attri et al. (2014), ISM represents a methodology that transmutes imprecise and vaguely defined mental constructs of systems into discernible, rigorously articulated models. Li et al. (2019) further delineate that a structural model (SM) concentrates on the meticulous selection of model components, clearly defining their interconnections. This implies that SM serves to illustrate the relationships between various variables, manifesting qualitatively in the form of graphs and interconnections rather than quantitatively. Warfield's transformative contribution to this model involved enhancing the SM by integrating the collective judgment of a panel of experts, thereby morphing it into ISM. In essence, the ISM model systematically determines the interrelationships between diverse facets of a problem, predicated on pairwise linkages that are interpreted by a cohort of specialists. The resulting SM, constituted by the interconnections of the components' verbiage and digraphs, can be comprehended as pragmatic intelligence that facilitates the crafting of managerial strategies to curtail identified waste. Because ISM relies on collective judgment to discern whether and how elements are interconnected, it functions as an interactive learning methodology. Its structural nature derives from the synthesis of an overarching structure from a multifaceted ensemble of objects based on their interrelationship within a digraph model (Singh et al., 2007).

3.2 Application of ISM

ISM can be employed at varying degrees of abstraction, from high-level abstraction suitable for long-term planning to a more concrete level for process design, maintenance, strategic planning, and decision-making (Beikkhakhian et al., 2015). This technique has been widely documented in the literature as a powerful tool for analyzing systems and problems across various domains. For example, through the use of ISM, it becomes feasible to impose a structured order and direction on the complex relationships existing between the components of a system (Geng et al., 2018). Additionally, the identification of both direct and indirect connections between variables using ISM offers a more comprehensive and accurate understanding of the situation.

As a result, ISM is often deployed to gain deeper insights into the collective understanding of the relationships between variables. For instance, Attri et al. (2013) employed ISM to identify and evaluate the correlations between obstacles to implementing total productive maintenance (TPM) within the Indian manufacturing sector. Similarly, Amrina and Vilsi (2014) assessed critical factors in the cement industry using ISM to analyze their direct and indirect linkages. Further, Kumar et al. (2021) utilized ISM to identify and scrutinize the barriers to IT-enabled supply chain operations, while Agrawal et al. (2019) applied ISM in the context of knowledge management. Lim et al. (2017) rigorously analyzed various critical vendor selection criteria using the ISM approach, demonstrating the connections between these criteria and their respective levels, and further classifying these criteria based on their driving strength and reliance.

In most scenarios, the implementation of ISM compels managers to reconsider perceived risks or opportunities, thereby enhancing their understanding of the relationships between essential issues.

3.2.1 Steps in ISM

The ISM method consists of the following steps:

Step 1: Assess whether the problem at hand is complex enough to necessitate the application of ISM. For example, the issue of "hospital waste management" includes multiple variables and interrelated factors, making it a suitable candidate for ISM analysis.

Step 2: Upon confirming the problem's suitability for ISM, identify all the variables that influence the solution. This identification can be executed through methodologies like surveys, brainstorming, nominal group technology, or the Delphi method.

Step 3: After the problem and its variables are clearly defined, determine the contextual relationships that will govern how these variables interact. This could involve Intent Structures or Priority Structures, helping to clarify how one variable contributes to or takes precedence over another.

Step 4: Create a Structural Self-Interaction Matrix (SSIM) that represents the intelligent connections between the identified variables (see Section 4.1).

Step 5: Utilize the SSIM to generate a reachability matrix (see section 4.2), which should be examined for transitivity. In ISM, if variable A connects to variable B, and variable B connects to variable C, then variable A should also connect to variable C.

Step 6: Partition the reachability matrix into multiple levels, helping to organize the variables and their interactions more effectively (see Section 4.3).

Step 7: Construct a directional graph based on the reachability matrix. Remove transitive connections that are logically redundant due to other direct connections.

Step 8: Transform the directional graph into an ISM model by replacing its nodes with specific statements about the variables involved (see Section 4.5).

Step 9: Finally, critically review the ISM model for any conceptual inconsistencies and revise as necessary.

4. Results

4.1 Structural Self-Integration Matrix

The panel of experts for this research was meticulously selected to comprise only individuals possessing comprehensive knowledge and experience in healthcare. Their qualifications were evaluated based on a multitude of criteria, including achievements recognized by peers. For instance, academic professionals were identified through an examination of their author biographies and citation patterns on Google Scholar. At the same time, the selection criteria for industry experts encompassed considerations such as prior experience, current position, and educational background.

In total, seven specialists contributed to this research: four were sourced from academic institutions and three from the Indian healthcare industry. A contextual connection of "lead to" was chosen as the foundational basis for the criterion analysis. The experts' perspectives, founded on various management methodologies such as brainstorming, nominal group technique, concept engineering, and others, were meticulously analyzed to establish the contextual relationships among the variables. Specifically, four symbols were designated to represent the connections between several critical areas likely to be influenced by LSS, symbolizing the direction of linkage between the parameters *i* and *j*.

- V – Variable *i* lead to variable *j*.
- A – Variable *j* lead to *i*.
- X – Variable *i* and *j* lead to each other.
- O – Variables *i* and *j* are unrelated.

The symbols V, A, X, and O are utilized in the following examples, and SSIM is built using contextual relationships, as indicated in Table 2.

- TW (1) lead to LPS (12); therefore, V has been given in (1, 12).
- DW (7) leads to OVP (6); therefore, A has been given in (6, 7).
- OPR (5) and OVP (6) lead to each other; therefore, X has been given in (5, 6).
- DW (7) and MW (3) are unrelated; therefore, O has been given in (3, 7).

Table 2. Structural Self-Interaction Matrix (SSIM).

Variables		12	11	10	9	8	7	6	5	4	3	2
1	TW	V	O	V	V	V	O	A	A	V	X	A
2	IW	V	V	V	V	V	V	V	V	V	V	
3	MW	V	O	V	V	V	O	O	A	V		
4	WTW	V	O	V	V	V	A	A	A			
5	OPR	V	V	V	V	V	V	X				
6	OVP	V	V	V	V	V	A					
7	DW	V	V	V	V	V						
8	SW	V	O	V	V							
9	HPWT	V	O	V								
10	LQ	V	O									
11	HC	V										
12	LPS											

4.2 Reachability Matrix

The SSIM was transformed into a binary matrix, originally called the reachability matrix, in which the V, A, X, and O values were assigned a 1 or 0 according to the following four rules:

Rule 1. If the SSIM value of (*i*, *j*) is V, then the value of (*i*, *j*) in the reachability matrix will be 1, and the value of (*j*, *i*) will be 0. Consequently, V (1, 12) in the SSIM becomes 1 in cells (1, 12) and 0 in cells (12, 1) in the initial reachability matrix.

Rule 2. If the SSIM value of (*i*, *j*) is A, then the value of (*i*, *j*) in the reachability matrix will be 0, and the value of (*j*, *i*) will be 1. Consequently, A (6, 7) in the SSIM becomes 0 in cells (6, 7) and 1 in cells (7, 6) in the initial reachability matrix.

Rule 3. If the SSIM value of (*i*, *j*) is X, then the value of (*i*, *j*) in the reachability matrix will be 1, and the value of (*j*, *i*) will also be 1. Consequently, X (5, 6) in the SSIM becomes 1 in both cells (5, 6) and (6, 5) in the initial reachability matrix.

Rule 4. If the SSIM value of (*i*, *j*) is O, then the value of (*i*, *j*) in the reachability matrix will be 0, and the value of (*j*, *i*) will also be 0. Consequently, O (3, 7) in the SSIM becomes 0 in both cells (3, 7) and (7, 3) in the initial reachability matrix.

Applying these principles resulted in creating an initial reachability matrix for the key regions where LSS has a significant impact, as shown in Table 3. As Step 4 of the ISM method mentions, Table 4 shows the final reachability matrix after integrating transitivities.

Table 3. Initial Reachability Matrix.

Enabler/Resultant Variables		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	TW	1	0	1	1	0	0	0	1	1	1	0	1
2	IW	1	1	1	1	1	1	1	1	1	1	1	1

3	MW	1	0	1	1	0	0	0	1	1	1	0	1
4	WTW	0	0	0	1	0	0	0	1	1	1	0	1
5	OPR	1	0	1	1	1	1	1	1	1	1	1	1
6	OVP	1	0	0	1	1	1	0	1	1	1	1	1
7	DW	0	0	0	1	0	1	1	1	1	1	1	1
8	SW	0	0	0	0	0	0	0	1	1	1	0	1
9	HPWT	0	0	0	0	0	0	0	0	1	1	0	1
10	LQ	0	0	0	0	0	0	0	0	0	1	0	1
11	HC	0	0	0	0	0	0	0	0	0	0	1	1
12	LPS	0	0	0	0	0	0	0	0	0	0	0	1

Table 4. Final Reachability Matrix.

Enabler/Resultant Variables		1	2	3	4	5	6	7	8	9	10	11	12	**Driving Power**
1	TW	1	0	1	1	0	0	0	1	1	1	0	1	7
2	IW	1	1	1	1	1	1	1	1	1	1	1	1	12
3	MW	1	0	1	1	0	0	0	1	1	1	0	1	7
4	WTW	0	0	0	1	0	0	0	1	1	1	0	1	5
5	OPR	1	0	1	1	1	1	1	1	1	1	1	1	11
6	OVP	1	0	1*	1	1	1	1*	1	1	1	1	1	11
7	DW	1*	0	0	1	1*	1	1	1	1	1	1	1	10
8	SW	0	0	0	0	0	0	0	1	1	1	0	1	4
9	HPWT	0	0	0	0	0	0	0	0	1	1	0	1	3
10	LQS	0	0	0	0	0	0	0	0	0	1	0	1	2
11	HCS	0	0	0	0	0	0	0	0	0	0	1	1	2
12	LPS	0	0	0	0	0	0	0	0	0	0	0	1	1
Dependency		6	1	5	7	4	4	4	8	9	10	5	12	**75/75**

Additionally, Table 4 elucidates the driving force and dependence associated with each variable. The driving power is characterized by the total number of variables that may contribute to a specific goal, while dependence represents the total number of variables that may be helpful in achieving it. These factors are subsequently employed to categorize variables into four distinct classifications: automation, dependents, linkage, and drivers (independent).

4.3 Level Partitions

The final reachability matrix determines the reachability and antecedent set for each component. Within the reachability set, components are linked by others that facilitate their accomplishment, whereas the antecedent set consists of elements connected by being crucial in their realization. The intersection of these sets is computed for each component, and each reachability and intersection set share the same top-level element in the ISM hierarchy. This top-level element aids any part above it in achieving its goals. Upon its identification, the top-level element is segregated from the remaining components, and utilizing the same methodology, the subsequent level of components is ascertained. The digraph and final model are constructed through these steps. In this instance, Tables 5–13 delineate the principal areas and factors along with their reachability set, antecedent set, intersection set, and level.

Table 5. Iteration 1.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,3,4,8,9,10,12	1,2,3,5,6,7	1,3	
2	1,2,3,4,5,6,7,8,9,10,11,12	2	2	
3	1,3,4,8,9,10,12	1,2,3,5,6	1,3	
4	4,8,9,10,12	1,2,3,4,5,6,7	4	
5	1,3,4,5,6,7,8,9,10,11,12	2,5,6,7	5,6,7	
6	1,3,4,5,6,7,8,9,10,11,12	2,5,6,7	5,6,7	
7	1,4,5,6,7,8,9,10,11,12	2,5,6,7	5,6,7	
8	8,9,10,12	1,2,3,4,5,6,7,8	8	
9	9,10,12	1,2,3,4,5,6,7,8,9	9	
10	10,12	1,2,3,4,5,6,7,8,9,10	10	
11	11,12	2,5,6,7,11	11	
12	12	1,2,3,4,5,6,,8,9,10,11,12	12	1

Table 6. Iteration 2.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,3,4,8,9,10	1,2,3,5,6,7	1,3	
2	1,2,3,4,5,6,7,8,9,10,11	2	2	
3	1,3,4,8,9,10	1,2,3,5,6	1,3	
4	4,8,9,10	1,2,3,4,5,6,7	4	
5	1,3,4,5,6,7,8,9,10,11	2,5,6,7	5,6,7	
6	1,3,4,5,6,7,8,9,10,11	2,5,6,7	5,6,7	
7	1,4,5,6,7,8,9,10,11	2,5,6,7	7	
8	8,9,10	1,2,3,4,5,6,7,8	8	
9	9,10	1,2,3,4,5,6,7,8,9	9	
10	10	1,2,3,4,5,6,7,8,9,10	10	2
11	11	2,5,6,7,11	11	2

Table 7. Iteration 3.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,3,4,8,9	1,2,3,5,6,7	1,3	
2	1,2,3,4,5,6,7,8,9	2	2	
3	1,3,4,8,9	1,2,3,5,6	1,3	
4	4,8,9	1,2,3,4,5,6,7	4	
5	1,3,4,5,6,7,8,9	2,5,6,7	5,6,7	
6	1,3,4,5,6,7,8,9	2,5,6,7	5,6,7	
7	1,4,5,6,7,8,9	2,5,6,7	7	
8	8,9	1,2,3,4,5,6,7,8	8	
9	9	1,2,3,4,5,6,7,8,9	9	3

Table 8. Iteration 4.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,3,4,8	1,2,3,5,6,7	1,3	
2	1,2,3,4,5,6,7,8	2	2	
3	1,3,4,8	1,2,3,5,6	1,3	
4	4,8	1,2,3,4,5,6,7	4	
5	1,3,4,5,6,7,8	2,5,6,7	5,6,7	

6	1,3,4,5,6,7,8	2,5,6,7	5,6,7	
7	1,4,5,6,7,8	2,5,6,7	7	
8	8	1,2,3,4,5,6,7,8	8	4

Table 9. Iteration 5.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,3,4	1,2,3,5,6,7	1,3	
2	1,2,3,4,5,6,7	2	2	
3	1,3,4	1,2,3,5,6	1,3	
4	4	1,2,3,4,5,6,7	4	5
5	1,3,4,5,6,7	2,5,6,7	5,6,7	
6	1,3,4,5,6,7	2,5,6,7	5,6,7	
7	1,4,5,6,7	2,5,6,7	7	

Table 10. Iteration 6.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,3	1,2,3,5,6,7	1,3	6
2	1,2,3,5,6,7	2	2	
3	1,3	1,2,3,5,6	1,3	6
5	1,3,5,6,7	2,5,6,7	5,6,7	
6	1,3,5,6,7	2,5,6,7	5,6,7	
7	1,5,6,7	2,5,6,7	7	

Table 11. Iteration 7.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
2	2,5,6,7	2	2	
5	5,6,7	2,5,6,7	5,6,7	7
6	5,6,7	2,5,6,7	5,6,7	7
7	5,6,7	5,6,7	7	

Table 12. Iteration 8.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
2	2	2	2	8

3.4 Classification of Critical Waste in the Healthcare Sector Using the ISM Model

Based on the driver's power and dependent, these critical wastes have been classified into four categories:

1. Autonomous
2. Dependent
3. Linkage
4. Drivers

The classification aligns closely with the methodology employed by Singh et al. (2017). Table 4 illustrates the driving power and dependence associated with each critical waste type, giving rise to the driving power dependency diagram depicted in Figure 2.

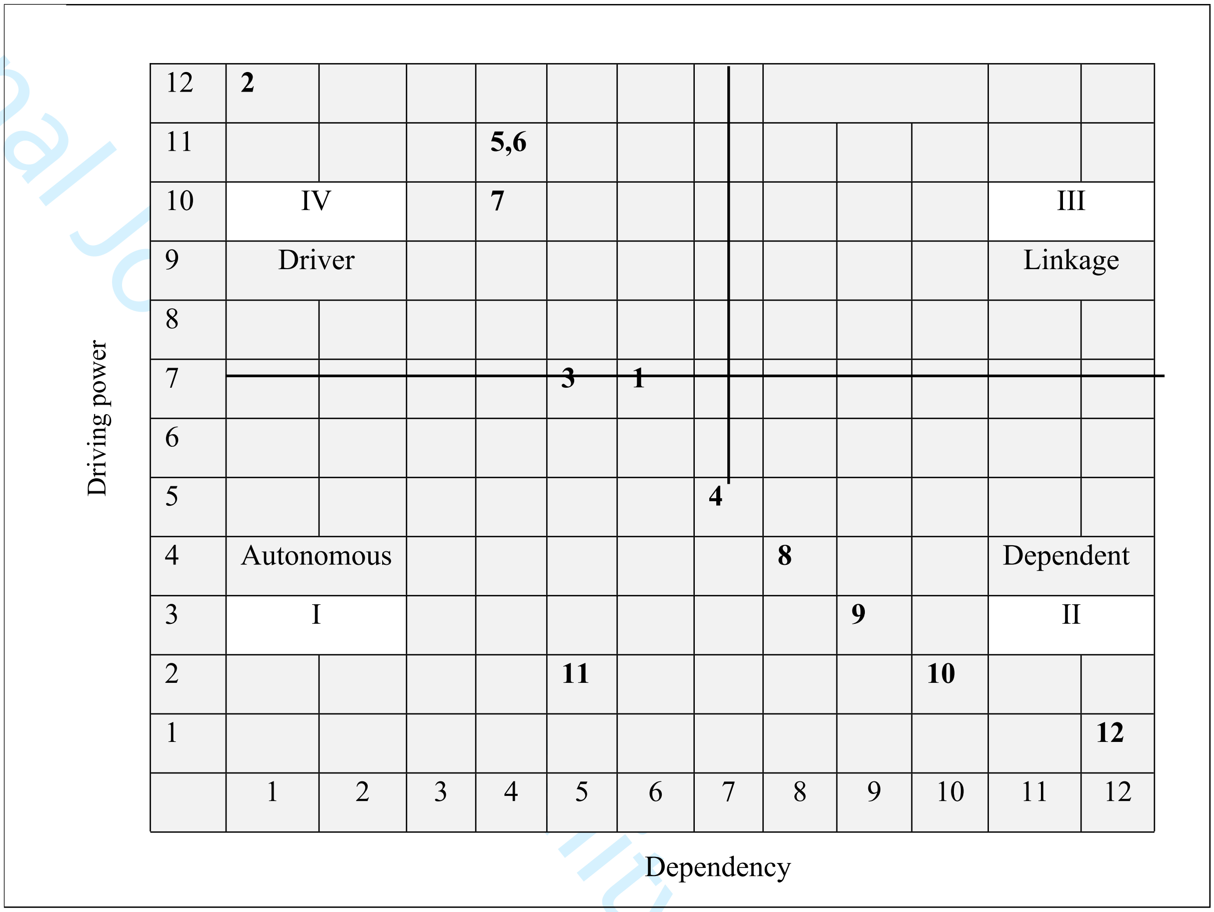

Figure 2. Driving Power and Dependence Diagram.

This illustrative figure is divided into four quadrants, representing the autonomous, dependent, linkage, and independent sectors. Within these sectors, all variables are strategically positioned, reflecting their specific driving and dependence powers. Organizations can formulate LSS implementation strategies based on the driving and dependency power of variable wastes. For instance, a factor with a driving power of 10 and a dependence power of 4 is situated at coordinates corresponding to these values, and can thus be defined as a driving variable. Conversely, a variable characterized by a driving power of 2 and a dependence power of 10 may be classified as a dependent variable. This categorization of critical waste is directed at a nuanced analysis of the driving power and dependency of the identified variables, facilitating an informed approach to waste management within the framework of LSS. The classification of waste in the system can be organized into four distinct clusters. The *first* cluster encompasses "autonomous waste," characterized by weak driving power and dependence. Such waste is relatively isolated from the system, with "high costs" falling into this category within the context of the present study. The *second* cluster comprises "dependent waste," marked by feeble driving power yet robust dependence. In this study, skill waste, low quality (services), and low patient satisfaction belong to this cluster. The *third* cluster encapsulates "linkage waste," demonstrating both strong driving power and dependence. Actions affecting these variables will reciprocally influence others, generating a feedback loop. Interestingly, no variables in this study were found to belong to this category. The *fourth* cluster is constituted of "independent variables" or "drivers," possessing significant driving power but weak dependence. This cluster includes variables like transportation, overproduction, overprocessing, and defect waste. Additionally, the study identifies three variables—transportation waste, motion waste, and waiting time waste—with shared tendencies. The first two may fall within the dependent or autonomous group, while the last, waiting time waste, may align with either the autonomous or driving group. The final positioning of these variables is contingent upon the specific context of the study.

4.5 Formation of ISM

The SM is crafted by leveraging the vertices, nodes, and edges of the final reachability matrix (as detailed in Table 4). Within this framework, an arrow drawn from variable ii to variable *j* illustrates a link between the different types of healthcare waste, forming what is often referred to as a directed graph or digraph. In accordance with the ISM technique, transitive relationships are removed, and the digraph undergoes a transformation, which is subsequently depicted in Figure 3.

5. Discussion

The healthcare sector serves a dual function of paramount importance: It is an essential contributor to economic growth and a fundamental pillar of societal well-being. A robust healthcare system constitutes a vital element in the formation of a contented society. Consequently, numerous studies have underscored the imperativeness of identifying the causes of waste within this sector to augment efficiency (Andreamatteo et al., 2015; Antony et al., 2018; Das et al., 2021). This present investigation undertakes a comprehensive review of existing literature, culminating in the extraction of eight primary types of waste. The outcomes of LSS initiatives across the global healthcare landscape have been meticulously examined to gather evidence from scholarly works. As posited by Abah and Ohimain (2011), the ability of healthcare management to embark on enduring waste reduction strategies will be significantly bolstered by an awareness of the substantial waste factors. These identified wastes may be appraised and integrated within the prospective scope of related research endeavours.

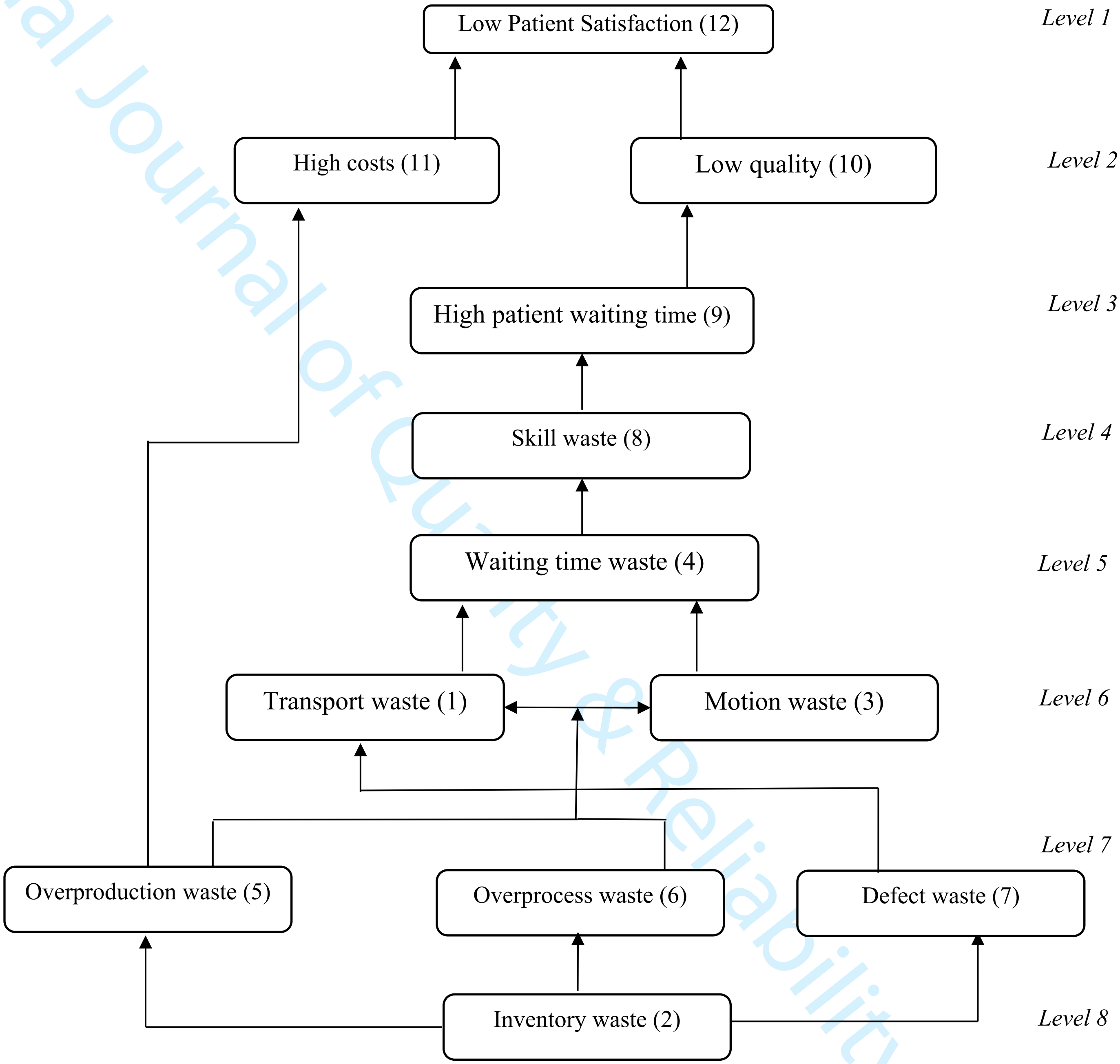

Figure 3. ISM-Based Model

Furthermore, the imperative of categorizing variables—specifically waste, in the context of this research—is underscored in scholarly literature as a means to discern their intrinsic characteristics, whether dependent, independent, linkage, or autonomous (Spagnol et al., 2013;

Yazdani et al., 2020). Within the framework of this study, ISM is employed to perform an intricate analysis of interactions, thereby classifying the identified wastes into the aforementioned categories. This investigation extends beyond mere categorization, delineating a hierarchical sequence of actions that managerial entities must undertake to mitigate prospective waste within the healthcare sector.

The driving power-dependency matrix (illustrated in Figure 2) provides insight into the identified wastes' relative significance and interconnectivity, along with the resultant variables. High operational expenses are frequently invoked as impetuses for enhancement initiatives aimed at reducing such costs (Agus & Hajinoor, 2012; Badri et al., 2000). Nevertheless, the driver-dependence matrix (represented in Figure 2) reveals that within the healthcare sector, "high cost" functions as an independent variable. Historically, autonomous variables have been characterized as feeble drivers, bearing minimal systemic reliance (Singh et al., 2007). Therefore, when scrutinizing cost as a variable in the healthcare context, scholars should accord careful consideration to this finding, as it represents the inaugural identification of "high cost" as an independent or autonomous variable.

Another crucial finding is the classification of low patient satisfaction and inferior service quality as feeble drivers yet highly dependent variables, situated at the zenith of the ISM hierarchy (as depicted in Figure 3). In accordance with studies by Lot et al. (2018) and Andreamatteo et al. (2015), patient satisfaction may function as an evaluative indicator for assessing the caliber of healthcare services. These scholars elucidated that patient satisfaction influences clinical outcomes, patient retention, and the punctual, efficacious, and patient-centric provision of care, all factors integral to the healthcare system's quality. Such findings resonate with existing literature on manufacturing and the service sector (Agus & Hajinoor, 2012; Andersson & Pardillo-Baez, 2020). The emergence of "high wait times" and "skill waste" as potential drivers was anticipated. For instance, Gijo and Antony (2014) classified "high waiting time" as an impetus for initiating an LSS project, expounding their conclusions in an article titled "Reducing Patient Waiting Time in the Outpatient Department Using Lean Six Sigma Methodology." Concurrently, Cuban (2016) and Babiker et al. (2014) underscored the exigency and executed projects to counter "skill waste" within the UK healthcare domain.

In a scientific study, a linking variable can function either as a moderator or a mediator. When acting as a moderator, it possesses the capacity to amplify, diminish, negate, or otherwise modify the relationship between the driver and the dependent variables (Badri et al., 2000; Rejikumar et al., 2020). As moderating variables, they exert influence over the directional trajectory of the relationship. Conversely, a mediating variable serves as a conduit that connects and elucidates the relationship between the drivers and the dependent variables. Often referred to as a mediator or an intervening variable, it establishes the linkage between the driver and the dependent. However, the findings of this study did not unearth any linking variable among the identified wastes that embody both characteristics, namely, drivers and dependents. Consequently, one inference that may be gleaned from this discovery is that all identified variables (consisting of 8 wastes and 4 reactive variables) manifest stability.

The examination of driving power dependence, as depicted in Figure 2, reveals that variables such as “inventory waste,” “overproduction waste,” “overprocessing waste,” and “defect waste” command significant driving power and are situated toward the foundation of the ISM model (Figure 3). Recognized as independent or driving variables, these elements assist LSS practitioners in the realization of their desired objectives. Unaffected by external influences, they are commonly perceived as the causative agents exerting influence over the dependent variable(s). This finding resonates with the established scholarship in the field, including the work of Teichgraber and de Bucourt (2012) and more recent research by Yazdani et al. (2020). For instance, Teichgraber and de Bucourt (2012) employed LSS to scrutinize the flow of materials and information, extending from external suppliers to patients. A current state value stream mapping (VSM) was meticulously crafted utilizing a decision point analysis to investigate the hospital’s stent procurement procedures. Following a comprehensive assessment of the existing VSM and the subsequent eradication of non-value-adding waste, a futuristic state VSM was conceived.

Yazdani et al. (2020) similarly contribute to this domain by proposing an optimal best–worst approach to healthcare waste disposal site selection employing interval rough numbers (IRN). Acknowledging the challenge posed by the absence of precise information, they innovatively utilized a novel IRN Dombi–Bonferroni (IRNDBM) algorithm to process raw data. In addition to providing theoretical insight, they conducted a case study to delineate the applicability and efficacy of the proposed multicriteria decision-making approach. This research underscores the potential to refine decision-making processes in healthcare waste management by harnessing advanced mathematical techniques.

Furthermore, the research meticulously endeavored to delineate the hierarchical levels for all pertinent variables. The ISM model conspicuously reveals that patient dissatisfaction (Level 1) stands as the paramount issue within the healthcare sector—a conclusion that resonates strongly with Gijo and Antony's (2014) case study as well as the comprehensive literary analysis by Andreamatteo et al. (2015). Another growing concern for the industry belongs to the deteriorating quality of healthcare services combined with rising costs (Level 2), an observation that mirrors the findings by Dickman et al. (2017), who underscored the impact of widening economic disparities on America's low-income population. Such inequalities have showed a 10–15-year difference in life expectancy between the wealthiest and poorest Americans. Additional critical issues ascending the ISM model include "high patient waiting times" (Level 3) prior to medical consultation and "skill waste" (Level 4). The remaining variables are relegated to lower tiers within the hierarchy (Levels 5–8), signifying their relative importance in this complex schema.

Possessing the highest driving power and exhibiting minimal dependency, "inventory waste" has been relegated to the lowest echelon in the hierarchical structure of the ISM model (Level 8). This finding is emblematic of a complex causality wherein excessive inventory waste begets additional layers of waste. It catalyzes a cascading effect, commencing with surplus production, encapsulating "overproduction waste," "overprocessing waste," and "defect waste" (Level 7), subsequently engendering "transport waste" and "motion waste" (Level 6). These manifestations at Level 6 result in a marked "waiting time waste" (Level 5), culminating in an escalation of both "skill waste" and protracted "patient waiting time." This nuanced analysis of waste, particularly within the healthcare sector, constitutes an innovative contribution to the research that remains unprecedented in published literature. In summation, the findings of this study provide a strategic insight, suggesting that healthcare management's initial efforts should be focused toward the reduction of inventory waste as a conduit to mitigate patient dissatisfaction.

6. Conclusion

This study has adeptly fulfilled the outlined research objectives. The satisfaction level of patients serves as an evaluative metric for the efficacy of healthcare institutions, reflecting multifaceted influences including wait time, service quality, and cost. In various industrial sectors, including healthcare, waste has manifested as a pervasive issue, precipitating systemic inefficiencies and underutilization of human talent. The current research undertakes a meticulous examination of extant literature, leading to the extraction of eight primary waste categories (RQ1). In this exploration, the outcomes of LSS initiatives executed globally in the healthcare arena have been assiduously examined. The specific wastes identified include (i) transport waste (TW), (ii) inventory waste (IW), (iii) motion waste (MW), (iv) waiting time waste (WTW), (v) overproduction waste (OPW), (vi) overprocessing waste (OVPW), (vii) defects waste (DW), and (viii) skills waste (SW). Additionally, four consequential variables have been discerned: (i) high patient waiting time (HPWT), (ii) low-quality service (LQS), (iii) high cost (HC), and (iv) high patient dissatisfaction (HPD).

ISM has proved helpful in classifying and establishing connections between discovered waste factors and consequential variables (RQ2). The ISM-oriented methodology culminates in the categorization of all discerned variables into four distinct classes: autonomous, dependent, linkage, and driver or independent. One salient finding of this investigation is the characterization of "high cost" as an autonomous variable within the healthcare sector. Consequently, scholars must exercise prudence in employing it as a variable within their studies. The second categorization (dependent variables) encompasses the inefficient utilization of staff time (skill waste), protracted wait times for patients (high patient waiting time), substandard service quality (poor quality), and elevated dissatisfaction levels among recipients (patient dissatisfaction). Upon juxtaposition with prior discussions, it becomes evident that the healthcare sector's efficacy may be assessed through the examination of this second category of variables (i.e., dependent variables) (RQ3). This conclusion is substantiated by the empirical findings of this research and congruent scholarly contributions. A further deduction gleaned from the study's pivotal findings posits that inventory waste, overproduction, overprocessing, and defect waste function as crucial drivers within the healthcare framework. Predicated on this conclusion, healthcare administrators may modulate, augment, oversee, and sustain their dependent variables through strategic alteration of these driving factors. Finally, the absence of any liking variable among the detected parameters affirms that the identified assembly of variables is both valid and reliable, providing valuable insights for subsequent research endeavors.

This study makes a salient and critical contribution by identifying inventory waste as a major issue that requires immediate and coordinated correction. In summary, the research explains how inventory waste, by ensuring dominant driving power and exhibiting the least dependency, solidifies its foundational position in the ISM-model hierarchy. The most important conclusion that can be drawn from this ISM hierarchy model is that high inventory wastage acts as a fundamental waste within the healthcare sector, producing a cascade of related problems (RQ4). The sequence commences with surplus production (overproduction waste), excessive processing (overprocessing waste), and defect waste, subsequently leading to “transport waste” and “motion waste.” Consequently, “waiting time waste” augments considerably, yielding an escalation in both “skill waste” and “patient waiting time.” This comprehensive waste analysis, especially within the realm of healthcare, emerges as an unprecedented finding of the present investigation. This insight constitutes the primary and most substantial contribution of this scholarly endeavor, advancing the proposition that healthcare management must initiate their efforts by curbing inventory waste as a strategic measure to alleviate patient dissatisfaction.

The SSIM approach fundamentally relies on the insights and responses of subject-matter experts. While this method offers valuable perspectives, it does bear a limitation that can be mitigated through empirical investigation. Specifically, the cadre of experts involved in this study was numerically constrained, leading to the implicit limitation that the findings may not be readily generalized across diverse scenarios. This constraint emphasizes the necessity for physical validation by direct engagement with real-world healthcare situations, thereby ensuring that the conclusions drawn are not merely context-specific but have broader applicability.

6.1 Study Implications and Future Scope of Research

The healthcare industry, in its constant expansion, has embraced lean principles as a means to curtail waste, streamline costs, and enhance patient care. The LSS approach has gained traction within healthcare for delivering greater value to patients using fewer resources. Prior research underscores that a full commitment to LSS principles and the lean business model can yield reductions in errors, costs, and overall patient dissatisfaction.

Although waste quantification and characterization serve as critical components of waste management and treatment, systematic methods for measuring, classifying, and prioritizing these factors are often overlooked. The intricate nature of healthcare operations presents significant challenges in embedding the LSS approach within systems. This study contributes a multifaceted perspective, bridging existing gaps in understanding.

Theoretical Implications

This research makes novel theoretical contributions by elucidating the broader landscape of healthcare waste and its ramifications. The findings enable a more nuanced comprehension of various healthcare waste types, laying the groundwork for formulating hypotheses using dependable and valid variables for future empirical inquiries. Understanding driving powers and dependencies further assists scholars in allocating variables between driver and dependent roles. The ISM employed herein offers unique insights into the hierarchy of healthcare waste and its resultant dynamics.

Practical Implications

The findings of this study have far-reaching applications for healthcare practitioners, administrators, and policymakers. Through the categorization and hierarchy model developed, healthcare organizations can better identify and eradicate detected waste, leading to more efficient and patient-centered care. The research defines eight types of healthcare waste and four emergent variables. By recognizing and eliminating unnecessary costs, executives may streamline processes and enhance patient satisfaction.

The identification of inventory waste as a foundational issue with cascading effects on other waste types suggests a strategic starting point for management intervention. Future work might use structural equation modeling to outline the relationships between identified driving and dependent variables. The study also invites further exploration using questionnaire-based research, quantitative analytical techniques such as exploratory factor analysis, and innovative solutions for reducing or mitigating identified wastes.

The findings of this research highlight the vital importance of inventory waste and provide a strategic roadmap for healthcare leaders. By utilizing the categorizations and insights gained, the healthcare industry can further refine practices, elevate patient satisfaction, and reduce inefficiencies. The comprehensive approach taken in this study sets a precedent and offers a valuable framework for ongoing and future research in healthcare waste management.

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