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The Maieutic-H Model: Integrating Machine Learning-Based Prioritisation, Interaction Analysis, and Motivational Strategies for Scalable Healthcare Waste Management

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Abstract

Healthcare waste mismanagement persists because the organisational and communicative dynamics driving erroneous practices remain largely unaddressed, particularly in high-turnover clinical units that concentrate the highest volumes of hazardous waste and operational pressure. Existing training interventions typically address motivational, analytical, or operational dimensions in isolation, lacking a systemic and adaptive framework. This study designs and theoretically validates Maieutic-H, a multilevel training ecosystem integrating narrative and gamified motivational strategies, Video-Based Interaction Analysis of communicative practices, and an AI-driven support system employing an interpretable Random Forest classifier to prioritise corrective actions, embedded within a six-phase adaptive cycle with longitudinal monitoring at one, six, and twelve months. Theoretical validation through comparison with eleven programmes from the literature identifies three recurring, sub-optimal configurations—single-component, parallel-component, and quasi-integrated interventions—none of which combines data-driven prioritisation with interactional analysis to surface operational blind spots. Preliminary qualitative validation against expert interviews showed 93% concordance between operator-perceived priorities and model-generated relevance scores, informing an adaptive recalibration ($\alpha = 0.70$) that weights field-derived evidence over the simulated training baseline. The Maieutic-H model offers a scalable, theoretically grounded framework for sustainable behavioural change and regulatory compliance in complex clinical environments, aligning interpretable machine learning with healthcare process engineering. This manuscript presents a model development and theoretical validation study. Evidence on effectiveness will require empirical testing of the full Maieutic-H pathway in hospital pilot studies.

Keywords: healthcare waste management; Random Forest; interpretable machine learning; circular economy; behavioural change; interaction analysis; decision support system

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Academic Editor: Antoni Sánchez

Received: 16 July 2026
Revised: 17 August 2026
Accepted: 23 August 2026
Published: 28 August 2026

1. Introduction

European institutions define the circular economy (CE) as an economy "in which the value of products, materials, and resources is maintained in the economy for as long as possible, and the generation of waste is minimised" [1]. Its core principles encompass resource use reduction, reuse, repair, regeneration, and recycling, commonly organised within so-called R-frameworks, which map different levels of circular strategies applicable to production systems [2,3].

Noskova [3] argues that R-frameworks constitute the most widely used conceptual architecture for defining and operationalising the circular economy, noting that several variants exist—such as 3R, 6R, and 10R—depending on the disciplinary and applied context. Tan et al. [4] and Riesener et al. [5] demonstrate that product design represents a key lever for the practical implementation of the circular economy: designers determine a significant proportion of a product's environmental impacts at the design stage itself, making design-for-circularity approaches essential for enabling reuse, maintenance, repair, and recycling strategies. In this context, Design for Disassembly (DfD) offers a particularly relevant design strategy, enabling the modular separation of product components and thereby facilitating maintenance, reuse, and material recovery. Approaches grounded in modular design and circular disassembly can thus reduce waste production and extend the service life of devices and equipment [6].

In the healthcare sector, however, implementing circular economy principles proves particularly complex: clinical, regulatory, and safety constraints limit the direct transferability of circular models developed by other sectors. Hospitals and healthcare facilities produce large volumes of heterogeneous waste spanning distinct categories—infectious risk waste, sharps and needlestick waste, pharmaceutical waste, and non-hazardous special waste—each requiring separate disposal protocols and a specific regulatory framework [7]. Nurses, nurse assistants, physicians, technical administrative staff, and external personnel all contribute to waste management at different stages of the waste cycle, from generation and segregation to temporary storage and transport for final disposal. This heterogeneity of roles and responsibilities makes healthcare waste management a critical node for any circularity strategy applied to the health sector.

Saha et al. [8], in a systematic literature review on the circular economy in healthcare, identifies four principal thematic areas: healthcare waste management, sustainable procurement, regulatory frameworks, and new circular business models. The literature, nevertheless, reveals that structural, organisational, and regulatory barriers impede the adoption of the circular economy in the health sector, and that existing approaches tend to address isolated dimensions of the problem. The growing prevalence of single-use medical devices—introduced primarily to ensure high standards of hospital infection control—represents one of the principal obstacles. This production model fosters linear supply chains in which workers use products once and then dispose of them, generating large quantities of healthcare waste and expanding the sector's environmental footprint [9].

Technical factors further complicate the transition towards circular models. Hoveling et al. [10] demonstrate that sterility requirements specific to the healthcare context, including infection control requirements, decontamination processes, and the operational workload of healthcare personnel, make the application of circular economy models more demanding than in other industrial sectors. Cultural, organisational, and professional competence factors also shape this transition. Bray et al. [11], in a systematic review of sustainable health education, show that educational programmes in the health professions do not yet adequately prepare students to address the environmental and climate challenges that healthcare systems face, despite the sector's growing environmental impact. Integrating sustainability and responsible resource management content into health curricula, therefore, stands as a priority for driving change in professional practices. Teherani et al. [12] similarly argue that sustainable healthcare education plays a crucial role in helping future professionals understand the interdependence between ecosystems, human health, and healthcare systems, and in steering them towards sustainable solutions in clinical and community settings.

Empirical evidence further shows that health professionals often hold limited knowledge of circular economy principles. Soares et al. [13], studying European radiotherapists, documents uneven knowledge of circular economy concepts and green skills, and recommends developing targeted training programmes to strengthen environmental competencies within the health professions.

Studies on healthcare waste reduction strategies confirm that educational interventions and targeted training programmes can improve waste management and promote more sustainable behaviours among healthcare workers [14], producing measurable effects on volume reduction, correct segregation, and regulatory compliance. Working in a Tunisian hospital, Baklouti et al. [15] demonstrates that a training programme significantly raises both theoretical knowledge and operational practices among staff, with a clear impact on the quality of waste classification. Shivashankarappa et al. [16], in an Indian context, documents an immediate increase in awareness and management competencies following training while emphasising the need for periodic updating activities to sustain results over time. Hosny et al. [17] records a radical transformation in the competence level and correct practices of medical waste managers in Egypt, shifting from a predominance of incorrect behaviours to near-complete adoption of appropriate practices. Botelho [18], on a European scale, establishes that education programmes constitute the most decisive factor for regulatory compliance in healthcare waste segregation in private facilities, underscoring the importance of systemic training policies for sustainable waste management in healthcare.

The literature on healthcare waste management confirms that educational interventions improve knowledge and operational practices; yet existing studies tend to focus on single dimensions of change—technical training, regulatory compliance, or environmental awareness—and leave a significant gap unaddressed: no integrated models currently combine motivational dimensions, analysis of professional interactions, and data-driven decision support tools within a single systemic intervention framework. Training models that simultaneously bring together innovative educational strategies, analysis of professional interactions, and data-driven decision support tools—with the aim of understanding how training-induced change translates into everyday healthcare waste management practices and sustaining that change over time—remain absent from the literature.

In light of these critical issues, the present study addresses the following research question: *How can a multilevel training ecosystem— integrating motivational educational strategies, analysis of professional interactions, and AI-based decision support tools—contribute to behavioural change and improved healthcare waste management practices among health professionals?*

The research pursues the primary objective of designing and theoretically validating a multilevel training framework (Maieutic-H) specifically conceived for the hospital setting. The framework integrates narrative and gamified educational strategies, analysis of professional interactions, and AI-based decision support tools to promote behavioural change in healthcare waste management. The study defines the structure, components, and operational mechanisms of a model conceived to:

- Evaluate the effectiveness of a motivational educational intervention in strengthening environmental awareness, attitudes, and motivation towards sustainable practices among the healthcare workers involved.

- Analyse professional interactions among healthcare workers in the workplace to observe how collaborative and communicative practices transform following the training intervention.
- Deploy an AI-Driven Circular Waste Management system, designed according to explainable AI principles suited to non-technical clinical audiences, to analyse collected data and identify priority operational actions for improving the healthcare waste management system.
- Identify operational criticalities and blind spots in professional practices by integrating qualitative observations of interactions with quantitative data analysis.
- Monitor, through structured feedback cycles, the effectiveness of implemented actions over time, and inform the design of subsequent organisational and training interventions grounded in empirical evidence.

To address these aims, this article develops the conceptual basis, methodological design, and theoretical assessment of the Maieutic-H framework. Section 2 reviews healthcare waste management training, emerging educational methods, and decision support tools, and delineates the gap addressed by the proposed model. Section 3 describes the framework's architecture and operational configuration. Section 4 reports the comparative theoretical validation against previously published interventions, and Section 5 summarises the main findings. Section 6 discusses implications and limitations, and Section 7 concludes this paper.

2. Theoretical Background

This section examines the current state of healthcare worker training in healthcare waste management, highlighting how learning shapes knowledge, operational practices, and regulatory compliance. It analyses the empirical findings that demonstrate training's potential to modify individual behaviours and transform organisational dynamics (Section 2.1). It then discusses innovative approaches that promise to overcome the limitations of traditional training methods (Section 2.2). Finally, it identifies the principal research gaps and proposes an integrated multilevel training model aimed at producing safer, more efficient, and more sustainable waste management (Section 2.3).

2.1. Training Interventions in Healthcare Waste Management: Effectiveness and Limits

Healthcare waste management constitutes a high-risk activity that engages heterogeneous professional figures operating under high operational pressure [10]. Errors in segregation, labelling, or internal waste transport can generate biological hazards, environmental contamination, and regulatory violations carrying significant legal and organisational consequences [19,20]. Training, therefore, serves not only as an instrument of professional updating but as a strategic lever for the clinical and environmental safety of healthcare facilities [11,14].

Several studies demonstrate that educational programmes and training interventions improve healthcare workers' knowledge and practices in healthcare waste management. In a quasi-experimental study conducted in Tunisia with 134 healthcare workers, Baklouti et al. [15] evaluated a healthcare waste management training programme and recorded a significant increase in knowledge scores and practices following the intervention. Thakan et al. [21] similarly delivered an intensive one-week training programme to 156 healthcare workers, administering pre- and post-intervention assessments on healthcare waste management; the results showed a significant improvement in mean knowledge scores and an increase in self-reported compliance with correct waste segregation.

Das et al. [22] compared two training modalities in a quasi-experimental study involving 100 healthcare workers from two institutions in Meerut: Group A attended structured lectures, while Group B received educational materials. Assessments at one, three, and six months revealed significant improvements in knowledge, attitude, and practice scores over time. Shivashankarappa et al. [16], working at a tertiary hospital in Bengaluru with 183 participants, implemented a structured healthcare waste management training programme built around an interactive three-hour audiovisual presentation; participants completed a pre-test, an immediate post-test, and a second post-test at three months, and the results showed significant improvement in both knowledge and practices. In the same vein, Sachan et al. [23] conducted a quasi-experimental study with 119 nurses in a tertiary healthcare facility in Uttar Pradesh, running four training sessions over four consecutive days; the intervention produced a significant improvement in knowledge and practices relating to waste segregation.

Several studies have integrated training with organisational interventions and monitoring systems. Chen et al. [24] describes a multicomponent quality improvement initiative in a high-volume cardiac catheterisation laboratory that combined staff training, waste tracking, segregation optimisation, the establishment of a dedicated sustainability team, and periodic performance updates; after one year, the team observed a significant reduction in infectious and general waste alongside improved recycling practices. Mondal [25] monitored 115 waste segregation containers daily across 23 hospital areas while simultaneously delivering a training programme to all staff; this combination of continuous monitoring and training produced a highly significant improvement in segregation practices over time. Torres-Pereda et al. [26] implemented an environmental education intervention over 20 months at a Mexican academic public health institution, using questionnaires, focus groups, and waste quantification before and after the intervention; the results showed a reduction in waste generation relative to the baseline. Shaheen et al. [27] also demonstrated the effectiveness of structured training: in a quasi-experimental study with 64 nurses, the team organised three days of training with pre- and post-intervention assessments and checklist-based observations of practices after one month, revealing improvements in healthcare waste management knowledge and practices.

The literature further underlines the importance of grounding training interventions in theoretical models of behavioural change. Robat et al. [28] evaluated a training intervention based on the Health Action Model with 128 hospital staff members in Iran, comparing healthcare waste management and behavioural intention before and after training; they observed improvements in both the management process and behavioural intention. Al-Omran et al. [29] integrated the Theory of Planned Behaviour (TPB) and the Norm Activation Model (NAM) to analyse the psychological factors that drive healthcare workers' intentions and behaviours in waste segregation; they showed that the integrated NAM-TPB model explains behavioural determinants more effectively by combining rational and moral drivers. This finding carries particular relevance in high-workload settings such as emergency departments and intensive care units.

Despite the effectiveness of training interventions, several studies reveal the persistence of a gap between knowledge and practice. Mlouki et al. [30], conducting two cross-sectional surveys in 2021 and 2023 at a Tunisian university hospital, observed a decrease in correct waste segregation despite improvements in available resources and materials, thereby exposing the gap between knowledge and behaviour. Baaki et al. [31] similarly analysed the knowledge, perceptions, and practices related to sustainable healthcare waste management across three NHS Trusts in North-West England, administering a questionnaire to 58 healthcare workers; they found low levels of knowledge regarding legislation and health and environmental risks, deficiencies in segregation practices, and significant differences in attitudes across age groups and professional roles—a pattern that suggests the need to tailor training interventions by professional role and operational context.

Several studies have directly addressed this knowledge-practice gap. Lee and Lee [32] combined a systematic literature review, a survey of hospital staff, and the Analytic Hierarchy Process (AHP) to identify and prioritise the factors influencing healthcare waste generation; they highlighted the importance of operational management, procedural training, awareness-raising, and environmental assessment for translating knowledge into concrete action. McCauley et al. [33], reviewing the literature from 2010 to 2024 on environmental sustainability in healthcare, showed that healthcare workers' favourable attitudes towards sustainability do not always drive changes in operational practice, owing to organisational barriers and the absence of systematic integration of educational initiatives within working environments.

Overall, these studies confirm that training interventions improve knowledge and practices in healthcare waste management, particularly when they combine theoretical training, practical activities, and monitoring systems. They also establish the need for organisational, behavioural, and motivational approaches that can close the gap between knowledge and its application in everyday practice. Table 1 summarises the studies reviewed in this subsection, reporting the setting/sample, design, intervention type, main findings, and remaining gaps relative to the integrated framework proposed here.

Table 1. Summary of training interventions in healthcare waste management. Abbreviations: HWM, healthcare waste management; CE, circular economy; HCWs, healthcare workers; KAP, knowledge, attitude and practice; QI, quality improvement; AHP, analytic hierarchy process; TPB, theory of planned behaviour; NAM, norm activation model; NHS, National Health Service; T2/T3, second/third follow-up time points.

Ref.	Setting/Sample	Design	Intervention	Key Findings	Gap
[10]	Healthcare sector (general)	Visual taxonomy, mapping study	Mapping of CE product and material flows in healthcare	Identifies sterility, decontamination, and workload constraints	Conceptual, mapping only; no training
[11]	Health professions curricula	Systematic review	Review of sustainable health education programmes	Curricula do not adequately prepare students	Educational curriculum focus; not workplace training
[14]	Healthcare facilities (general)	Conference study	HWM reduction education and training	Confirms effectiveness of educational interventions	No motivational, interactional, AI integration
[15]	Tunisia, 134 HCWs	Quasi-experimental	HWM training programme	Significant increase in knowledge and practice scores	No interactional analysis; no data-driven prioritisation
[16]	Bengaluru, 183 HCWs	Pre-/post-test, 3-month follow-up	3-h audiovisual training	Improvement at post-test, partial regression at 3 months	Confirms need for sustained, adaptive design
[19]	Healthcare materials sector	Review	CE opportunities/challenges in healthcare materials	Identifies regulatory and safety barriers behind HWM errors	Review-level; no training/behavioural component
[20]	Healthcare supply chains	Conference study	Barriers to CE implementation	Identifies structural/organisational barriers to CE adoption	No training intervention; supply chain focus
[21]	156 HCWs	Pre-/post-test	One-week intensive training	Significant improvement in knowledge scores and self-reported compliance	Single time point; no long-term follow-up
[22]	Meerut, 100 HCWs, 2 institutions	Quasi-experimental, 2 arms	Structured lectures vs. educational materials	Significant improvements in KAP at 1, 3, 6 months	No motivational/narrative strategy; no feedback loop
[23]	Uttar Pradesh, 119 nurses	Quasi-experimental	4 sessions over 4 days	Significant improvement in knowledge and practices	No behavioural theory framework; no interactional phase
[24]	Cardiac catheterisation laboratory	QI initiative, 1 year	Training + waste tracking + sustainability team	Reduction in infectious and general waste	No interactional analysis; managerial rather than algorithmic
[25]	23 hospital areas, 115 containers	Longitudinal monitoring + training	Daily monitoring combined with training	Highly significant improvement in segregation over time	No motivational/narrative component
[26]	Mexico, academic public-health institution	20-month intervention	Environmental education	Reduction in waste generation relative to baseline	No algorithmic prioritisation or feedback loop

Table 1. *Cont.*

Ref.	Setting/Sample	Design	Intervention	Key Findings	Gap
[27]	Pakistan, 64 nurses	Quasi-experimental	3-day training	Improved knowledge and practices at 1-month follow-up	No T2/T3 longitudinal follow-up
[28]	Iran, 128 staff	Pre-/post-test	Health Action Model-based training	Improved management process and behavioural intention	No interactional or AI-based component
[29]	—	Model-based (TPB + NAM)	Analysis of psychological determinants	Explains behavioural determinants of segregation	Theoretical only; no intervention or feedback design
[30]	Tunisia, university hospital	Longitudinal (2021 vs. 2023 surveys)	—	Decrease in correct segregation despite improved resources	Demonstrates persistent knowledge–practice gap
[31]	North-West England, 58 HCWs, 3 NHS Trusts	Cross-sectional questionnaire	—	Low knowledge of legislation; deficiencies in segregation practices	Confirms need to tailor training by role and context
[32]	South Korea	AHP + survey	Prioritisation of HWM factors	Identified weighted priority factors	Expert-judgement based; not data-driven or adaptive
[33]	—	Literature review, 2010–2024	—	Favourable attitudes do not always translate into practice	Organisational barriers unaddressed; no systemic framework

2.2. Innovative Approaches to Training in Healthcare Settings

Innovative approaches to healthcare worker training in waste management include gamification, simulation, analysis of professional interactions to understand collaborative dynamics, and digital tools. These approaches target a specific challenge of the healthcare context: overcoming resistance to behavioural change, where operational routine and regulatory constraints tend to entrench practices even when those practices prove incorrect or inefficient.

2.2.1. Gamification and Game-Based Learning

Gentry et al. [34] conducted a systematic review on the use of serious gaming and gamification in health profession education, evaluating their effectiveness against traditional learning, other types of digital education, and other serious gaming/gamification interventions across patient outcomes, knowledge, skills, professional attitudes, and satisfaction. The authors argue that serious gaming and educational gamification can deliver a high-quality, cost-effective, and innovative approach that is flexible, portable, and enjoyable, enabling interaction with tutors and peers. Drawing on a bibliometric study analysing 475 articles published between 2012 and 2024, Yıldız et al. [35] show that the number of studies on gamification in health education has grown in recent years, reflecting its potential to increase student motivation, engagement, interest, and learning outcomes. Researchers have tested specific applications of gamification across various areas of health education. Bai et al. [36] conducted a systematic review on the effectiveness of gamified teaching in disaster nursing education for healthcare workers, arguing that traditional training methods often struggle to capture students' interest and enthusiasm and to simulate emergencies in real-life scenarios effectively—a limitation that gamification overcomes. This pedagogical approach enhances the enjoyment and practicality of learning by embedding game elements into the training experience. The authors of [37] evaluated a gamified educational triage app (GTEA) as a learning tool for emergency nurses; the team developed the app using no-code-based software and expanded it relative to previous iterations, adding points, leaderboards, instant feedback, and stories. The results showed a significant increase in triage accuracy, a substantial reduction in overtriage, and improvements in critical thinking disposition, triage competence, and triage knowledge. Focusing directly on waste management, Barricelli et al. [38] described the design process of a serious game for occupational safety training in waste treatment plants, incorporating a scoring system, nonplayer characters, and workplace environment simulations to strengthen engagement and promote an inclusive educational approach. This study exemplifies the direct application of gamification to waste management training in occupational settings.

2.2.2. Beyond Gamification: Simulation-Based Approaches

Yoshikawa et al. [39] conducted a systematic review comparing simulation-based educational strategies against traditional ones in infection prevention and control education, finding that while educators have traditionally delivered this content in lecture-based formats, simulation-based strategies have become increasingly prevalent in medical education in recent years. Lee and Yang [40] investigated the effect of scenario-based simulation training on infection control knowledge, self-efficacy, and adherence to standard precautions; the experimental group achieved significantly higher mean scores for both infection prevention and control knowledge and self-efficacy than the control group and also showed significant improvement in adherence to standard precautions. Building on this line of inquiry, Lee and Yang [41] assessed scenario-based simulation training designed to improve infection control knowledge, self-efficacy, and adherence to standard precautions among clinical nurses; the intervention comprised four scenario-based simulation sessions on standard precautions and transmission routes, and nurses in the experimental group demonstrated significant improvements across all outcomes.

2.2.3. Professional Learning in Healthcare

Workers build waste management competence through coordination processes among figures with distinct roles and responsibilities, acting in concrete work situations and responding to the communicative dynamics of clinical teams. Studies in conversational analysis converge on the view that communication and interaction constitute the mechanisms through which professionals construct knowledge, organisational coordination, and clinical safety. Research drawing on conversation analysis shows that communication structures healthcare work by enabling professionals to negotiate roles, responsibilities, and clinical decisions through interaction [42,43]. Studies on simulation and conversation analysis applied to training demonstrate that researchers can analyse interactions and use them as a pedagogical tool to improve communication and collaboration among professionals [44–46]. Studies on team training and interprofessional communication show that strengthening communicative dynamics reduces medical errors and adverse events [47,48]—a finding that carries direct relevance for waste management, where coordination errors among workers can produce waste misclassification, failure to report incidents, or incorrect practices that become entrenched over time without anyone detecting them. Table 2 summarises the innovative approaches reviewed above, including their focus, study design, main findings, and gaps relative to Maieutic-H.

Table 2. Summary of innovative training approaches. Abbreviations: HWM, healthcare waste management; CA, conversation analysis; CABS, conversation-analysis-based simulation; GTEA, gamified triage educational app; AI, artificial intelligence.

Ref.	Focus	Design	Key Findings	Gap Relative to Maieutic-H
[34]	Gamification in health profession education	Systematic review	Positive effects on engagement, knowledge, skills, satisfaction	General; not applied to waste management
[35]	Gamification in health education	Bibliometric study, 475 articles (2012–2024)	Growing research trend on motivation/engagement	Confirms absence of applications in HWM
[36]	Gamified disaster-nursing education	Systematic review	Improves engagement vs. traditional training	Not applied to waste management
[37]	Gamified triage educational app (GTEA)	App evaluation	Increased triage accuracy, reduced overtriage	Domain-specific (triage); no interactional or AI-based prioritisation

Table 2. *Cont.*

Ref.	Focus	Design	Key Findings	Gap Relative to Maieutic-H
[38]	Serious game for occupational safety in waste treatment plants	Design study	Enhanced engagement via scoring system and simulation	Occupational safety focus; not behavioural change in clinical HWM
[39]	Simulation vs. lecture-based infection-control education	Systematic review	Simulation increasingly prevalent and effective	Not integrated with algorithmic prioritisation or feedback loop
[40]	Scenario-based simulation for infection control	Quasi-experimental	Improved knowledge, self-efficacy, adherence to precautions	No motivational/narrative component; no AI-driven decision support
[42]	Conversation analysis in primary healthcare communication	State-of-the-art literature review	Communication structures how professionals negotiate roles and decisions	Focused on primary care communication; not waste management coordination
[43]	Conversation analysis of expertise enactment in medical education	Empirical CA study	Shows how professionals construct and display expertise in interaction	Focused on clinical/educational settings, not HWM practices
[44]	Conversation-Analysis-Based Simulation (CABS)	Method development study	Interaction analysis used as pedagogical tool to improve communication skills	Not applied to waste management coordination
[45]	Interdisciplinary simulation-based teaching	Systematic review and meta-analysis	Positive effects of simulation on interprofessional learning	General healthcare education; not HWM-specific
[46]	Interprofessional simulation for healthcare students	Systematic review and meta-analysis	Simulation improves interprofessional collaboration outcomes	Not linked to algorithmic prioritisation or waste management context
[47]	Interdisciplinary, interprofessional communication intervention	Empirical study	Psychological safety fosters communication, increasing patient safety	Focused on patient safety broadly; not HWM coordination
[48]	Communication training in obstetric care	Qualitative interview study	Communication training improves birth experience outcomes	Domain-specific (obstetric care); not HWM practices

2.3. Identifying the Gap: Towards an Integrated Multilevel Framework

The literature on training for healthcare waste management reveals that most training interventions still rely on traditional educational approaches, focusing primarily on transmitting regulatory knowledge and ensuring procedural compliance [15,16,23]. More recent studies have explored innovative educational strategies—such as gamification and serious games—to increase engagement and promote behavioural change among health professionals [34,35,38]. Research in medical education has demonstrated that professional learning frequently emerges through situated interactions and collaborative practices among healthcare workers, as interactional analysis studies have shown [42,44,49].

These strands of research, nevertheless, remain largely separate. Researchers have rarely applied gamification strategies to healthcare waste management, and interactional analysis studies have concentrated primarily on clinical decision-making processes or professional learning dynamics, without specifically examining the coordination practices that govern waste management in hospital settings [43,49].

In recent years, a further research strand has emerged around the use of artificial intelligence (AI) and decision support systems in healthcare. Several studies have developed tools based on machine learning, the Internet of Things, and robotic systems to improve the classification, prediction, and management of healthcare waste flows in hospitals, contributing to operational efficiency and regulatory compliance [50]. The medical education literature simultaneously shows that AI can support advanced learning processes through intelligent simulations, adaptive learning environments, and automated competence assessment systems [51]. Despite these technological innovations, most studies applying AI to healthcare waste management focus primarily on the technical and operational dimensions of the systems while paying limited attention to healthcare worker training and the collaborative processes through which practitioners actually integrate these technologies into everyday practice. Moreover, existing AI applications in this domain typically function as black-box classification or prediction systems, with limited attention to model interpretability or to validation strategies suited to the small, context-specific, and often unlabelled datasets characteristic of single-institution healthcare settings [50]. Integrated training approaches that combine behavioural engagement strategies, analysis of professional interactions, and interpretable, context-adaptive intelligent decision support tools to improve healthcare waste management therefore remain largely unexplored.

To close this gap, researchers need to develop a multilevel training ecosystem [52] capable of intervening simultaneously on the motivational, analytical, and operational dimensions of professional behaviour [53]. To this end, the training model presents three components that are complementary and structured to create a sequential intervention and analysis process articulated across three complementary levels.

The first motivational and educational component introduces knowledge 'pills' through the educational device 'Greenopoli', designed and implemented by De Feo [54], which uses narrative and creative tools such as rap, storytelling, and gamification. The objective extends beyond the transmission of technical knowledge about healthcare waste management; it aims to activate participants' cognitive and emotional engagement, fostering active and participatory learning processes. This approach, orientated towards stimulating critical reflection and the internalisation of sustainability principles, reduces cultural resistance and opens practitioners to sustainable practices. The training action concentrates primarily on attitudinal and motivational dimensions, shaping attitudes towards sustainability, strengthening environmental awareness, and stimulating the intention to change behaviour.

The second analytical component focuses on the analysis of professional interactions. It follows the educational intervention chronologically, observing and recording interactions among workers in the real work context. This approach draws on the interactional analysis described by Filliettaz and other scholars [49,55,56], according to which professionals construct professional activities through coordination processes among actors during interactions. This analysis makes it possible to observe whether and how the training intervention modifies communicative and collaborative dynamics among health professionals. In particular, the analysis identifies changes in communicative behaviours, new modes of operational coordination, and potential criticalities in work practices that quantitative compliance indicators alone fail to surface.

The third operational component employs a tool called AI-Driven Circular Waste Management—a decision support system designed to assist health professionals and hospital waste management officers. The tool rests on an integrated approach that combines the systematic identification of corrective actions—derived from the analysis of regulations, literature, and best practices—with their prioritisation through machine learning techniques [57,58]. The tool processes data collected through the analysis of professional practices and operational actions, assigning each intervention an importance score between 0 and 1 that integrates empirical evidence from observed practices. The system automatically ranks interventions in descending order of relevance and classifies them into three importance levels—high, medium, and low—enabling immediate identification of operational priorities, defined as those interventions scoring 0.5 or above. This approach enables the team to identify the actions with the greatest impact on the waste management system; define evidence-based organisational intervention priorities; map the operational, managerial, or regulatory gaps that emerge from the analysis of professional practices; guide the design of targeted subsequent training interventions; and monitor the effectiveness of implemented measures over time through structured feedback cycles. Most published interventions address these dimensions in isolation or as loosely coupled components. Maieutic-H integrates them within a single six-phase adaptive cycle, combining narrative/gamified activation, Video-Based Interaction Analysis of workplace practices, and an interpretable AI-based prioritisation module that can be recalibrated as field evidence accumulates. This integration is intended to surface operational weaknesses that may not emerge from training or audits alone and to support context-specific prioritisation of corrective actions. Section 4 substantiates this claim through a taxonomy of single-component, parallel-component, and quasi-integrated interventions. Building on the gaps identified above, the following section presents the conceptual architecture and operational structure of the Maieutic-H model.

3. Methodology

3.1. Conceptual Architecture of the Maieutic-H Model

The intervention model proposed in the present study bears the name *Maieutic-H* (Maieutic for Health), a name that explicitly evokes Socratic maieutics, from the Greek *maieutikos* (literally "of the midwife"). In the *Theaetetus*, Plato records Socrates' words: "I am like the midwife, for I cannot myself give birth to wisdom. The many admirable truths they bring to light have been discovered by themselves from within" [59]. This analogy orients the entire intervention: the trainer does not transmit knowledge frontally, but through guiding questions, simulations, and critical reflection, facilitates participants' "delivery" of new professional awareness and behaviours. The name *Maieutic-H* thus designates a training approach that, in the manner of the Athenian philosopher, accompanies health professionals in autonomously discovering—rather than receiving as a regulatory imposition—their own areas for improvement in waste management, thereby generating lasting behavioural change.

The present model follows a logic of integrated and adaptive design, combining three complementary components—motivational, analytical, and operational—into a six-phase cyclical process equipped with adaptive feedback mechanisms that allow the intervention to be reoriented when results prove unsatisfactory, without restarting the process from the beginning. This design responds directly to the gaps identified in the literature, which documents that existing training interventions in healthcare waste management predominantly cover only one component of the change process—motivational, analytical, or operational— without integrating them into a systemic framework. The added value of the proposed model lies precisely in this integration, which enables simultaneous action on workers' cultural awareness, on the understanding of the interactional dynamics that structure real practices, and on the evidence-based prioritisation of the corrective interventions most relevant to the specific context.

The model articulates into six sequential operational phases with feedback loops (A1–A6). The first three phases (A1–A2–A3) correspond to the motivational, analytical, and operational components, respectively, while the final three phases (A4–A5–A6) constitute sequential stages that implement, monitor, and adapt the outcomes of the preceding components. Phase A1 activates cultural motivation through the Greenopoli method. Phase A2 observes and analyses real work practices through the interactional analysis of Filliettaz and others [49,55,56]. Phase A3 applies a machine learning-based prioritisation model (Random Forest) to rank corrective interventions according to context-specific relevance scores. Phase A4 concretely implements the prioritised actions in everyday practices. Phase A5 monitors results at three time points—T1 after one month, T2 after six months, and T3 after twelve months—through non-participatory observations using a structured checklist and statistical analyses. Phase A6 analyses the monitoring results and activates the feedback loop towards the appropriate phase when criticalities arise or certifies sustainable improvement when all parameters prove positive and stable over time.

3.2. Multilevel Objectives: Motivational, Analytical and Operational Dimensions

The present training model articulates its objectives across four distinct levels: the first three correspond to the motivational, analytical, and operational components of the framework, while the fourth concerns the consequential phases of implementation, monitoring, and feedback that ensure the operational translation and empirical evaluation of the preceding components' objectives. This multilevel architecture reflects the nature of the problem itself: healthcare waste management in hospital settings cannot be reduced to a question of regulatory compliance but involves attitudinal, interactional, and organisational dimensions that require distinct and complementary theoretical frameworks. Olum et al. [60] underlines that 'proper healthcare waste management can be obtained by applying different theoretical approaches as they complement one another', justifying an integrated and multilevel theoretical architecture.

3.2.1. Objectives of the Motivational Component

The motivational component articulates its objectives across the cognitive and affective domains of Bloom's taxonomy, as revised by Anderson et al. [61], which provides the framework for defining a progression from declarative knowledge objectives—knowing the regulations on healthcare waste management and understanding the environmental impact of incorrect practices—to higher-order objectives, such as the capacity to autonomously evaluate the compliance of one's own practices and propose improvement solutions within one's own ward. On the motivational plane, the Theory of Planned Behaviour (TPB) by Ajzen [62] justifies the need to act explicitly on attitudes, subjective norms, and perceived behavioural control as determinants of behavioural intention. Shahab et al. [63], in the context of hospital waste management, shows that educational interventions based on the TPB produce significant improvements across all these constructs, with measurable effects on separation and disposal practices. Akulume and Kiwanuka [64] demonstrates that perceived behavioural control and behavioural intention constitute the strongest predictors of healthcare workers' segregation behaviour, explaining 52.5% of the observed variance. Şimşek and Özsoy [65] confirmed analogous results: a TPB-based training intervention produced a 200% increase in recyclable waste.

To ensure the sustainability of change over time, the model integrates the principles of Self-Determination Theory [66,67], which identifies autonomy, competence, and relatedness as the fundamental psychological needs for intrinsic motivation. The central motivational objective is not to produce externally imposed normative conformity but to shift behavioural regulation towards integrated and autonomous forms, fostering training environments 'where motivation and thriving can take root' [68]. The Greenopoli method realises this dynamic through a peer-to-peer approach and content co-creation processes in which healthcare workers actively participate in producing, sharing, and reworking training materials related to waste management practices. This type of interaction activates the needs for relatedness and competence, as participants learn collaboratively, compare real experiences, and develop shared solutions. Behavioural change thus emerges as the outcome of a participatory and contextualised process rather than as a response to regulatory prescriptions perceived as external or coercive.

The specific objectives of the motivational component are: to increase knowledge of circular economy principles applied to healthcare waste; to develop positive attitudes towards sustainable practices; to reduce cultural resistance to change; and to activate behavioural intention by strengthening perceived behavioural control.

3.2.2. Objectives of the Analytical Component

The analytical component pursues a collective understanding of situated practices. The reference framework is the interactional analysis of Filliettaz et al. [49], which considers professional activities as practices progressively co-constructed through participants' contributions and the resources they mobilise in context. From this perspective, the unit of analysis is the interaction among workers, and the objective is to understand how communicative and coordination dynamics produce or impede practices that conform to standards. This approach aligns with Situated Learning Theory, which shows that learning in professional healthcare contexts occurs through authentic participation in communities of practice within the real work context [69]. The observation of real practices before introducing corrective solutions draws further support from the application of the COM-B model (Capability, Opportunity, Motivation—Behaviour) and the Theoretical Domains Framework in hospital contexts, which demonstrates that identifying the determinants of behaviour enables the selection of the most effective intervention functions—including education, training, environmental restructuring, modelling, and enablement—in a contextually appropriate manner [70].

The specific objectives of the analytical component are: to document the real communicative dynamics among workers during waste management in daily activities; to identify the concrete coordination modes and blind spots in professional practices that standardised questionnaires cannot detect; and to produce an empirical map of specific operational criticalities that provides the contextual basis for the subsequent algorithmic prioritisation phase.

3.2.3. Objectives of the Operational Component

The operational component pursues objectives of a strategic and organisational nature, distinct from the training objectives of the preceding components. It builds on the Random Forest decision support framework described by Cappelli et al. [57,58]. Random Forest was selected for stable performance on limited, heterogeneous data and for transparent prioritisation through variable importance measures. The AI tool based on a Random Forest algorithm targets the systemic transformation of hospital practices: it prioritises corrective actions with the greatest potential impact on regulatory compliance, tailors the action plan to the specific hospital context based on the criticalities identified in the analytical phase, and optimises resource allocation towards interventions scoring above 0.5 in importance among the 55 available across 13 thematic macro-categories. In this framework, the predictors are the implementation states of 55 corrective actions (grouped into 13 thematic areas and linked to operational indicators derived from regulations, the literature, and best practices; see Section 2.1 and Table A2 in [57]). The outcome is the overall implementation status of the healthcare waste management system, treated as a compliance classification task. No a priori feature selection is applied; the model estimates action importance via the Mean Decrease Gini metric, which is then used to rank and prioritise interventions. Validation on synthetic data is reported in [57], and the qualitative validation based on professional interviews is presented in [58]. These objectives align with the logic of quality improvement applied to healthcare waste management, which the recent literature identifies as an essential approach for producing sustainable improvements. Naqvi et al. [71] demonstrate that improving healthcare waste management requires 'an integrated approach combining continuous training, QI-driven system redesign, regular monitoring and digital traceability', directly summarising the integrative logic of the model's operational component. Robat et al. [28] further confirm that structured training interventions produce significant changes in knowledge, attitude, and motivation among health professionals, provided that a theoretical framework guides them by identifying the specific determinants of behaviour in the observed context.

The specific objectives of the operational component are: to produce an evidence-based action plan with a quantitative ranking of corrective interventions; to contextualise actions to the specific criticalities identified in the analytical phase; to provide an implementation roadmap with clear priorities; to progressively validate and recalibrate the algorithmic relevance scores against field-collected evidence as longitudinal data accumulate; and to ensure the traceability of implemented actions through longitudinal monitoring.

3.2.4. Objectives of Implementation, Monitoring, and Feedback

Implementation, monitoring, and feedback constitute sequential stages of the process that operationally translate the objectives of the three preceding components, ensuring their concrete implementation, empirical evaluation, and continuous adaptation through feedback mechanisms.

The specific implementation objectives consist of translating the prioritised action plan into concrete modifications of healthcare personnel's daily practices, ensuring complete traceability of implemented actions through registration systems, and guaranteeing adherence to planned timelines and the standardised operating procedures defined in the phase controls.

The longitudinal monitoring and evaluation objectives consist of measuring behavioural change through objectively observable indicators (a 5-point Likert scale across five thematic categories) collected at three post-implementation time points (T1: 1 month, T2: 6 months, T3: 12 months). The study will also statistically validate the effectiveness of the intervention by comparing the experimental and control groups using a mixed ANOVA, with particular attention to the Group × Time interaction. The analysis will calculate effect sizes (Cohen's d, partial eta squared η_p^2) to quantify the practical relevance of the change and will assess the sustainability of improvement over the long term by verifying the maintenance of results at 12 months.

The decision and adaptive feedback objectives consist of classifying the types of residual criticalities emerging from monitoring—motivational, operational, or strategic—using multivariate regression models that control for potential confounding variables (group membership, training hours, sex, age, prior training, professional category, and years of experience). On the basis of this classification, the process activates the feedback loop towards the appropriate phase (A1 for motivational criticalities, A2 for operational criticalities, A3 for strategic criticalities), avoiding the need to restart the entire cycle. The process finally verifies sustainable improvement over time, defined by the joint presence of favourable statistical evidence (significant Group × Time interaction, relevant effect sizes) and the maintenance of results at the 12-month follow-up (T3).

3.3. Operational Structure: A Six-Phase Adaptive Cycle

The study represents the structure and intervention process of the Maieutic-H model through the Integration Definition for Function Modelling (IDEF0) standard, a formal method for the functional modelling of complex systems derived from the Structured Analysis and Design Technique (SADT) and standardised by the United States National Institute of Standards and Technology [72]. IDEF0 describes a system through the ICOM methodology—Input, Control, Output, Mechanism—organising functions into a hierarchy of progressively decomposed diagrams: from the context diagram (level A—0), which represents the entire system as a single function and defines its relationships with the external environment, to the decomposition diagrams (level A0 and beyond), which articulate that function into distinct and interrelated sub-processes [73].

The ICOM methodology articulates four distinct and complementary elements. *Inputs* represent what the process transforms—in the case of the Maieutic-H model, the existing professional practices of healthcare workers and the operational data on waste management. *Outputs* represent the result of the transformation: the measurable behavioural change and the implemented corrective actions. *Controls* represent the regulatory and normative constraints that govern the process, including healthcare waste management guidelines, institutional standards, and safety protocols. *Mechanisms* represent the resources, tools, and technologies that enable the process: the Greenopoli method, Video-Based Interaction Analysis, and the AI-driven system based on machine learning.

The choice of IDEF0 to represent the Maieutic-H model rests on three converging reasons. The first is structural: IDEF0 is specifically designed to model systems in which one must explicitly distinguish what the process transforms (input), what normatively constrains it (control), what executes it (mechanism), and what results from it (output). This distinction proves particularly relevant in healthcare training contexts, where regulatory guidelines, human and technological resources, and behavioural outcomes must remain analytically separate to avoid design ambiguities that would compromise the replicability of the intervention. The second reason is applicative: the literature documents the established use of IDEF0 in healthcare across various clinical–logistical contexts, from mapping hospital care processes [74] to reorganising radiology departments [75], from modelling home care [76] to structuring complex diagnostic processes [77]. Although these applications focus primarily on clinical–logistical rather than training processes, they demonstrate the method's capacity to represent complex healthcare systems with heterogeneous and interdependent components—a characteristic that justifies its transfer to pedagogical design, where analogous heterogeneity and interdependence among motivational, interactional, and algorithmic components characterise the Maieutic-H model. The method's functional hierarchy also enables decomposition of the training process from the highest level of abstraction (A-0) to detailed operational sub-processes, ensuring a systemic and unambiguous view of the entire intervention. The third reason is epistemological: in a model contribution, the graphical representation of the process is not decorative but constitutive, rendering visible the logical chain connecting the framework's components and enabling verification of its internal coherence [78].

The use of IDEF0 in pedagogical design in healthcare is epistemologically legitimate insofar as an integrated training intervention shares with clinical–logistical systems the same need to distinguish between resources that enable the process, constraints that regulate it, transformations that constitute it, and outcomes that validate it—a structure that the ICOM language is specifically designed to make visible and verifiable.

Figure 1 presents the context diagram (level A-0) developed according to the IDEF0 modelling standard. It provides a macroscopic and synthetic representation of the Maieutic-H project, describing the entire system as a single overarching function that interacts with the external environment.

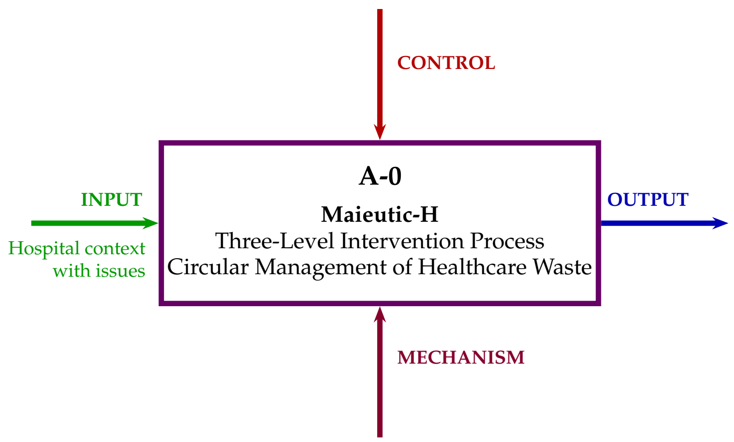

Figure 1. IDEF0 diagram level A-0: contextual view of the Maieutic-H intervention.

The central node (A-0) identifies the global activity: a "Three-Level Intervention Process" aimed at "Circular Healthcare Waste Management". The system operates across four fundamental dimensions following the ICOM methodology:

- **INPUT** (arrows entering from the left—green): The starting condition or data that the process must elaborate. The input here is the "hospital context with criticalities"—the set of inefficiencies, incorrect habits, and operational problems related to waste disposal within the healthcare facility prior to the intervention.
- **CONTROL** (arrows entering from above—red): The constraints, rules, and directives that guide and condition the process without themselves being transformed by it. The Maieutic-H intervention operates under "international guidelines" (e.g., WHO), "European regulations," and "national regulations". These elements ensure that every action taken in waste management complies with legal, safety, and sustainability standards.
- **MECHANISM** (arrows entering from below—purple): The resources—human, technological, and instrumental—required to execute the central function. The model engages "healthcare personnel" (the human actor at the centre of the process), supported by advanced technological tools such as "artificial intelligence (Random Forest algorithm)" for data analysis, and "educational tools" (such as the Greenopoli methodology) to stimulate learning and ecological awareness.
- **OUTPUT** (arrows exiting to the right—blue): The final result that the process produces, representing the transformation of the Input. By applying the resources (Mechanism) within the bounds of the rules (Control), the initial criticality transforms into "sustainable improvement in circular management", guaranteeing waste disposal practices that are more virtuous, safer, and lower in environmental impact.

Figure 2 presents the decomposition of level A-0 into six phases.

The intervention process consists of the following phases:

- **Phase A1**—The process begins with Phase A1, which serves a predominantly formative and motivational function. In this phase, healthcare workers are engaged through educational and narrative tools designed to develop environmental awareness and reduce resistance to change. The underlying rationale is that, in the absence of initial motivation, organisational change is unlikely to be durably established. The output of this phase consists in strengthening staff awareness regarding the correct management of waste and in fostering greater openness toward the adoption of new operational practices.
- **Phase A2**—The process then moves to Phase A2, which is an observation phase focused on actual work practices. Rather than introducing solutions at the outset, this phase examines how operators effectively manage waste within their daily work context. Through observations, recordings, and analysis of interactions among operators, concrete problems are identified: errors in waste classification, coordination difficulties among staff, or insufficiently clear procedures. It should be noted that the A2 observation does not constitute a neutral baseline. Operators had already been sensitised through the A1 phase, a condition which, as Filliettaz et al. [55] demonstrate, facilitates the emergence of otherwise latent communicative dynamics. The A1–A2 sequence therefore reflects a theoretically grounded design logic, constitutive of the model in the sense of Meredith [79] and Jaakkola [78], rather than a standard empirical evaluation protocol. The outcome of this phase is a precise map of operational issues.
- **Phase A3**—This information is utilised in Phase A3, in which the decision support system intervenes. Specifically, the operational issues documented in Phase A2 are formalised as verifiable statements and mapped onto one or more of the 13 predefined

thematic areas of the framework (e.g., regulatory compliance, staff training, traceability, waste segregation, and pharmaceutical waste management). For each activated thematic area, the system retrieves from the database the set of potentially applicable corrective actions and subsequently applies a contextual filter, retaining only those consistent with the specific characteristics of the case under analysis.

At this point, the Random Forest algorithm assigns each action an importance score ranging from 0 to 1; values equal to or greater than 0.5 identify the priority actions. The Random Forest model used in Phase A3 follows the decision support approach presented in [57,58]. Interpretability is provided through Mean Decrease Gini importance scores, which are used to produce a transparent ranking of corrective actions for end users. The final score is calculated as a weighted average between the score provided by the machine learning model and empirical relevance, as described in Cappelli et al. [58]. As field data accumulate through Phase A5, this score will be progressively refined via cross-validated retraining, consistent with the validation strategy outlined in Section 3.4.3.

Finally, the system ranks the actions in descending order of relevance, placing the highest-impact interventions at the top of the list.

- **Phase A4—**The subsequent phase is A4, which represents operational implementation. This phase translates the prioritised action plan (the output of A3) into concrete modifications of daily practices and ensures full traceability of the implemented actions through recording systems and adherence to planned timelines. Here, the actions suggested by the system are concretely applied in hospital activities. Healthcare personnel modify their practices–for example, by changing waste collection procedures, improving material segregation, or adopting new modes of inter-departmental coordination. In this phase, change moves from the theoretical plan to daily practice.
- **Phase A5—**Following implementation, Phase A5 intervenes, dedicated to monitoring and longitudinal evaluation. In this phase, outcomes are recorded through non-participant observations using a structured checklist organised into six thematic categories and rated on a five-point Likert scale. Measurements are conducted at three post-implementation time points: T1 (1 month), T2 (6 months), and T3 (12 months). The effectiveness of the intervention is evaluated using a mixed ANOVA design, with time as a within-subject factor and group (experimental vs. control) as a between-subjects factor, with particular attention to the Group × Time interaction. Effect sizes are estimated through Cohen's d and partial eta-squared η_p^2.
- **Phase A6—**Finally, A6 analyses these results by applying a multiple linear regression model that controls for confounding variables such as group membership, training hours delivered, sex, age, prior training, professional category, and years of experience, and determines whether to activate a feedback loop directed toward the appropriate function. Phase A6 has a decisional and adaptive feedback function, implemented through a multiple linear regression model that controls for confounding variables (group membership, training hours, sex, age, prior training, professional category, years of experience).

  When monitoring and evaluation (A5) detect that objectives have not been achieved in a sustainable manner, the decisional function A6 classifies the type of issue that has emerged. In this case, several scenarios arise:

  - A return to Phase A1 for motivational issues when the experimental group does not exhibit a pattern of improvement exceeding that of the control group;
  - A return to Phase A2 for operational issues when field practices do not improve;
  - A return to Phase A3 for strategic issues when the prioritised actions do not produce the expected impact.

During the intermediate measurement time points (T1 and T2), should issues emerge, the feedback is activated promptly without waiting for subsequent monitoring phases. Conversely, at the end of the observation period (T3), in the presence of statistically positive and temporally stable parameters, the attainment of sustainable improvement in healthcare waste management within the hospital setting under consideration is confirmed.

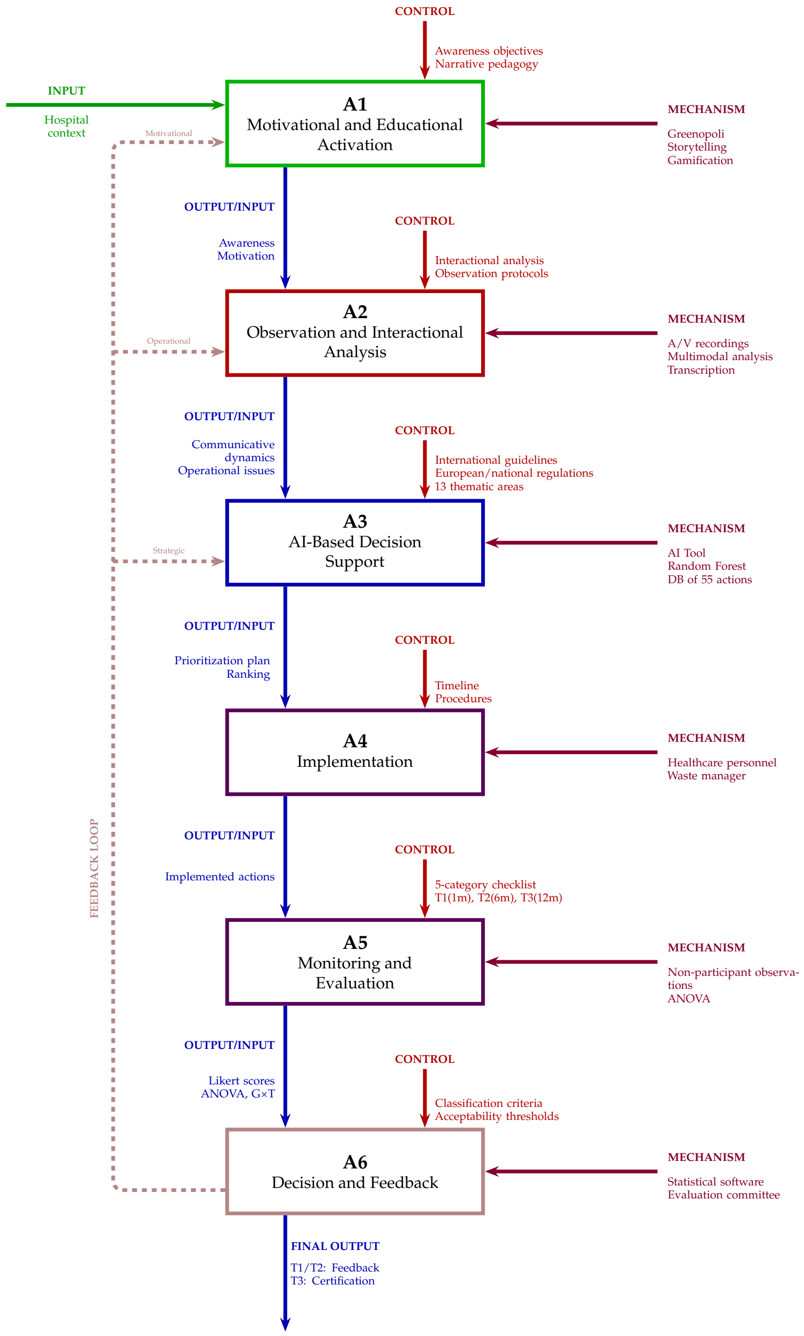

Figure 2. IDEF0 diagram level A0: detailed functional decomposition.

3.4. Empirical Validation Design: Longitudinal Monitoring and Statistical Framework

The monitoring and evaluation process follows a precise temporal structure that commences after the completion of the implementation of corrective actions in the daily practices of hospital waste management (Phase A4). The choice of a longitudinal monitoring design articulated across multiple time points reflects a well-established principle in the literature on intervention sustainability: the evaluation effectiveness should encompass not only the continuation of the intervention but also the maintenance of behavioural change and the ongoing production of benefits for individuals and systems [80], thereby requiring the collection of data at multiple time points to understand how the process evolves over time. The contemporary methodological literature recommends that longitudinal intervention studies adopt clear logic models to specify the theoretical mechanisms and mediators through which the intervention influences outcomes [81,82]. At the same time, it is essential to plan explicit statistical strategies for managing missing data arising from participant attrition over time [83]; to this end, current guidelines advise against the deletion of incomplete cases, recommending instead the use of modern techniques such as Full Information Maximum Likelihood (FIML) estimation or Multiple Imputation (MI) [84,85]. This statistical framework addresses two distinct but interdependent evaluation needs within the model: the assessment of behavioural change at the individual and group levels (Phases A5–A6, detailed below), and the empirical calibration of the AI-driven prioritisation component (Phase A3), whose validation strategy is outlined in Section 3.5.3 and revisited here in relation to the feedback logic of Phase A6.

3.4.1. Study Population and Allocation Procedure

The study recruits participants from two hospitals of comparable size and organisational structure, selecting three homologous departments in terms of clinical and care activities and bed capacity—general surgery, internal medicine, and the emergency department—at each site. The target population comprises healthcare workers directly involved in waste management (including nurses, nurse assistants, and physicians) who have accumulated at least six months of tenure in the same department and are available to participate in all planned activities. Once researchers inform participants and obtain their consent, they assign them as complete departmental units. The plan aims to include approximately thirty professionals per group, with a balanced distribution of nurses, nurse assistants, and physicians, and with similar mean age and seniority, so as to minimise pre-existing differences between the two groups.

The two groups differ exclusively in the presence or absence of the Maieutic-H model, while the observational conditions remain identical in both. Table 3 summarises the principal differences.

Table 3. Comparison between the experimental group and the control group.

Dimension	Experimental Group	Control Group
Intervention	Full Maieutic-H pathway (A1–A4)	No additional intervention
Training	Motivational, interactional, AI-driven	Standard training already in use at the institution
Assessments	T1, T2, T3 with structured checklist	T1, T2, T3 with structured checklist
Observers	Non-participant, blind	Non-participant, blind
Feedback loop	Activated in the event of issues (A5–A6)	Not planned
End of study	Certification of sustainable improvement	Receives the full Maieutic-H pathway
Function	Measures the specific effect of the intervention	Comparative baseline for spontaneous trends

The design does not include a separate baseline measurement (T0) before the intervention. This is intentional: the control group serves this purpose precisely, as it is observed at the same time points (T1, T2, T3), with the same checklist and the same blinded observers as the experimental group. By comparing the two groups longitudinally, it is possible to distinguish improvements genuinely attributable to the intervention from changes that would have occurred naturally over time. Initial equivalence between the groups is ensured by selecting participants from wards with comparable characteristics. Since this study is a Model contribution rather than an empirical trial [78,79], the addition of a formal T0 measurement is acknowledged as a limitation and is recommended as a priority refinement for the pilot phase.

The experimental group receives the complete training pathway across Phases A1–A4—motivational activation, interactional analysis, AI-driven prioritisation, and operational implementation—followed by longitudinal monitoring across Phases A5–A6, with the activation of feedback loops in the event of issues. The control group receives none of the Maieutic-H model phases and continues its ordinary activities with the standard training already in use at the institution. Researchers observe both groups at the same time points—T1, T2, and T3—using the same structured checklist, with the same non-participant observers who remain blind to group membership. This symmetry in observational conditions ensures that any differences the researchers observe between the groups are attributable exclusively to the intervention and not to variables related to the observation procedure. At the end of the study, the control group will receive the complete Maieutic-H pathway in compliance with the ethical principles that preclude the prolonged withholding of potentially beneficial interventions.

3.4.2. Observational Instrument and Temporal Structure of Measurements

The first assessment, designated T1, takes place one month after the completion of Phase A4, allowing researchers to evaluate the initial uptake of new practices and identify any early issues in the adoption of target behaviours. The second assessment, T2, takes place six months after implementation, by which point practices should have consolidated and stabilised within the daily operational routine, providing evidence of the medium-term sustainability of the change. The third and final assessment, T3, takes place twelve months after implementation and constitutes the terminal evaluation point for the certification of long-term sustainable improvement. This three-time-point structure is consistent with methodological recommendations for longitudinal analysis [86] and with the empirical findings of Collado et al. [87], who, in a quasi-experimental study on education for sustainable development, demonstrate that analysing effects across multiple time points allows researchers to distinguish immediate improvements from those that are stable over time, thereby producing more robust evidence of intervention effectiveness compared with immediate cross-sectional evaluations.

At each assessment time point, non-participant observers apply the same structured checklist across five thematic categories in accordance with the scientific evidence [88,89]: (a) waste generation, (b) waste collection, (c) segregation and sorting, (d) internal waste transport, (e) knowledge of regulations. Observers assign each observed behaviour a score using a five-point Likert scale, where one indicates non-compliant behaviour and five indicates fully compliant behaviour with minimal waste. Researchers then aggregate the scores to calculate a total and mean score for each participant, as well as a mean score for each thematic category. To ensure the reliability of the observational instrument, the checklist must satisfy the minimum criterion of a Cronbach's Alpha of 0.70 for basic research, with a corrected item-total correlation exceeding 0.30 for each item; researchers should consider items falling below this threshold as candidates for elimination [90].

3.4.3. Data Analysis

The data analysis proceeds on two complementary levels. The within-group analysis examines score variations within each group across the three assessment time points, using repeated-measures ANOVA or paired-samples t-tests to determine whether significant improvement occurs over time. The between-group analysis compares the experimental group with the control group through a mixed ANOVA model, in which the between-subjects factor is group membership and the within-subjects factor is assessment time point. The choice of mixed ANOVA is methodologically justified, since this model evaluates relative change between groups over time via the interaction effect (Time × Group). This approach enables researchers to test the intervention's effectiveness by focusing on differences in trajectories of change, making the model robust and valid even in the presence of any initial (baseline) physiological differences between the groups [91–93]. It also represents the most appropriate statistical tool for verifying the specific effect of the intervention over and above natural temporal trends. In line with current methodological guidelines for the evaluation of complex interventions [81,94,95], researchers should triangulate quantitative and qualitative data to build a more comprehensive evidence base. Specifically, this implies that the observational data derived from the structured checklist can usefully complement the qualitative observations of the interactional dynamics identified in Phase A2.

The same decision-making logic applies at T2, (6 months post-implementation), enabling the research team to detect issues that may emerge during the consolidation phase of practices. If the results at T1 were positive and the team activated no feedback loop, but a degradation in performance or a failure to stabilise improvements emerges at T2, the system can still intervene by directing the process to the appropriate phase.

At the end of the observation period (T3, 12 months), the team conducts the final evaluation. If all statistical parameters are positive and stable over time—that is, if the Group × Time interaction is significant with substantial effect sizes, and the experimental group's scores are higher than the control group's across all five thematic categories, and these categories remain stable across T1, T2, and T3—the process confirms the attainment of sustainable improvement concludes successfully. If issues persist at T3, the system activates a final feedback loop directed toward the appropriate function, signalling that the improvement has not reached the required sustainability threshold.

The critical element of the data analysis is the test of the Group × Time interaction, which verifies whether the pattern of change over time differs significantly between the experimental group and the control group, thereby providing specific evidence of the integrated intervention's effect beyond ordinary temporal trends. All analyses use a significance level of $\alpha = 0.05$ and calculate effect sizes using Cohen's d for comparisons between two means, and partial eta-squared (η_p^2) for analyses of variance. The interpretive benchmarks for Cohen's d follow the standard conventions: small (0.2), medium (0.5), and large (0.8) [96]. In addition, as the methodological literature recommends for small sample sizes, the research team calculates Hedges' g, which mathematically corrects for the overestimation of the effect typical of sample-based Cohen's d [97,98]. These measures allow researchers to quantify the practical significance of the observed changes, distinguishing effects that are statistically significant but clinically negligible from effects of substantial magnitude in hospital waste management.

In parallel with the behavioural analyses, the AI-driven prioritisation component (Phase A3) is evaluated using a staged validation strategy. In the absence of ground-truth labels for action relevance, the Random Forest ranking is first examined through construct validation against field evidence, operationalised as concordance between model-generated relevance scores and expert-perceived priorities (Section 3.5.3). As longitudinal data become available (T1–T3), the model will be re-evaluated using stratified k-fold cross-validation, progressively shifting from simulated-data calibration to field-data validation. Future empirical testing of Maieutic-H should also assess four additional domains: waste-segregation accuracy, staff adherence to procedures, regulatory compliance, and cost-effectiveness. These outcomes complement the structured checklist by capturing both operational performance and organisational impact. Table 4 summarises the corresponding indicators, instruments, and time points for implementation studies. Cost-effectiveness should be examined by comparing waste management expenditure, quantities of misclassified waste, and the resources required for corrective measures before and after implementation, consistent with the quality improvement perspective in Section 3.2.3 [71]. At this stage, the economic analysis remains exploratory; cost results should therefore be reported descriptively.

Table 4. Evaluation dimensions, metrics, and instruments planned for the real-world implementation of Maieutic-H.

Dimension	Metric	Instrument/Time Points
Waste segregation accuracy	Proportion of correctly classified waste items; Likert score, "segregation and sorting" category	Observational audit + structured checklist, T1/T2/T3
Staff compliance	Mean Likert score, "waste collection" and "internal transport" categories	Structured checklist, T1/T2/T3
Behavioural change	Group × Time interaction; Cohen's d, Hedges' g, partial η^2	Mixed ANOVA, experimental vs. control, T1/T2/T3
Regulatory adherence	Mean Likert score, "knowledge of regulations" category; action traceability records	Structured checklist + Phase A4 registration systems
Cost-effectiveness	Cost per corrective action; cost avoidance from reduced hazardous-waste volume and misclassification	Administrative/financial records, T1/T2/T3

3.4.4. Adaptive Feedback Logic

At T1, one month after implementation, if statistical analysis reveals that the Group × Time interaction is not significant—that is, the experimental group does not show a pattern of improvement exceeding that of the control group—the A6 function classifies the issue as motivational and immediately activates the feedback loop directed toward A1. This finding indicates that, despite the Greenopoli educational intervention, environmental awareness and motivation for change have not translated into operational behaviours that differ from those of the control group, signalling the need to reactivate the educational intervention with revised or intensified strategies. If, by contrast, the thematic categories relating to collection and segregation or the promotion of good practices show particularly low Likert scores even in the experimental group, the A6 function classifies the issue as operational and directs the feedback toward A2 for renewed observation and more in-depth interactional analysis in order to understand which communicative dynamics or coordination modalities are hindering the adoption of target behaviours despite the presence of motivation.

If the multivariate regression model reveals that certain actions with a high importance score assigned by the Random Forest did not produce the expected impact after the model controls for confounding variables—group membership, training hours delivered, sex, age, prior training, professional category, and years of experience—the A6 function classifies the issue as strategic and returns the feedback to A3 for a recalibration of the action plan based on revised criteria of contextual relevance. This recalibration mechanism operationalises, at the level of the full longitudinal design, the same adaptive reweighting logic introduced in Section 3.5.3 (linear combination of model-based and empirically derived scores), progressively shifting the Random Forest's relevance estimates toward field-observed outcomes as monitoring data accumulate across T1–T3. Table 5 illustrates the process through a summary table indicating, for each function, the inputs and/or context, the expected outputs, and the methodological instruments to use.

Table 5. Summary of the Maieutic-H process: for each function, the table specifies inputs (or context), control factors, expected outputs and operational tools.

Function	Input	Control	Output	Mechanism
A1—Motivational and Educational Activation	Hospital context: criticalities in waste management; healthcare personnel lacking awareness; cultural resistance to change. Optional motivational feedback from A6 (cycles following T1).	Environmental awareness objectives; narrative and playful pedagogy; strategies to reduce cultural resistance; reference regulations (WHO, EU, national) as a values framework.	Environmental awareness activated; intrinsic motivation for change; cognitive and emotional openness towards sustainable practices.	*Greenopoli* as an integrated educational device; storytelling and creative narrative; gamification (rap, creative engagement tools).
A2—Observation and Interactional Analysis	Personnel with activated awareness (from A1); daily professional interactions in the real work context; operational waste management activities. Optional operational feedback from A6.	Filliettaz interactional analysis methodology; structured observation protocols; predefined coding categories.	Communicative dynamics documented; specific operational criticalities identified; blind spots in professional practices surfaced.	Audio-video recording devices; multimodal analysis tools; software for systematic transcription and coding.
A3—AI-Based Decision Support	Operational criticalities documented (from A2); quantitative and qualitative field data collected; professional practices mapped. Optional strategic feedback from A6.	13 reference thematic areas; importance score threshold ≥ 0.5 for action selection; contextual relevance criteria; cross-validated relevance scoring (pending field data).	Prioritised action plan; quantitative ranking of corrective actions; importance scores for each action.	AI-Driven Circular Waste Management Tool; Random Forest model; database of 55 corrective actions; contextual filter algorithm.
A4—Implementation	Prioritised action plan with ranking (from A3); available hospital resources.	Implementation timeline; standard operating procedures; applicable organisational and regulatory constraints.	Corrective actions implemented in the field; operational modifications consolidated in daily practices; documentary records for accountability.	Operational healthcare personnel; waste management officers; progress tracking tools; activity registration systems.
A5—Monitoring and Evaluation	Implemented actions (from A4); observable staff behaviours; experimental group and control group.	Checklist across 5 thematic categories with 5-point Likert scale; three measurement time points T1 (1 month), T2 (6 months), T3 (12 months); experimental design with control group.	Aggregated Likert scores; repeated-measures ANOVA and mixed ANOVA analyses (Group × Time); Cohen's d and partial η_p^2; residual criticalities identified per time point.	Structured non-participating observations; systematic thematic coding; statistical software for ANOVA; behavioural annotation register.
A6—Decision and Feedback	Statistical results from A5 at the current time point (T1, T2 or T3); aggregated Likert scores; ANOVA output and interaction test results; calculated effect sizes.	Classification criteria for residual criticalities (motivational, operational, strategic); improvement acceptability thresholds (significant G×T interaction, relevant effect size, maintenance at T3).	T1/T2: identification of criticality type and activation of feedback loop towards A1, A2 or A3; T3: certification of sustainable improvement if all parameters are positive, stable and significant.	Statistical software for multiple linear regression with confounding variables; evaluation of R^2, residuals and standardised coefficients; multidisciplinary evaluation committee.

3.5. Core Components of the Maieutic-H Model

Maieutic-H is organised around three core components: a motivational component (Section 3.5.1), an analytical component (Section 3.5.2), and an operational component (Section 3.5.3).

3.5.1. The Motivational Component Implemented Through the Greenopoli Method

Greenopoli is an innovative educational framework for sustainability and waste management. Giovanni De Feo conceived and implemented the method, launching it in Southern Italy in 2006; from 2014 onwards, he has engaged approximately 600 schools and over 90,000 students, primarily in Italy, through workshops, projects, and public engagement events. The framework rests on the idea that children and young people can understand environmental issues as well as adults and can act as agents of change within their families and communities of belonging—whether school, family, or professional communities [54]. The method centres on two fundamental concepts: sharing, understood as an interactive peer-to-peer pedagogical approach in which participants co-create and disseminate knowledge among students, educators, and communities; and sustainability, understood as an orientation toward environmental protection, waste reduction, recycling, and the Sustainable Development Goals [99]. The approach combines scientific rigour with playful and creative pedagogy to simplify complex topics and stimulate peer-to-peer learning through storytelling, games, field visits, and 'green raps' (original environmental songs that students co-create with the educator). In the Greenopoli method, the educator shifts from the role of a traditional instructor to that of a facilitator or "moderator" of learning, creating a friendly and inclusive atmosphere and guiding students through discussions and activities. This moderated, discussion-driven style aligns with constructivist and mediated learning approaches, according to which students construct deeper understanding when they actively process information and teach one another, with the teacher providing scaffolding to the process.

Within the context of the Maieutic-H model, the Maieutic-H team adapts the Greenopoli method to the adult healthcare setting and to the specific profile of the healthcare workers involved, who already possess a professional culture and work in environments subjected to strong normative pressure. The adaptation preserves the fundamental principles of the method—co-creation, the peer-to-peer approach, and the use of narrative and creative languages–while replacing school-based content with themes directly relevant to hospital waste management: classification of healthcare waste categories, segregation protocols, the environmental impact of single-use devices, and the principles of the circular economy as applied to clinical settings.

The team reinterprets the method's characteristic tools for the adult context. It uses green rapping (short rhythmic sequences that participants co-create to summarise key concepts) not merely as a mnemonic device but as an instrument for disrupting the formal register, capable of lowering the cultural resistance typically encountered in mandatory training contexts within healthcare settings. Where the original method draws on narratives designed for childhood, the adapted approach uses narrativized clinical cases and recognizable hospital scenarios in which professionals can identify themselves and recognize their own practices. Interactive games, in their adult versions, take the form of simulations and role-playing exercises centered on real ward situations—such as managing an overfull sharps container, coordinating during a shift handover, or deciding how to classify a pharmaceutical waste item—actively engaging participants without reducing the experience to a purely normative drill. The team calibrates the duration and structure of the sessions on the basis of the effective availability of healthcare personnel, taking into account work shift constraints and the heterogeneity of the professional figures present.

The overarching objective is not to convey technical information in a frontal manner—already available through traditional training channels—but rather to activate emotional and cognitive engagement that reduces cultural resistance to change and fosters behavioural intention toward more sustainable practices. The method also promotes intergenerational and peer learning: in hospital settings, this translates into dynamics in which operators who are most attuned to the subject become multipliers of change within their own departments, analogous to what the literature documents with the 'Little Environmental Guards' in school contexts.

3.5.2. The Analytical Component Implemented Through Interactional Analysis

Filliettaz [49] proposes a conception of interactional analysis that treats it simultaneously as an object of study and a method of inquiry within the educational and vocational training sciences. From this perspective, social activities are not predetermined structures but rather processes that emerge in the course of situated action. As Filliettaz emphasises, practices such as teaching, healthcare, teamwork, or the provision of public services do not exist as abstract entities independent of the participants; participants bring them into being and stabilise them at the moment when they coordinate their actions in interaction [56].

In this sense, interaction constitutes the constitutive principle of social action. Participants progressively construct professional and educational activities through their contributions and the resources they mobilise within the context. Studies on learning in work settings show that professional environments generate learning opportunities precisely through the ways in which participants coordinate their actions and make resources available to less experienced workers. Analysing action and context allows researchers to understand 'the conditions under which work production environments may or may not afford rich learning opportunities to novice workers,' highlighting how situated learning depends on the quality of interactions rather than on the formal transmission of content.

A second fundamental principle of interactional analysis concerns the sequential structure of interaction. Communicative actions are not isolated; participants organise them into temporal chains in which each contribution orients toward what precedes it and prepares what follows. Within this framework, a question makes a response conditionally relevant, which may in turn generate an evaluation, an explanation, or a repair. The conversation analysis literature has shown that human interaction unfolds 'step-by-step, one action after the other,' and that participants use this sequential organisation as the mechanism through which they construct and maintain social order in everyday interactions [100–102].

Filliettaz et al. [49] highlight that researchers cannot reduce interaction to verbal language alone. Communicative practices mobilise an articulated set of semiotic resources encompassing gestures, gaze, body posture, movement through space, and the manipulation of material objects. Contemporary research defines this phenomenon as the multimodality of interaction, emphasising that social action unfolds through the simultaneous coordination of multiple expressive modalities [103]. From this perspective, researchers who seek to understand interaction need analytical tools capable of describing how these different modalities articulate in time and space to produce recognisable social actions.

From a methodological standpoint, interactional analysis rests on the systematic observation of empirical data drawn from naturally occurring interactions. Researchers collect audio-video recordings of authentic situations—such as lessons, work meetings, or professional interactions—without intervening in or manipulating the observed context. The fundamental assumption of conversation analysis is that everyday language displays 'order at all points,' a social order that researchers can identify only through the detailed analysis of recordings of natural speech [104]. Researchers then transform the recordings into detailed multimodal transcripts, annotating pauses, overlaps, and intonation alongside gestures, gaze orientations, and object manipulations. The widespread adoption of video recordings in social research has placed multimodal transcription at the centre of methodological debate; such transcription must render visible the different modalities through which participants coordinate their actions in interaction [105].

To implement this approach, Filliettaz et al. [49] proposes a stepwise procedure for turning video recordings into analysable data. Brief, information-rich episodes relevant to ward-level problems are selected and transcribed multimodally (speech, gaze, gesture, body movement, and object use). Analysts then define the units of analysis (e.g., turns, sequences, episodes) and apply coding categories derived from the data or adapted from existing frameworks (e.g., turn-taking, clarification requests, deictic gestures, interactional tempo). Trained coders document occurrence, frequency, and duration, generating indicators that can be compared across the Phase A5 monitoring points (T1, T2, T3). Quantification complements, rather than replaces, qualitative interpretation: numerical patterns are interpreted in relation to the interactional sequences from which they arise [49]. The procedure is conducted by an interaction analysis group (researcher-trainers and healthcare professionals) trained in recording, transcription, and analytic observation, and then applied to concrete ward problems.

A further theoretical principle underpinning interactional analysis is the idea that speaking means acting. Utterances do not merely serve to transmit information; they realise social actions such as asking, promising, explaining, correcting, or teaching. Researchers who apply conversation analysis to educational contexts have demonstrated, for example, that pedagogical practices do not simply consist of the transmission of content but are situated activities that participants accomplish in interaction [106]. Similarly, studies on professional mentoring reveal that mentors influence the work of early-career practitioners through interactional mechanisms that are often indirect and difficult to observe, which emerge only through a micro-interactional analysis of communicative practices [107].

Because video data may include identifiable staff and other individuals, collection and analysis must follow a documented ethics and data protection protocol. Participants provide explicit informed consent specifying the study purpose, authorised access, intended uses (e.g., research, training, publication), and the right to withdraw. Recordings and transcripts are stored in secure, access-controlled systems restricted to the interaction analysis team. Any material considered for external presentation is anonymised (e.g., facial blurring, pseudonymisation, removal of contextual identifiers). Materials used only for internal analysis or training remain under restricted access, whereas external dissemination requires additional consent and strengthened anonymisation. Procedures follow applicable data protection requirements and require approval by the relevant institutional ethics committee.

3.5.3. The Operational Component Implemented Through the AI-Driven Instrument

The AI-Driven Circular Waste Management tool is a decision support system that assists healthcare workers and hospital waste management coordinators in implementing circular practices, in compliance with international regulatory standards and sustainability objectives [57].

The tool functions as an interactive application integrating several components: a checklist system organised by thematic areas, accompanied by indicators and corrective actions; a prioritisation algorithm based on relevance scores; and operational modules that enable users to monitor implementation progress, plan activities, annotate observations, and evaluate performance.

The system's architecture organises 13 macro-thematic categories covering the principal domains of healthcare waste management, including regulatory compliance, source reduction, and the management of specific waste streams such as pharmaceutical waste. Overall, the tool identifies 55 corrective actions distributed across the different categories.

Each action carries a relevance index that a Random Forest algorithm estimates on simulated datasets relating to compliance levels. The predictive feature set is structured around five domains: ward typology (surgical, medical, intensive care, oncology), waste category and volume, staff turnover rate, historical non-conformity frequency, and prior audit outcomes. Given the anticipated scale of field data—typically small and unbalanced samples characteristic of single-institution compliance records—Random Forest was selected over gradient boosting or logistic regression alternatives for its lower variance on limited training sets and its native robustness to class imbalance through bootstrap aggregation. Model performance will be assessed via stratified k-fold cross-validation once longitudinal data from phase A5 become available; the scores reported below derive from a preliminary simulated dataset used for calibration purposes only.

The system normalizes scores within a range of 0 to 1 and ranks them in descending order, enabling users to identify operational priorities immediately. Consistent with the methodological approach, the tool further classifies actions into three levels of importance (high, medium, and low) on the basis of quartiles of the distribution. Actions with higher values require greater attention and monitoring, while those with lower relevance depend more heavily on the operational context.

The research team conducted the initial validation of the model through four simulated case studies representative of real hospital settings, analysing operational, managerial, and regulatory issues. The team formalised the identified problems as verifiable statements and linked them to the corresponding thematic categories of the tool. The system then selects the relevant set of actions and returns a prioritisation based on relevance scores.

This concordance rate is used as an indicator of agreement between the algorithmic ranking and expert prioritisation in the absence of ground-truth relevance labels; accordingly, it is treated as evidence of construct validity for the ranking logic rather than as a measure of predictive accuracy.

The alignment between the priorities that operators express and the scores the model generates is particularly high for the most relevant actions, while it decreases for less frequent actions that depend more heavily on context.

The framework was further examined in the qualitative validation study reported in Cappelli et al. [58], based on 11 semi-structured interviews with healthcare waste management professionals. Using thematic analysis, the interview material was organised into 20 subtopics and mapped to the tool's thematic areas, indicators, and operational actions. Of the 55 corrective actions, 51 (93%) were supported by evidence from professional practice, indicating substantial alignment between the framework and practitioners' operational needs. Reported priorities also broadly matched the Random Forest ranking for the highest-scored actions, while greater variability appeared among lower-ranked, context-dependent actions. The 93% value is therefore interpreted as qualitative construct validity (framework–practice alignment), not as predictive accuracy or a formal inter-rater reliability statistic.

Following these findings, the importance scores were updated by linearly combining the model-derived importance with the empirical relative frequencies observed in the interviews [58]. A weighting factor of $\alpha = 0.70$ was used to give greater weight to the interview evidence while retaining the contribution of the original scores. Future work will assess how sensitive the prioritisation is to alternative values of α as additional data become available.

Overall, the system allows users to identify and prioritise the most relevant interventions, supporting a structured, adaptive, and evidence-based decision-making process that fosters the transition toward circular models of healthcare waste management [58]. In this perspective, the specific value of the tool within the Maieutic-H model lies in its capacity to integrate the qualitative and quantitative dimensions: it systematises the evidence that Phase A2 observation of interactional practices produces and translates that evidence into a structured intervention plan, prioritised on the basis of relevance scores and adapted to the specific characteristics of the context. In this way, the tool bridges the gap between understanding real operational dynamics and defining corrective actions grounded in empirical evidence and supported by an analytical model.

4. Theoretical Validation: A Comparative Analysis of Existing Interventions

The Maieutic-H model is a theoretical model not yet empirically applied; consequently, no results derived from its implementation are available. This constitutes the object of a subsequent research phase. The present study, therefore, aims to assess its theoretical plausibility and internal coherence through a critical re-reading of the training interventions documented in the literature. To this end, the study selected eleven cases, all focused on healthcare waste management, spanning infectious waste segregation, single-use device disposal, pharmaceutical waste management, and waste flow control in operating theatres. The team analysed each case in relation to the three model components—motivational, analytical, and operational—and to the process phases (A1–A6), in order to identify which elements of the framework find confirmation in already empirically validated interventions and which, instead, represent original contributions of systemic integration.

4.1. Motivational Strategies in Existing Interventions: Convergences and Gaps

This section examines existing sustainable healthcare waste management interventions, focusing specifically on the motivational strategies they adopt and comparing them with the Greenopoli method, which constitutes phase A1 of the proposed model. The Greenopoli method is characterised by a playful-narrative and peer-to-peer approach based on storytelling, green rap, and interactive activities, aimed at transforming environmental awareness into deep cultural commitment through the emotional engagement of practitioners. The interventions are presented as case studies (A through F) followed by a comparative analysis.

Case A—Scarfe and Hughes [108] conducted an intervention at Oxford University Hospitals in operating theatre settings involving anaesthetic nurses, theatre practitioners, and scrub nurses. The motivational strategy employed an initial survey that simultaneously functioned as a data collection instrument and an awareness-raising intervention, encouraging staff to question their own working practices. The motivational lever was the behavioural paradox identified: 96% of staff recycle at home, while only 60% do so in the workplace. The intervention used this cognitive dissonance as a trigger to stimulate critical reflection. It delivered targeted training during clinical governance days for specific groups, with the operational support of flow algorithms positioned beside the new recycling containers. A motivational feedback loop element was introduced through the visualisation of recycling data to stimulate positive competition among different operating theatres. The Oxford intervention relies on rational-cognitive motivation, exploiting the dissonance between domestic and workplace behaviour without activating structured emotional engagement. The Greenopoli method could replace mechanical inter-ward competition with peer-to-peer engagement grounded in storytelling and co-creation, producing deeper and more lasting cultural change. The intervention also lacks systematic longitudinal monitoring at T1, T2, and T3, and the algorithmic prioritisation of corrective interventions envisaged in phase A3.

Case B—Hosny et al. [17] conducted a study across 11 governmental hospitals in the Alexandria Governorate, targeting healthcare waste management workers. The motivational component relied on frontal lectures and open discussions, designed to be accessible even to workers with low literacy levels. The authors noted that workers showed interest and a desire to learn and change. To overcome comprehension barriers, the intervention used high-impact visual teaching aids, PowerPoint presentations projected via laptops or iPads, and demonstration videos covering the hazards of healthcare waste, disposal procedures, and incident management. Pre- and post-intervention evaluation detected a significant increase in knowledge across almost all items, with the exception of four specific ones. The motivational strategy flows in one direction: from the training to the worker. The Greenopoli method could supplement this phase with storytelling, green rap, and interactive games to make the message more memorable and culturally embedded. The algorithmic prioritisation of phase A3 could also help understand why the four knowledge items failed to improve—a gap the model's Random Forest tool could close by identifying the most relevant corrective interventions for those specific criticalities. The authors themselves acknowledge the need for a longitudinal study to validate results over time.

Case C—Prenestini et al. [109] presented the strategies adopted by IRCCS Istituto Clinico Humanitas in Rozzano, Italy. The hospital adopted a motivational strategy grounded in internal organisational culture and the engagement of all stakeholders through internal awareness campaigns. The main instrument is the *Verde Humanitas* column, which provides practical guidance and suggestions on healthy and sustainable lifestyles within the hospital. In 2023, 53% of the waste produced was channelled to recovery. The Humanitas motivational component is predominantly communicative and top-down. Relative to the proposed model, Greenopoli could introduce peer-to-peer dynamics to transform workers from passive recipients of institutional messages into active agents of cultural change in their own wards. Applying the model to this case would additionally enable the systemisation of the analytical-interactional training envisaged in phase A2, which would surface micro-operational criticalities in high-turnover wards—such as medical and surgical departments—that the sole use of aggregate recovery indicators cannot detect.

Case D—Michael et al. [110] conducted an intervention in governmental tertiary healthcare facilities in North-East Nigeria, targeting waste management workers. The motivational component rests on the logic of capacity building, according to which the presentation of evidence and the rationale for change are sufficient to produce behavioural change. A preliminary stakeholder engagement phase preceded the motivational training to determine the areas requiring intervention. The training programme followed a manual developed in accordance with WHO and United Nations Development Programme (UNDP) standards, covering collection, segregation, storage, treatment, and disposal. Pre- and post-test evaluations with paired-sample *t*-tests documented significant improvements, though the authors themselves acknowledge that maintaining results requires structured follow-up mechanisms. The motivational approach is hierarchical, resting on the vertical transmission of knowledge within an instructivist logic. The Greenopoli method would replace this approach with emotional and peer-to-peer engagement, acting on the values and professional identity of workers as well as their declarative knowledge. The introduction of a structured feedback loop—guaranteed in the proposed model by function A6—would also allow the intervention to be reoriented if results fail to consolidate over time.

Case E—Shahab et al. [63] conducted a study at Hafez Hospital in Shiraz, involving healthcare workers and service personnel responsible for waste management. The educational intervention was explicitly structured on the basis of the TPB, acting simultaneously on knowledge, attitudes, subjective norms, perceived behavioural control, and behavioural intention. Pre- and post-intervention evaluation identified statistically significant differences across all these constructs, both in the healthcare worker group and the service personnel group, with concrete improvements in separation, collection, and disposal practices. The intervention acts on TPB constructs through traditional structured training, without activating the peer-to-peer dynamics and narrative emotional engagement characteristic of the Greenopoli method. The proposed model would have strengthened the motivational effect by replacing the vertical transmission of content with the co-creation of meaning through storytelling and green rap, capable of acting more deeply on the affective domain and the internalisation of environmental values. Longitudinal monitoring at T2 and T3 and the structured feedback loop envisaged in phases A5 and A6 are also absent.

Case F—Şimşek and Özsoy [65] evaluated the effectiveness of a hospital recycling programme for nurses based on TPB constructs. The intervention produced significant improvements in nurses' attitudes, perceived behavioural control, and behavioural intentions, with a measurable effect on actual practices: recyclable waste increased by 200% and undifferentiated medical waste decreased correspondingly. These results demonstrate that explicitly targeting the motivational constructs of the TPB produces effects not only on stated intentions but also on measurable operational behaviours. The programme focuses on the motivational component without providing for an analytical phase of real practice observation (A2) or algorithmic prioritisation of corrective interventions (A3). Integration with further phases could combine the motivational results achieved with interactional analysis of the coordination dynamics among nurses, identifying the specific operational criticalities that impede recycling in daily practice beyond individual motivation. Structured longitudinal monitoring at three time points could additionally verify the stability of the 200% increase over time.

4.2. Interactional Analysis in Professional Training: A Methodological Gap

This section examines existing interventions that include a phase of observation and analysis of real work practices, comparing them with the analytical component of the proposed model, implemented through the interactional analysis [49,55,56]. This component, corresponding to phase A2, distinguishes itself through multimodal observation of interactions among workers via audio-video recordings and multimodal transcripts, aimed at identifying submerged operational criticalities undetectable through standardised questionnaires or checklists. The interventions are presented as case studies (A through D) followed by a comparative analysis.

Case A—[110] described a preliminary stakeholder engagement phase aimed at determining which areas required intervention, followed by personal checklist-based observation to record critical areas in hospital waste management. This initial mapping provided the basis for formulating the training action plan. The underlying logic is capacity building: identify knowledge and competence gaps before designing the intervention, following the UNDP phases of training needs analysis, plan formulation, implementation, and final evaluation. Checklist-based observation detects declared gaps or visible behaviours in an aggregated manner but does not penetrate the communicative and coordination dynamics that structure workers' real practices. The interactional analysis of Filliettaz envisaged in phase A2 would instead observe how workers coordinate their actions in daily interaction, revealing submerged criticalities such as waste classification errors linked to implicit communication dynamics among colleagues, inter-ward coordination difficulties undetectable through aggregated observation tools, and formally correct procedures applied in differing ways in situated practice.

Case B—Shaheen et al. [27] conducted an intervention at Lady Aitchison Hospital in Lahore, Pakistan. A checklist-based assessment of nurses' practices conducted before the training intervention mapped operational criticalities, revealing that the majority of nurses displayed incorrect practices prior to the training sessions and providing the empirical basis for intervention design. Practice assessment was repeated one month after training through re-evaluation, with statistical analysis using paired *t*-tests and chi-square tests documenting significant improvements in observed practices. Like the Nigerian case, the checklist detects compliance or non-compliance of behaviours against pre-defined standards, but does not explore the interactional and communicative reasons underlying incorrect practices. Multimodal interactional analysis could explain why specific practices deviate from standards, for example, identifying whether the errors detected are attributable to individual knowledge gaps, dysfunctional collective coordination dynamics, or contextual constraints of the work environment. The intervention also lacks the T2 (six months) and T3 (twelve months) assessments that could verify the sustainability of change over time and activate the feedback loop towards the appropriate phase in the event of behavioural regression.

Case C—Scarfe and Hughes [108] conducted an intervention that included a workflow observation phase to identify the principal actors involved in the production and disposal of physical waste in operating theatres. This observation pinpointed the critical nodes of the process and enabled the design of a contextually appropriate operational solution: the positioning of 70 recycling containers and flow algorithm 'aide memoires' beside each container. The workflow observation represents the element closest to the logic of phase A2, as it starts from the analysis of the real context before introducing operational solutions. Despite the presence of an observational phase, the analysis limits itself to mapping the physical flows of waste and the actors involved, without examining the interactional and communicative dynamics that structure disposal practices in the operating theatre. Video-Based Interaction Analysis would identify not only who produces which waste and where, but also how workers coordinate their actions in situated interaction, which semiotic resources they mobilise, and how the sequential structure of interaction produces or impedes behaviours that conform to the standards for classifying surgical waste.

Case D—Cook et al. [70] applied the COM-B model and the Theoretical Domains Framework to investigate the behavioural determinants of conducting food waste audits in hospital catering services, drawing on 20 interviews with healthcare workers. The analysis identified psychological capability (knowledge and skills), physical opportunity (environmental context and resources), and reflective motivation (social and professional role and beliefs about one's own capacities) as the dominant constructs. On the basis of these determinants, the study identified the intervention functions with the greatest potential: education, training, environmental restructuring, modelling, and enablement. The approach relies on interviews and deductive analysis of behavioural determinants, without providing for the direct observation of real interactions among workers. The analytical component of the proposed model would have integrated this mapping of determinants with Filliettaz's Video-Based Interaction Analysis, capable of capturing not only the factors declared in interviews but also the implicit communicative dynamics and the non-conscious coordination mechanisms that structure real waste management practices. This analytical depth would have identified operational criticalities not surfaced through interviews alone, producing a more precise empirical map on which to base the algorithmic prioritisation of phase A3.

4.3. Data-Driven Decision Support: Alignment with Existing Operational Approaches

This section examines existing interventions that include an operational implementation phase, comparing them with the operational component of the proposed model. This component comprises phase A3—in which the AI tool based on the Random Forest algorithm prioritises 55 corrective interventions across 13 thematic macro-categories, assigning each an importance index from 0 to 1, and phase A4, in which the prioritised actions are concretely implemented in daily practices, followed by longitudinal monitoring at three time points (A5) and the decisional feedback loop (A6). The interventions are presented as case studies (A through E) followed by a comparative analysis.

Case A—Kumar et al. [111] conducted the Intensive Healthcare Waste Management (IHWM) programme in two tertiary teaching hospitals in Rawalpindi, Pakistan, targeting physicians, nurses, paramedics, and health personnel. The operational intervention comprised three six-hour training sessions conducted at four-week intervals, hands-on practicals focused on the correct use of personal protective equipment, and the practical phases of infectious waste management, along with a reinforcement service through reminders managed by administrators at weekly morning meetings for three months. Pre- and post-intervention evaluation using a five-point Likert scale, with follow-up at 18 months, documented significant improvements in practitioners' practices. The weekly reminder service acts as a rudimentary form of a continuous feedback loop during the initial consolidation phase. The IHWM programme selects training content based on categories pre-defined by WHO guidelines but applies no algorithmic criteria for contextual prioritisation. The Random Forest tool envisaged in phase A3 of the model would have instead identified, among the 55 available corrective interventions, those with the highest relevance index for the specific context of the two hospitals, optimising the allocation of training resources. The 18-month follow-up represents a strength that approaches the logic of the longitudinal monitoring envisaged in phase A5, although it lacks the statistical structure based on repeated-measures ANOVA and multiple linear regression that characterises the proposed model. The interactional analytical component (A2) is also absent, which would have allowed the targeted correction of the practical errors observed among auxiliary health personnel.

Case B—Lee and Lee [32] employed the Analytic Hierarchy Process (AHP) as a decision-making method to determine the priorities among the key factors of healthcare waste management, following a logic conceptually analogous to phase A3 of the proposed model. The priority actions identified through this process were operating standards for healthcare waste, with a weight of 35.2%, and safe, watertight storage of infectious waste, with a weight of 33.4%. The programme's explicit objective was to integrate waste management into daily work activities to prevent segregation from being perceived as an additional task alongside ordinary duties. The difference between the AHP approach and phase A3 of the proposed model lies in the source of prioritisation: the AHP method relies on expert judgments structured through pairwise comparisons, while the model's Random Forest system automates and objectivises prioritisation through an algorithm trained on simulated compliance datasets, producing numerical relevance indices for each of the 55 corrective interventions. This shift reflects a broader transition documented in clinical decision support literature—from rule-based and expert-weighted scoring systems (as in AHP) toward data-driven, ensemble-based classifiers capable of capturing non-linear interactions among contextual variables that pairwise comparison methods cannot represent. Also, this objectivisation allows priorities to be updated based on data collected during monitoring. The integration of waste management into daily activities—the explicit objective of the Korean programme—is precisely what the feedback loop of phase A6 is designed to certify through longitudinal monitoring at T1, T2, and T3.

Case C—Wu et al. [112] conducted a study in a Taiwanese tertiary hospital, using a virtual reality simulated environment in which participants had to correctly dispose of 10 random objects among hazardous, contaminated, and infectious waste. The system provides real-time feedback based on accuracy rate and scenario completion time, increasing workers' operational confidence in waste segregation. This innovative technological approach enables the simulation of critical situations in a controlled environment before real implementation, reducing the risk of errors in daily practice. The VR simulation focuses on the technical-individual dimension of segregation, training the individual worker to recognise and correctly classify waste in isolation. The proposed model would integrate this tool as a component of phase A4, embedding it within a broader process that includes the observation of collective coordination dynamics among workers (A2), algorithmic prioritisation of interventions (A3), and structured longitudinal monitoring (A5). The coordination criticalities among colleagues that Filliettaz's interactional analysis is designed to detect are not addressable through individual simulation, however technologically advanced.

Case D—Sommese and Pantusa [113] described a programme realised at the MultiMedica Group and Montecchi Hospital, involving health personnel, transport workers, and waste collection staff. The operational intervention included the installation of Newster technology for on-site sterilisation of waste—based on powerful rotating movement that finely shreds materials to reach a temperature of 150°C—and the transition from single-use cardboard to reusable polyethylene. Monitoring documented a 30% reduction in waste weight for disposal and a 70% reduction in volume. The feedback loop operated through meetings between project managers and the respective Strategic Directorates to decide on the transition to the next project phase based on the pilot results. Digital support included cloud software with e-learning modules for workers and real-time data monitoring. The MultiMedica project is the closest among all examined cases to the integrated logic of the proposed model, as it includes an initial motivational component, waste mapping assimilable to phase A2, a structured operational intervention (A4), monitoring with quantitative data (A5), and a decisional feedback loop (A6). However, the prioritisation of interventions rests on managerial evaluations rather than on an automated algorithm such as the Random Forest envisaged in phase A3. The proposed model would have added algorithmic prioritisation to scale the intervention systematically across all facilities of the group.

Case E—Joshi et al. [114] conducted a study in private tertiary hospitals in Dehradun, India, targeting laboratory technicians, nurses, physicians, and cleaning personnel. The intervention aims to close gaps in waste segregation practices, safe disposal, and the use of personal protective equipment through structured awareness initiatives. Evaluation proceeded through a 20-item questionnaire and Pearson correlation tests to validate the link between training participation and improved practices. The intervention is purely quantitative, detecting the gaps as perceived by practitioners without translating this into a prioritised and contextually calibrated action plan. The proposed model would have added phase A2 to observe why gaps persist through the analysis of real interactions and phase A3 to manage the complexity of the 55 available corrective interventions through algorithmic prioritisation, replacing intuitive selection of interventions with a decision-making process based on objective relevance indices. A structured feedback loop enabling the intervention to be reoriented in case of unsatisfactory results—an element guaranteed in the proposed model by the decisional function A6—is entirely absent.

Beyond the case-by-case comparison, it is worth situating the choice of Random Forest against alternative machine learning approaches reported in adjacent waste management literature, such as gradient boosting and logistic regression-based classifiers. Random Forest was preferred for its robustness to small and noisy datasets typical of hospital settings, its native handling of mixed categorical and numerical predictors, and the interpretability afforded by feature importance rankings—a property particularly valuable for translating model output into actionable, ward-specific recommendations for non-technical clinical staff.

5. Results

Table 6 demonstrates the originality and completeness of the proposed model (Maieutic-H), highlighting the methodological gaps in the current literature.

Figure 3 summarises the comparative assessment in Table 6. The reviewed interventions predominantly address initial training (A1) and operational implementation (A4). By contrast, interactional analysis (A2) and AI-based prioritisation (A3) are uncommon, and longitudinal monitoring (A5) with structured feedback (A6) is rarely reported. Ref. [113] is a partial exception, as it includes monitoring and a decision process, although without a fully specified algorithmic prioritisation stage.

The matrix highlights three patterns. First, implementation (A4) is the most frequently reported phase (present in 13/15 interventions and partial in 2/15), indicating a strong focus on practical measures. Second, interactional analysis (A2) and AI-based prioritisation (A3) are comparatively rare (A2: partial in 7/15 and absent in 8/15; A3: present/partial in 2/15). Third, long-term mechanisms are uncommon: monitoring (A5) and feedback (A6) are jointly observed, even partially, only in [113]. Overall, the gap concerns the integration of interactional assessment, data-informed prioritisation, and longitudinal monitoring within a coherent adaptive process.

In summary, Table 6 supports the rationale for Maieutic-H by showing that the reviewed literature rarely connects motivational activation, interactional assessment, algorithmic prioritisation, and longitudinal monitoring within a single process. The algorithmic component (Section 3.5.3) also shows 93% concordance between model-generated relevance scores and expert-perceived priorities, which is reported as qualitative construct validity rather than evidence of predictive performance. Because the underlying classifications are categorical (present/partial/absent), the heatmap is presented as a descriptive synthesis rather than an inferential or continuous quantitative analysis (see Figure 4).

Table 6. Comparative analysis of the literature against the six phases of the Maieutic-H model.

Case/Study	A1—Motivation	A2—Interactional Analysis	A3—Algorithmic Prioritisation	A4—Operational Implementation	A5—Longitudinal Monitoring	A6—Feedback Loop
Proposed model (Maieutic-H reference)	**Greenopoli** Storytelling, peer-to-peer, structured emotional engagement	**Filliettaz** Audio-video recording, multimodal transcription, implicit dynamics	**Random Forest** 55 interventions × 13 categories, 0–1 indices, automatic prioritisation	**Structured** Prioritised actions implemented in daily practices	**T1, T2, T3** Repeated-measures ANOVA + mixed ANOVA + multiple linear regression	**Decisional A6** Automatic reorientation if regression detected
Motivational component						
A—[108] Oxford Univ. Hospitals	**Partial** Cognitive dissonance home/workplace; competitive feedback between wards	**Partial** Physical waste flow observation, not interactional dynamics	**Absent** Static flow algorithms, no contextual prioritisation	**Present** 70 containers positioned contextually	**Absent** No follow-up at T1, T2, T3	**Absent** Data visualisation but no reorientation
B—[17] 11 hospitals, Alexandria	**Partial** Frontal lectures; unidirectional, no peer-to-peer	**Absent** Pre/post test only; no observation of real practices	**Absent** Structural causes not identified	**Present** Broad thematic coverage (hazards, disposal)	**Absent** Authors themselves acknowledge the need	**Absent**
C—[109] IRCCS Humanitas	**Partial** Top-down campaigns; workers as passive recipients	**Absent** Aggregate recovery indicators only; micro-criticalities invisible	**Absent**	**Partial** Practical guidance but without systematisation	**Partial** Annual aggregate indicators, no T1–T2–T3 structure	**Absent**
D—[110] North-East Nigeria	**Partial** Hierarchical capacity building; instructivist logic	**Partial** Aggregate observational checklist; no communicative analysis	**Absent** Areas defined by stakeholder judgement, not by algorithm	**Present** WHO/UNDP manual; segregation, storage	**Absent** Recognised need for structured follow-up	**Absent**
E—[63] Hafez Hospital, Shiraz	**Present** Explicit TPB: attitudes, perceived control	**Absent** No observation of real practices	**Absent**	**Present** Improvements in separation, collection, disposal	**Absent** Pre/post only; no T2–T3	**Absent**
F—[65] Nurse study	**Present** TPB; reduction in undifferentiated waste measured	**Absent** No observational phase of real practices	**Absent** No algorithmic prioritisation	**Present** Effects on measurable operational behaviours	**Absent** Stability not verified over time	**Absent**
Analytical component						
A—[110]	**Partial**	**Partial** Stakeholder engagement + checklist; no communicative dynamics	**Absent**	**Present**	**Absent**	**Absent**
B—[27] Lady Aitchison, Lahore	**Partial**	**Partial** Pre/post checklist; compliance detected but not reasons for errors	**Absent**	**Present**	**Partial** Re-evaluation at 1 month; 6 and 12 months absent	**Absent**
C—[108]	**Partial**	**Partial** Physical workflow observation; no interactional structure	**Absent**	**Present**	**Absent**	**Absent**

Table 6. *Cont.*

Case/Study	A1—Motivation	A2—Interactional Analysis	A3—Algorithmic Prioritisation	A4—Operational Implementation	A5—Longitudinal Monitoring	A6—Feedback Loop
D—[70] COM-B + TDF	**Present** Psychological capability, reflective motivation	**Partial** 20 interviews; deductive analysis; no direct observation	**Absent**	**Present** Functions: education, training, environmental restructuring	**Absent**	**Absent**
Operational component						
A—[111] IHWM, Rawalpindi	**Partial** Reinforcement via weekly reminders; no emotional engagement	**Absent**	**Absent** Content from WHO guidelines, not prioritised	**Present** 3 sessions + practicals + 3-month reinforcement	**Present** 18-month follow-up; without ANOVA	**Partial** Reminders but no algorithmic reorientation
B—[32] AHP study South Korea	**Partial**	**Absent**	**Partial** AHP based on expert judgements; subjective	**Present** Priority operating standards	**Partial**	**Absent**
C—[112] VR simulation Taiwan	**Partial** Increased confidence but no emotional engagement	**Absent** Individual simulation; no coordination dynamics	**Absent**	**Present** Real-time feedback on accuracy and time	**Absent**	**Absent**
D—[113] MultiMedica Lombardy, Italy	**Partial** Technical training; risk perception not addressed	**Partial** Waste mapping but not interactional	**Partial** Managerial evaluations; no algorithm	**Present** Newster technology; −30% hazardous waste	**Present** Quantitative monitoring; without T1–T2–T3 structure	**Present** Decisional feedback present but unstructured
E—[114] Dehradun, India	**Partial**	**Absent** Perceived gaps but no interactional observation	**Absent** No contextually prioritised action plan	**Partial** Awareness-raising without A2 and A3	**Absent**	**Absent**

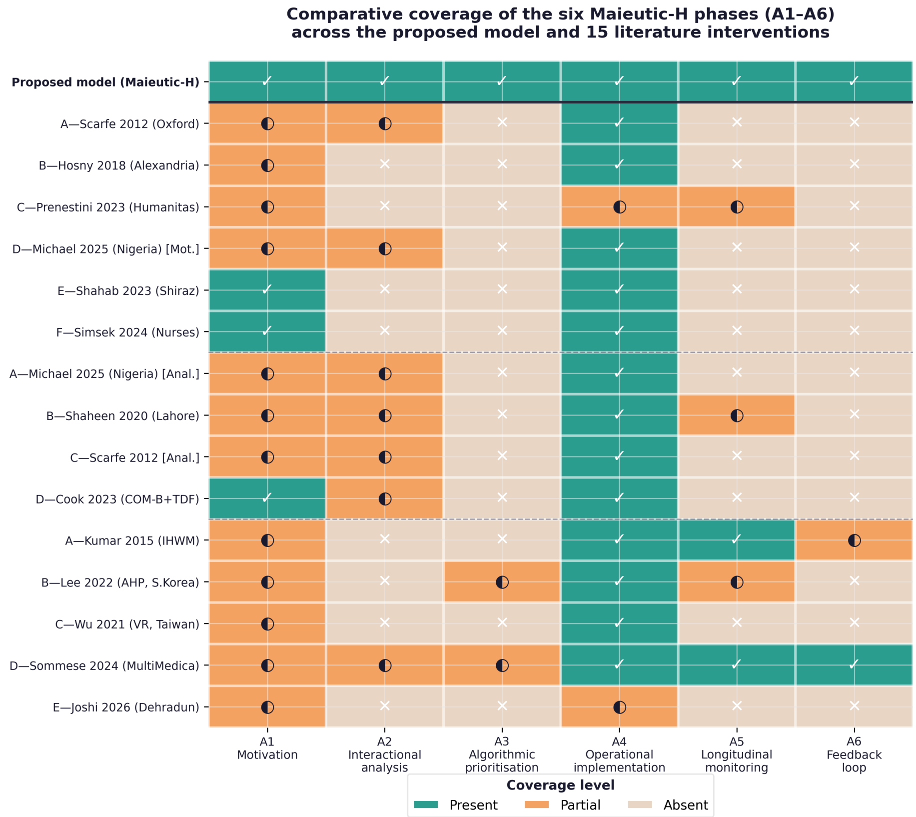

Figure 3. Heatmap visualisation of Table 6, comparing the proposed Maieutic-H model against the 15 literature interventions across the six phases (A1–A6). [17,27,32,63,65,70,108–114]. Symbols denote coverage level: "✓" = Present (full coverage), "∘" = Partial (limited coverage), and "×" = Absent (no coverage). The thick solid line separates the proposed model from the literature interventions; dashed lines demarcate thematic subgroups.

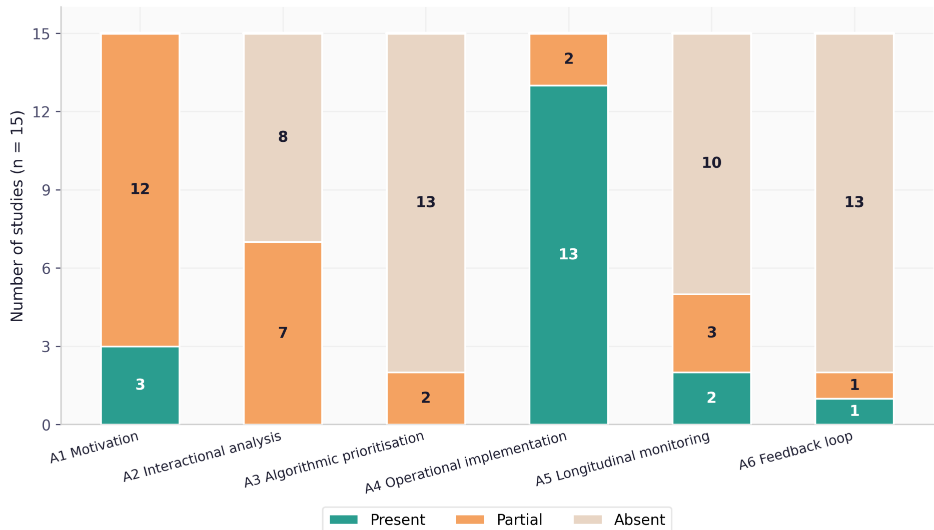

Figure 4. Summary distribution of present/partial/absent classifications for each phase (A1–A6) across the 15 literature interventions examined.

6. Discussion

The examined literature reveals that the programmes most effective in the short term—particularly those grounded in the TPB [63,65]—are not necessarily the most robust in terms of longitudinal sustainability. This misalignment between immediate effectiveness and stability over time suggests that behavioural change in healthcare waste management is not primarily a problem of individual motivation but a systemic issue. In hospital settings, high-turnover wards—such as internal medicine, surgery, and intensive care units—are also those that produce the highest risk waste categories, including infectious, sharps, and pharmaceutical waste, where operational pressure makes the consolidation of new practices particularly difficult [10]. In these care settings, incorrect practices of waste segregation and classification persist not for lack of workers' willingness but because the organisational and communicative dynamics that generate them go unobserved and unaddressed [30]. This interpretation aligns with the tradition of interactional analysis, according to which professional practices emerge from situated interactions among actors in specific organisational contexts and are not reducible to individual behaviours. The case comparison provides indirect empirical support for this perspective: interventions focusing exclusively on the individual—frontal training, simulations, or questionnaires—produce measurable but structurally fragile improvements because they do not modify the interactional conditions that generate error. Shivashankarappa et al. [16] document a significant improvement in healthcare waste management practices immediately after the intervention but a progressive reduction of effects at the three-month follow-up, confirming that technical training alone does not produce stable changes in ward practices.

Among the principal gaps identified, the near-systematic absence of a feedback loop (A6) represents a critical point. The analysed programmes follow a linear logic—design, implementation, evaluation—without incorporating structured mechanisms for reorientation in the event of behavioural regression. This approach is consistent with pre-test/post-test evaluation models but proves epistemologically inadequate relative to the dynamic nature of organisational change in healthcare facilities. Behavioural change among health professionals is a continuous process, exposed to contextual variables—staff turnover, reorganisations, workload variations, and health emergencies—that can progressively erode results. Without monitoring and correction systems, the sustainability of change cannot be guaranteed, and improvements documented in segregation or regulatory compliance scores risk not surviving beyond the immediate evaluation period. McCauley et al. [33] confirm that workers' favourable attitudes do not always translate into operational practices due to organisational barriers and the absence of systematic integration of educational initiatives within working environments. The only case presenting an embryonic form of feedback loop [113] does not integrate an algorithmic structure or a multi-level temporality, confirming that this domain remains largely unexplored. The evidence reviewed above supports a systemic reading of behavioural change, while recognising that this study does not provide direct empirical proof. Several studies report a persistent knowledge–practice gap even when awareness and resources improve [30,31], and organisational constraints may limit the translation of pro-sustainability attitudes into routine behaviour [33]. Compliance outcomes are also shaped by staffing, leadership, and organisational culture [115]. Accordingly, healthcare waste management practices can be interpreted as the result of interactions among people, technologies, organisational arrangements, and context, consistent with sociotechnical perspectives [115]. This article is a model-development and theory-building contribution, not an intervention trial [78,79]. The contribution is evaluated in terms of conceptual coherence, theoretical grounding, and explanatory scope rather than observed effectiveness. The feasibility of Maieutic-H is supported by: (i) the use of components that have each been previously examined in the literature (motivational training, interactional analysis, and AI-based decision support); (ii) the qualitative assessment reported in Section 3.5.3, which found 93% concordance between expert priorities and algorithm-generated relevance scores; and (iii) the longitudinal evaluation protocol specified in Section 3.4. Empirical evidence on effectiveness remains to be established through future hospital-based field studies. The comparison also reveals partial convergences with the theoretical frameworks integrated into the Maieutic-H model. On the motivational plane, TPB-based interventions confirm that activating attitudes, subjective norms, and perceived behavioural control produce observable effects on operational behaviours, providing theoretical support for phase A1 of the model. Şimşek and Özsoy [65], documenting a 200% increase in recyclable waste, demonstrate that these effects are measurable not only in stated intentions but also in the volumes of correctly managed waste, confirming that the model's motivational component—orientated towards deeper internalisation through narrative and gamified strategies—translates into quantifiable operational indicators.

On the analytical plane, the divergence is sharp: no case adopts a logic attributable to Video-Based Interaction Analysis. Even the most advanced approaches remain limited to mapping physical waste flows, without accessing the communicative and semiotic dimensions of situated practices. This gap is particularly significant in multiprofessional hospital contexts, where waste management simultaneously engages figures with distinct roles and responsibilities—nurses, nurse assistants, physicians, and collection workers—who coordinate their actions through implicit communicative mechanisms that checklists or interviews cannot easily detect. As Barnes and Woods [42] and van Braak and Huiskes [43] document, communication structures healthcare work in that professionals negotiate roles, responsibilities, and operational decisions—including those relating to the classification and disposal of waste produced during clinical procedures—through interaction. The high methodological complexity required by Video-Based Interaction Analysis partly explains its absence from the examined interventions, but it does not diminish its relevance as a tool for detecting the submerged operational criticalities that compliance-orientated approaches cannot identify.

Implementing Video-Based Interaction Analysis in clinical settings raises four feasibility issues. First, multimodal transcription and coding are time- and labour-intensive, and analysts must make explicit choices about segmentation and which modalities to represent [116,117]. Second, reliability requires an iterative coding protocol (units of analysis, categories, double-coding strategy, and a procedure for resolving disagreements) rather than a single agreement check [118,119]; Phase A2 specifies these elements. Third, recording in healthcare settings introduces practical and ethical constraints (consent, privacy, anonymisation, and data protection) [120,121]. Participation may also be affected by staff mobility, shift rotation, and workload [122], and initial camera effects should be managed through familiarisation and cautious interpretation of early recordings [120,123,124]. Fourth, extending the procedure across multiple wards over a 12-month period increases organisational requirements (infrastructure, trained personnel, protected time, and local adaptation) [122,125]. Relative to lighter tools (e.g., checklists and short audits), these demands are harder to sustain in high-pressure environments [126,127]. Scalability should therefore be treated as structured contextual adaptation rather than uniform replication.

On the operational plane, AHP-based models represent the closest attempt to a prioritisation logic but remain bound to expert judgement and cannot be dynamically updated. The shift to data-driven models such as Random Forest implies a substantial epistemological change: from judgement to measurement, with a consequent increase in replicability and contextual adaptability. This transition also carries a methodological caveat common to ensemble learning applications in emerging clinical domains: the quality of algorithmic prioritisation is bounded by the representativeness of its training data, underscoring why the model's current calibration against simulated datasets is treated as provisional pending field validation. This aspect is particularly relevant in complex hospital contexts, where intervention priorities vary significantly across wards with heterogeneous waste production profiles: surgical and sharps waste in operating theatres, high-volume infectious waste in emergency departments, and hazardous pharmaceutical waste in oncology. A static prioritisation system cannot adapt to this variability. The Random Forest algorithm, instead, enables customisation of the action plan for each specific context, identifying the corrective interventions with the greatest potential impact in each ward [57].

A further contribution of the comparison consists of the possibility of outlining a taxonomy of interventions according to their completeness relative to the six dimensions of the model. Three recurring configurations emerge: single-component interventions, focused on a single element—typically motivation or implementation—characterised by limited and non-sustainable effects; parallel-component interventions, incorporating multiple dimensions but without systemic integration, producing better but unstable outcomes; and quasi-integrated interventions, represented primarily by Sommese and Pantusa [113], which approach a systemic logic without achieving full algorithmic and longitudinal integration. Mlouki et al. [30] additionally observe a decrease in correct waste segregation despite improvements in available resources, confirming that optimising parallel components alone—in the absence of an integrated and adaptive framework—does not guarantee the sustainability of change in hospital waste management practices. This classification pinpoints the innovative contribution of the Maieutic-H model, grounded in the structural and temporal integration of components and designed specifically to address the organisational and regulatory complexity of healthcare waste management in hospital settings. Although Maieutic-H was conceived mainly for hospital wards characterised by frequent staff turnover, its underlying architecture could also be adapted to other healthcare contexts, such as outpatient services, diagnostic laboratories, community clinics, or facilities operating with limited resources. In line with Medical Research Council guidance on complex interventions [81,82], the model is intended to preserve its core mechanisms while allowing the way these mechanisms are implemented to change according to local circumstances. Such adaptability should not, however, be interpreted as evidence of established transferability. At present, the extension of Maieutic-H beyond hospital wards remains a theoretical possibility, one that will need to be tested through future pilot studies across different healthcare environments. This empirical step will show whether the framework can retain its function when the organisational setting changes—and whether it can, in practice, travel as well as it appears to do in theory.

7. Conclusions

This study has proposed the Maieutic-H model as a response to the structural fragility of existing training interventions in healthcare waste management. Theoretical validation conducted through comparison with eleven programmes documented in the literature has confirmed three principal findings that directly address the research question formulated.

First, none of the examined interventions simultaneously integrate the motivational, analytical, and operational dimensions of behavioural change within a cyclical framework equipped with adaptive feedback. The proposed taxonomy—single-component interventions, parallel-component interventions, and quasi-integrated interventions—positions the model's contribution relative to the state of the art and precisely identifies the gap it aims to close. The taxonomy thus clarifies both the recurrent limitations of existing interventions and the contribution claimed for Maieutic-H. The following points specify this contribution.

Second, behavioural change in hospital waste management is not primarily a problem of individual motivation but a systemic issue generated by organisational and communicative dynamics that traditional interventions neither observe nor address. Video-Based Interaction Analysis represents a methodologically unprecedented tool in the domain of healthcare waste management, capable of rendering visible the submerged operational criticalities in wards that no questionnaire or checklist can detect.

Third, the Random Forest-based algorithmic prioritisation introduces an epistemological shift relative to existing models: from expert judgement to contextually adaptive measurement, with the possibility of differentiating the action plan across wards with heterogeneous waste production profiles, ensuring replicability and scalability of the intervention.

Maieutic-H targets multiprofessional hospital settings in which nurses, physicians, nursing assistants, and collection staff coordinate waste management activities through both formal procedures and routine interaction. The six-phase architecture and 12-month monitoring are designed to accommodate wards with heterogeneous waste profiles and operational conditions. This is particularly relevant for units such as surgery, intensive care, and oncology, where workload and waste composition can change over time.

This study has limitations. The theoretical assessment relies on a selected set of programmes identified in the peer-reviewed literature and may omit relevant evidence from grey literature or under-represented contexts. In addition, component coding depends on the level of detail reported in the original studies, which may lead to under-coding of some dimensions. Contextual differences (resources, organisational structure, and staff characteristics) were not modelled systematically. Future work should therefore expand the literature mapping, apply predefined coding criteria, and analyse contextual factors more explicitly.

The next step is empirical validation in hospital settings. Longitudinal results will indicate whether the integrated design produces stable improvements and will help identify which components require refinement if outcomes are partial or inconsistent. The taxonomy developed in this study provides a framework for interpreting the contribution of individual components. Implementation requires multidisciplinary expertise because the model combines narrative education, Video-Based Interaction Analysis, and algorithmic decision support. The transcription and coding workload and the constraints of clinical environments (Section 6) limit straightforward replication across wards [122,125]. In addition, a 12-month design requires organisational continuity despite turnover, reorganisation, and workload variation. Implementation should therefore be phased and supported through institutional agreements, adequate staffing, protected time, and GDPR-compliant infrastructure.

Author Contributions: Conceptualisation, M.A.C.; methodology, M.A.C.; software, M.A.C. and F.C.; validation, M.A.C., E.C. and F.C.; formal analysis, M.A.C.; data curation, M.A.C., E.C. and F.C.; writing—original draft preparation, M.A.C.; writing—review and editing, M.A.C., E.C., F.C., G.M., G.G., G.D.F.; supervision, M.A.C.; project administration, M.A.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article.

Acknowledgments: During the preparation of this manuscript, the authors used a generative AI tool (Claude (Sonnet 5), Anthropic, accessed in 2026) to assist with language refinement and copy-editing support. The authors reviewed and edited all AI-assisted outputs and verified them against the original materials. The authors made all analytical and editorial decisions and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANOVA	Analysis of Variance
CE	Circular Economy
COM-B	Capability, Opportunity, Motivation—Behaviour (model)
DfD	Design for Disassembly
EU	European Union
FIML	Full Information Maximum Likelihood
HCWs	Healthcare Workers
HWM	Healthcare Waste Management
ICOM	Input, Control, Output, Mechanism
IDEF0	Integration Definition for Function Modelling
IHWM	Intensive Healthcare Waste Management
IoT	Internet of Things
IRIS	Institutional Repository for Information Sharing
KAP	Knowledge, Attitude and Practice
MI	Multiple Imputation
MMAT	Mixed Methods Appraisal Tool
NAM	Norm Activation Model
NHS	National Health Service
NIST	National Institute of Standards and Technology
QI	Quality Improvement
SADT	Structured Analysis and Design Technique
SPSS	Statistical Package for the Social Sciences
T2/T3	Second/Third Follow-up Time Points
TDF	Theoretical Domains Framework
TPB	Theory of Planned Behaviour
UNDP	United Nations Development Programme
VR	Virtual Reality
WHO	World Health Organization

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