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Methodological Comparison Between an AI-Based Sustainable Healthcare Waste Management Approach and Expert Evidence

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Abstract

This study assesses the extent to which an AI-driven circular waste management tool, previously developed by the same authors as a decision-support system for the circular management of healthcare waste in compliance with international guidelines, reflects the operational needs and perceived priorities of healthcare professionals and environmental managers. Within a context characterised by high regulatory complexity and increasing pressure toward more sustainable management models, the research adopts a qualitative approach based on the thematic analysis of 11 semi-structured interviews, followed by a systematic mapping of the emergent themes onto the tool's thematic areas, indicators, and operational actions. The results demonstrate a high degree of alignment between the tool and operational practice, with 93% of the tool's actions supported by empirical evidence and the emergence of a shared core cluster focused on hard-to-manage waste streams, mandatory training, and day-to-day operational challenges. The alignment between the priorities expressed by interviewees and the importance scores generated by the computational model is high for actions of greater relevance, while it decreases for less frequent actions that are more context-dependent. Circular economy practices are recognised as relevant but remain predominantly positioned at a strategic rather than an operational level. Overall, the study confirms the conceptual robustness of the tool and identifies its main limitations and the conditions required for its integration into hospital workflows.

Keywords: healthcare waste management; circular economy in healthcare; AI-driven decision support system; hospital sustainability; circular waste management; environmental management in hospitals; healthcare waste governance; sustainable healthcare systems; qualitative thematic analysis; healthcare waste circularity

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1. Introduction

Safe healthcare waste management constitutes a core component of broader efforts in water, sanitation, and hygiene (WASH) and infection prevention and control (IPC) strategies. It directly contributes to the achievement of the Sustainable Development Goals (SDG), particularly SDG 3 (Good Health and Well-being), SDG 6 (Clean Water and Sanitation), and SDG 12 (Responsible Consumption and Production) [1,2].

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The World Health Organisation (WHO) published the guidelines "Safe Management of Wastes from Health-Care Activities" in 2014 [3], followed by a summary action plan in 2017 [2], with the aim of providing practical guidance to improve healthcare waste management practices. These documents target policymakers, healthcare professionals, and facility managers, emphasising key elements required to ensure safety and operational effectiveness. The WHO defines five fundamental principles that guide the safe management of healthcare waste:

- The polluter pays principle—the waste producer bears responsibility for its management.
- Precautionary principle—actors adopt preventive measures even in the absence of definitive scientific evidence.
- Duty of care—waste handlers manage waste safely and responsibly.
- Proximity principle—treatment should occur as close as possible to the point of generation.
- Prior informed consent—exporting hazardous waste requires consent from the receiving country.

Healthcare facilities play a central role in the sustainable management of healthcare waste by ensuring that disposal and recovery operations comply with circular economy principles and public health protection requirements [4]. The WHO stresses that achieving more sustainable waste management in healthcare requires the adoption of concrete strategies that harmonise regulations, constraints, and operational practices to minimise impacts on human health, the environment, and economic performance [3,5,6].

In line with these principles, the report "Sustainable healthcare waste management in the EU Circular Economy model" published by HCWH Europe [7] highlights the responsibility of healthcare facilities to improve recycling performance through targeted actions. These include optimised waste segregation and management practices aimed at reducing the volume of waste incorrectly classified as hazardous, thereby avoiding unnecessary costs and environmental impacts. Healthcare facilities must also promote a culture of waste reduction and recycling by developing strategies to reduce packaging use and encourage material reuse. Finally, facilities should collaborate with public authorities and specialised companies to improve the recycling of healthcare materials and reduce the dependency on incineration, according to European circular economy and environmental policies [7].

Inappropriate management of healthcare waste represents a major challenge for the healthcare sector, with direct consequences for both public health and the environment. Healthcare waste includes infectious materials, pharmaceutical residues, hazardous chemicals, and single-use medical devices. Improper disposal practices can facilitate the spread of infectious diseases, contaminate soil and water resources, and increase greenhouse gas emissions [8].

The managerial dimension of healthcare waste was the focus of a previous study in which we proposed an AI-based decision-support tool for the circular management of healthcare waste [9]. We initially validated the tool through four simulated case studies, which provided preliminary evidence of its functionality and alignment with operational needs. In the present study, we perform a qualitative evaluation of the tool through semi-structured interviews with 11 hospital waste management professionals. This approach allows us to assess the consistency of the tool with real-world operational needs and hospital contexts while identifying strengths, gaps, and areas for improvement.

We base the methodological approach on a thematic analysis of eleven interviews, followed by systematic mapping between the identified themes and the components of the tool. This process enables the study to examine how practitioners recognise certain issues as priorities and how the tool represents, supports, or overlooks these issues.

Integrating qualitative evidence with the tool's structure allows us to: (a) assess whether and to what extent the predefined categories, indicators, and operational actions embedded in the digital tool comprehensively and coherently cover the critical issues emerging from practitioners' direct experience; (b) identify which practitioner-relevant aspects the tool does not adequately represent or support; (c) detect operational needs, managerial challenges, or priority solutions identified by interviewees that the tool omits, under-represents, or insufficiently supports; (d) determine whether the operational priorities expressed by the interviewees align with those computed by the system through importance scores; (e) analyse the degree of alignment between the expert perception priorities and the importance scores generated by the tool's computational model, identifying potential discrepancies between expert judgement and algorithmic logic; (f) identify factors that can facilitate or hinder the integration of the tool into hospital workflows; and (g) explore organisational, regulatory, economic, and cultural barriers and enabling factors that can influence the adoption, integration, and effectiveness of the digital tool in routine hospital practice.

Based on these objectives, we formulate the following research question: *"To what extent does the digital tool for healthcare waste management reflect, support, and respond to the operational needs and perceived priorities of healthcare professionals and environmental managers, as identified through qualitative interview analysis?"*

From this main research question, we derive four sub-questions:

- RQ1: How do the themes emerging from the interviews correspond to the thematic areas, indicators, and operational actions included in the AI tool?
- RQ2: Which aspects relevant to practitioners are not adequately represented or supported by the AI tool?
- RQ3: Do the operational priorities expressed by the interviewees coincide with those calculated by the system through importance scores?
- RQ4: Which factors can facilitate or hinder the integration of the AI tool into hospital workflows?

This systematic approach connects empirical evidence with the operational logic of the tool, ensuring that its development and implementation remain grounded in the actual needs of practitioners and the concrete conditions of hospital settings.

2. Literature Review

Despite the growing diffusion of decision support systems (DSS) and AI-based digital tools in healthcare waste management, the extent to which these systems reflect the operational realities and perceived priorities of end users remains insufficiently examined. Existing contributions largely privilege technical performance and optimisation outcomes, while comparatively less attention is devoted to the alignment between algorithmic decision logics and day-to-day operational practice. Addressing this gap is essential, particularly in healthcare settings characterised by complex workflows and tightly constrained decision-making environments.

Against this background, the present review adopts a user-centred and practice-orientated perspective, critically examining whether and how DSS and AI-driven tools effectively reflect real-world operational needs, rather than simply offering theoretically optimal solutions. Adoption challenges have frequently been attributed not to deficiencies in predictive accuracy, but to design choices that do not adequately account for work routines, organisational constraints, and the distribution of decision-making responsibilities among healthcare operators [10,11]. In contrast, empirical evidence consistently indicates that both effectiveness and user acceptance are dependent on coherence with everyday practices and seamless integration into existing decision-making processes, thereby requiring iterative design strategies and active participation of end users [12].

In parallel, scholarly work addressing the digital transformation associated with Industry 4.0 documents the increasing deployment of advanced technologies—including

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the Internet of things (IoT), big data analytics, RFID, intelligent tracking systems, and cloud-based infrastructures—in healthcare waste management. These technologies have improved efficiency, traceability, and monitoring of waste streams in the life-cycle, allowing more granular control and data-driven decision making [13,14]. Nevertheless, accumulated evidence suggests that the introduction of DSS and AI-based tools alone does not ensure operational effectiveness, nor does it guarantee alignment between model-embedded priorities and those that are practically relevant to healthcare professionals and environmental managers [10].

A further line of inquiry indicates that purely quantitative or model-driven approaches may inadequately capture the complexity of real clinical environments. Guo et al. [15], for example, demonstrate that predictive models and simulations are effective only when complemented by the practical experience of the operators, while Rauwerdink et al. [16] observe that DSS assessments often prioritise randomised controlled trials and performance metrics, overlooking critical stages of planning, development, and implementation. Together, these contributions point to the necessity of integrating quantitative methods with qualitative user-centred evaluations to ensure that DSS are not only effective in principle but also usable in routine clinical practice.

These limitations become particularly salient in the management of healthcare waste, a domain marked by high regulatory complexity, stringent compliance requirements, and substantial environmental and public health risks in cases of non-compliance [17,18]. Previous research identifies a persistent gap between regulatory prescriptions and the ability of digital tools to support realistic operational decisions in dynamic hospital contexts [19]. This gap extends beyond technical considerations, including organisational, procedural, and contextual factors that can hinder the integration of DSS into established workflows and ultimately undermine their practical utility.

When DSS are coupled with artificial intelligence (AI) and machine learning (ML) algorithms, these challenges tend to intensify. Although such systems enable the analysis of complex datasets, scenario forecasting, and support for operational and strategic decision making [13,18], their performance remains critically dependent on the specification of indicators, weighting schemes, and objective functions [10]. If these parameters fail to adequately represent real operational constraints—such as limited resources, fluctuating waste volumes, or procedural complexity—the resulting recommendations may prove impractical or applicable only at the design stage, diverging from actual waste management requirements [20]. This misalignment between algorithmic rationales and operational practice represents one of the principal risks associated with advanced DSS: despite generating theoretically optimal outputs, such systems may produce recommendations that require substantial human mediation to be implemented. In particular, this issue remains unexplored in sufficient depth within the current literature.

In parallel, a substantial body of work acknowledges the potential of DSS and AI to support the transition to circular economy models in the healthcare sector by enabling material recovery, optimising logistical flows, and fostering integrated digital ecosystems across the value chain [1,14]. Integration of DSS and AI is widely regarded as a transformative factor in healthcare waste management, changing it from a predominantly reactive approach to a more proactive, adaptive, and data-driven process [13,21]. Nevertheless, existing contributions tend to privilege technological and strategic dimensions, devoting limited attention to empirical assessments of how these tools are actually perceived, used, and considered relevant by end users in real operational settings. As a result, a critical question remains insufficiently addressed: whether and to what extent advanced DSS and AI-based systems effectively respond to the concrete operational needs, priorities, and constraints experienced by healthcare practitioners.

This gap provides a strong rationale for complementing quantitative and model-driven approaches with a qualitative, user-centred validation phase. In this perspective, semi-structured interviews are not used for general exploratory purposes but rather as a contextual comparative instrument aimed at systematically contrasting the logical and operational structure of the DSS—namely its categories, indicators, actions, and algorithmic priorities—with the lived experience of healthcare professionals and environmental managers [22]. This comparison enables the identification of potential misalignments between the logic of the system and the needs of the user while providing empirically grounded insights into both the strengths and limitations of the tool [23].

A growing body of empirical research demonstrates that qualitative approaches based on interviews or focus groups are essential for the validation of clinical decision support systems (CDSS), as they help uncover latent needs and explain why technically sound systems may fail to be adopted. These methods are particularly effective in revealing user adaptations, usability issues, and discrepancies between algorithmic logic and everyday decision-making processes. For example, Frisinger et al. [24] examined CDSS in hospital clinical management; Clausen et al. [25] investigated CDSS in child and adolescent mental health services; Westerbeek et al. [26] analysed medication-related CDSS in the context of fall prevention in primary care; and Wohlgemut et al. [27] evaluated mobile CDSS in emergency clinical settings.

Consequently, the present study adopts a sequential multi-method design, in which a qualitative phase aimed at eliciting user needs, priorities, and operational practices precedes a subsequent quantitative evaluation of the tool [28,29]. This methodological integration facilitates a direct link between DSS-generated outputs and real-world practice, enabling a more nuanced understanding of operational processes and constraints [30]. The qualitative validation specifically addresses the first three research sub-questions by assessing the correspondence between user-relevant themes and the structural components of the tool (RQ1), identifying overlooked or unsupported aspects (RQ2), and examining the coherence between human-perceived priorities and those computed by the system (RQ3).

We conducted the analysis following the six recursive phases described by Braun and Clarke [31]: we familiarised ourselves with the data, generated initial codes, searched for themes, reviewed them, defined and named them, and finally produced the analytical report. We transcribed all interviews verbatim and imported them into qualitative analysis software to ensure traceability of coding decisions. We assigned codes at a semantic level, focusing on explicit statements to preserve transparency and limit interpretive bias. Next, we grouped conceptually related codes into higher-order categories that captured organisational constraints, regulatory awareness, implementation barriers, and perceived benefits of the DSS. We then systematically compared these themes with the structural components of the decision-support system to identify convergences and mismatches between the designed architecture and everyday operational practice. To strengthen analytical rigour, we documented each coding revision and theme refinement in an audit trail. When disagreements emerged, we discussed them until we reached consensus. Through this process, we ensured that the final thematic structure accurately reflected participants' perspectives while remaining coherent with the system design framework [32].

In this context, thematic analysis of textual data derived from interviews enables systematic coding of the experiences, perceptions, and priorities of healthcare professionals and environmental technicians, thereby generating the empirical basis required to compare the structure of DSS with actual operational practice [31]. The targeted integration of descriptive techniques—such as frequency counts—and non-parametric analyses supports the assessment of the relative importance of emergent themes [28,33], allowing for the mapping of alignment or misalignment between discursive prominence and strategic relevance as perceived by the involved actors. In general, this approach provides information on decision-making and organisational dynamics at multiple levels [30].

Figure 1 illustrates the study selection process adopted for the systematic literature review. It presents a five-step methodological framework used to identify, screen, and evaluate relevant studies retrieved from scientific databases. Through successive phases—identification, screening, eligibility assessment, and final inclusion—the initial pool of articles is progressively refined according to predefined criteria. The flowchart therefore clarifies the transparency and rigor of the selection procedure. The studies retained at the end of the process are then classified into three complementary macro-domains, which together provide the conceptual basis for developing an AI-based clinical decision support system for healthcare waste management.

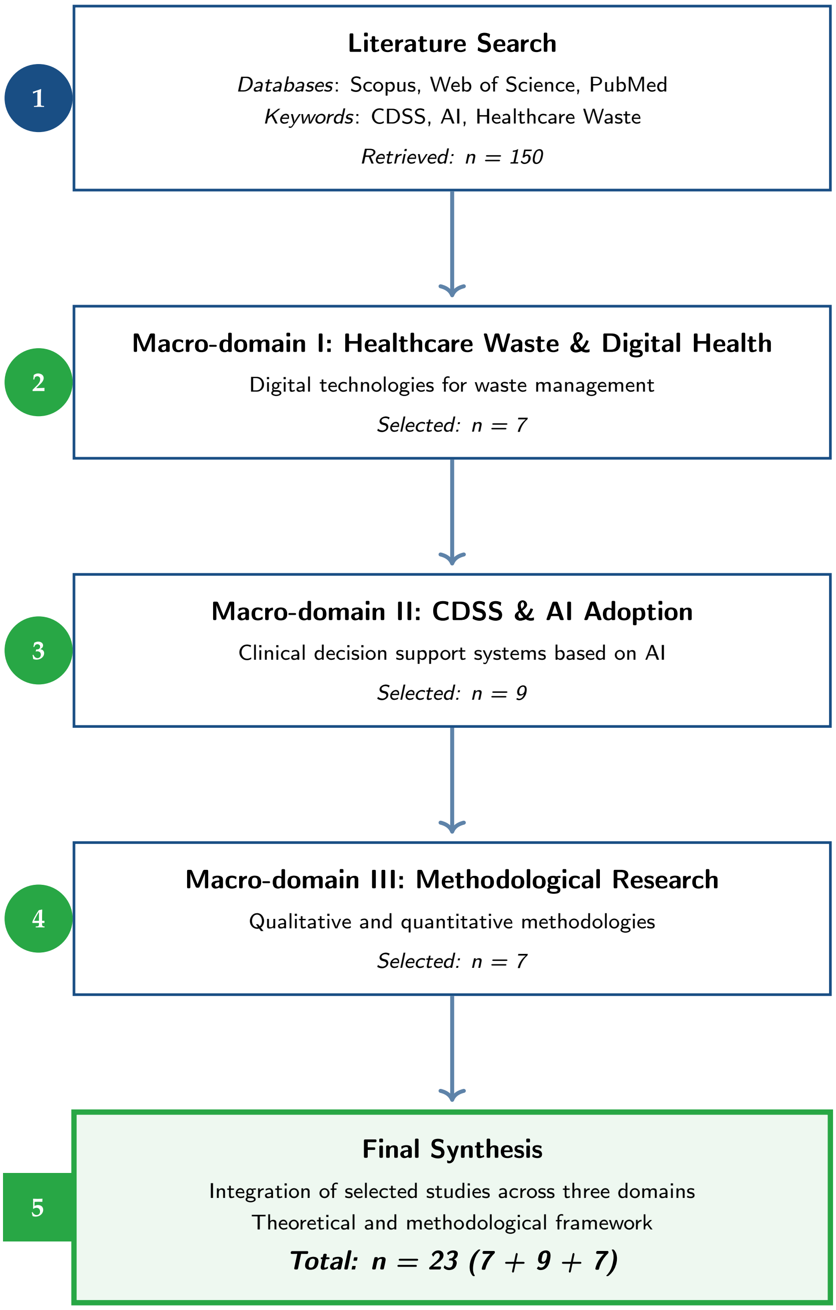

Figure 1. Study selection process for the systematic literature review.

Table 1 provides a structured synthesis of the literature underpinning the study by organizing the selected contributions across methodological research, healthcare waste management, and AI-based CDSS. The table classifies each study according to research design, application context, and analytical contribution, highlighting how methodological frameworks, technological approaches, and user-centred perspectives collectively inform the development and validation of the proposed decision-support tool. This synthesis clarifies the interdisciplinary foundations of the research and situates the study within existing debates on digital health, sustainability-oriented waste management, and AI-enabled decision support.

Table 1. Overview of literature supporting methodological and conceptual positioning of the study.

Author(s)	Macro-Domain	Study Type	Context	Relevance to Current Study
Cappelli and Akkari [29]	Methodological research	Empirical qualitative	Higher education	Implementation barriers and ICT training analysis
Creswell et al. [28]	Conceptual	Mixed-methods methodology	Methodological framework	Guide for mixed methods integration and metainferences
McGrath et al. [23]	Methodological research	Conceptual	Medical education research	Framework for qualitative research interviews
Adeoye-Olatunde and Olenik [22]	Methodological research	Conceptual	Pharmacy services research	Seven-step guide for semi-structured interviews
Braun and Clarke [31]	Methodological research	Conceptual	Qualitative psychology research	Framework for reflexive thematic analysis
Bazeley [33]	Methodological research	Theoretical	Mixed methods research	Conceptualisation of methodological integration
Costa [30]	Methodological research	Empirical mixed-method	Educational large-scale studies	Integration of qualitative perspectives into secondary data analysis
Sepetis et al. [14]	Healthcare waste management	Empirical quantitative case study	Hospital bio-waste management	Performance and sustainability assessment
Sharma et al. [13]	Healthcare waste management	Systematic literature review	Global healthcare waste systems	Digital transformation and Industry 4.0 perspective
Bayor et al. [10]	CDSS and AI adoption	Systematic review	Clinical decision support systems	User-centred CDSS design challenges
Quttainah and Singh [19]	Healthcare waste management	Mixed-method	Developing healthcare systems	Barrier prioritisation framework
Koohkan et al. [18]	Healthcare waste management	Empirical quantitative	Healthcare waste chain	Technology optimisation framework
Homayouni and Pishvaee [17]	Healthcare waste management	Empirical quantitative	Hazardous hospital waste networks	Optimisation of collection and disposal networks
Mohamed et al. [21]	Healthcare waste management	Systematic review	IoT-based medical waste systems	Digitalisation barriers in waste management
Soori et al. [20]	AI decision support systems	Review	Industry 4.0 sectors	Overview of AI-based DSS architectures
Clausen et al. [25]	CDSS adoption	Empirical qualitative	Mental health services	User perception and adoption barriers
Westerbeek et al. [26]	CDSS adoption	Empirical qualitative	Primary care	Workflow integration requirements
Frisinger and Papachristou [24]	CDSS adoption	Empirical qualitative	Primary care	Organisational adoption barriers

Table 1. *Cont.*

Author(s)	Macro-Domain	Study Type	Context	Relevance to Current Study
Wohlgemut et al. [27]	CDSS adoption	Systematic review	Emergency healthcare	Usability evaluation approaches
Rauwerdink et al. [16]	Digital health technologies	Scoping review	Multiple medical specialties	Evaluation gaps in digital health adoption
Guo et al. [15]	Digital health evaluation	Conceptual review	Healthcare settings	Evidence generation challenges
Sutton et al. [11]	CDSS adoption	Narrative review	Hospital and primary care	Benefits and risks of CDSS implementation
Kovari [12]	AI decision support systems	Mixed-method review	Cross-sectoral applications	Trust, transparency, and explainability in AI DSS

While the categorisation into macro-domains provides analytical clarity, we acknowledge that several studies span multiple thematic areas. This overlap reflects the inherently interdisciplinary nature of DSS and AI research in healthcare environments and further supports the narrative review approach adopted.

3. Materials and Methods

3.1. Overview AI-Driven Circular Waste Management Tool

The AI-driven circular waste management tool functions as a decision-support system that facilitates the management of circular healthcare waste according to the main international guidelines [9]. The system operates through an interactive software interface that healthcare professionals and hospital waste management officers can use directly. The application integrates several functionalities, including a thematic checklist structured around indicators and corrective actions, a priority-setting mechanism based on importance scores, and tools that allow users to record implementation status, timelines, operational notes, and indicator-related assessments. The tool builds on a three-tier hierarchical structure (themes–indicators–actions) systematically developed through the content analysis described in Cappelli et al. [9]. At the first tier, themes represent broad categories grouping related concepts addressing the same overall issue in healthcare waste management. At the second tier, indicators constitute measurable criteria—quantitative, normative, or qualitative—used to monitor progress or performance within each theme. At the third tier, actions consist of concrete practices or proposed interventions to address each theme and improve waste management. This complete structure is fully documented in Table A2 of Cappelli et al. [9], which represents the operational translation of the regulatory sources and scientific literature into a structured framework that constitutes the qualitative foundation on which the tool is based.

The tool structures its framework around 13 predefined thematic areas that systematically address the main dimensions of healthcare waste management, including regulatory compliance, waste prevention, pharmaceutical waste management, training, and separate collection practices. Across these thematic areas, the system includes 55 corrective actions derived from the qualitative analysis. The AI importance scores adopted in the present study are derived from the methodological framework developed in [9]. In that study, healthcare facility responses were simulated across the 55 actions. For each action, facilities provided a qualitative assessment of implementation status (*done*, *partially implemented*, *under implementation*, and *not yet implemented*), converted into numerical values of 1, 0.5, 0.25, and 0, respectively. This linear scale preserves the ordinal structure of responses while enabling the computation of an aggregate compliance score. For each facility, a total compliance score was computed as the sum of the individual action scores, $S = \sum_{i=1}^{55} s_i$, where s_i represents the numerical value assigned to action i. This aggregate measure reflects the overall degree of regulatory implementation. To facilitate modelling and interpretation, the total compliance score was transformed into a categorical target variable Y with three levels: *low*, *medium*, and *high* compliance. The thresholds were determined empirically based on the distribution of S and correspond approximately to the first and third quartiles. Specifically, given Q_1 and Q_3 as the first and third quartiles of the empirical distribution of S: low compliance if $S < Q_1$; medium compliance if $Q_1 \leq S < Q_3$; high compliance if $S \geq Q_3$. This segmentation ensures consistency with the empirical distribution, avoids significant class imbalance, and reflects meaningful differences in implementation levels across facilities.

A random forest classification model was trained to predict the compliance class Y using the 55 actions as input variables. Feature importance was computed using the mean decrease Gini coefficient. This model-specific measure quantifies the extent to which each action contributes to reducing node impurity across the ensemble of decision trees. Because it derives directly from the internal structure of the trained model, it reflects how strongly each action influences compliance classification. To ensure comparability across actions, importance scores were globally normalised to the interval $[0, 1]$ and ranked in descending order. Based on the distribution of normalised importance values, actions were classified into three categories using the interquartile range: *highly important* (above the third quartile), *moderately important* (between the first and third quartiles), and *slightly important* (below the first quartile). This classification resulted in 14 highly important actions, 27 moderately important actions, and 14 slightly important actions. For operational prioritisation within case studies, actions with a normalised importance score ≥ 0.5 were considered priority interventions. This threshold does not define importance categorically but serves as a practical cut-off to highlight actions contributing at least at a medium-to-high level to compliance classification. Lower-scoring actions were considered only when strictly necessary to address specific operational or regulatory gaps that could not be mitigated through higher-priority measures.

The validation process presented in this study involved eleven semi-structured interviews with healthcare professionals and environmental managers to assess whether the themes, indicators, and actions embedded in the tool correspond to the operational priorities, practices, and critical issues experienced by end users in real hospital settings. This user-centred validation approach allows us to identify potential misalignments between the tool's algorithmic logic and practitioner-relevant concerns, thereby addressing a gap that has been insufficiently explored in existing DSS literature.

It should be noted that the tool employs a static knowledge base grounded in the regulatory frameworks and scientific literature analysed during its development (Cappelli et al. [9]). The modular architecture of the tool—with its clear separation between thematic structure, indicator definitions, and action specifications—would facilitate systematic updates when regulations or best practices evolve. However, any such updates would require retraining the importance-scoring model using updated compliance datasets that reflect changes in regulatory priorities, a development that falls beyond the scope of the present validation study and represents a direction for future operational deployment in dynamic regulatory contexts.

Figure 2 shows the development of the AI-driven circular waste management tool following a systematic methodological process articulated in four integrated phases.

Figure 2 represents the internal phases of the AI-driven tool for circular healthcare waste management, illustrating how the thematic checklist with indicators and corrective actions is constructed. The first phase consists of the manual collection of hospital operational data, including practices, implementation status, notes, and identified gaps, which provide the initial information to determine the relevant themes. In the second phase, the regulatory and scientific knowledge base analyses guidelines and literature to structure themes, define indicators, and suggest corrective actions, creating a three-level hierarchical structure (themes–indicators–actions). The third phase evaluates the data through checklists and indicators, while in the fourth phase an AI model assigns importance scores to the actions, identifying priority ones. The fifth phase presents the tool's decision-support interface, enabling users to visualise and monitor actions and priorities, thereby providing operational support for checklist completion. Finally, the sixth phase represents the implementation of the selected actions and includes a feedback loop to update the collected information. The arrows and distinct colours highlight the logical flow between phases, clarifying that the figure describes the methodological process leading to the development of the checklist, rather than the physical management of waste or a software system that automatically generates outputs.

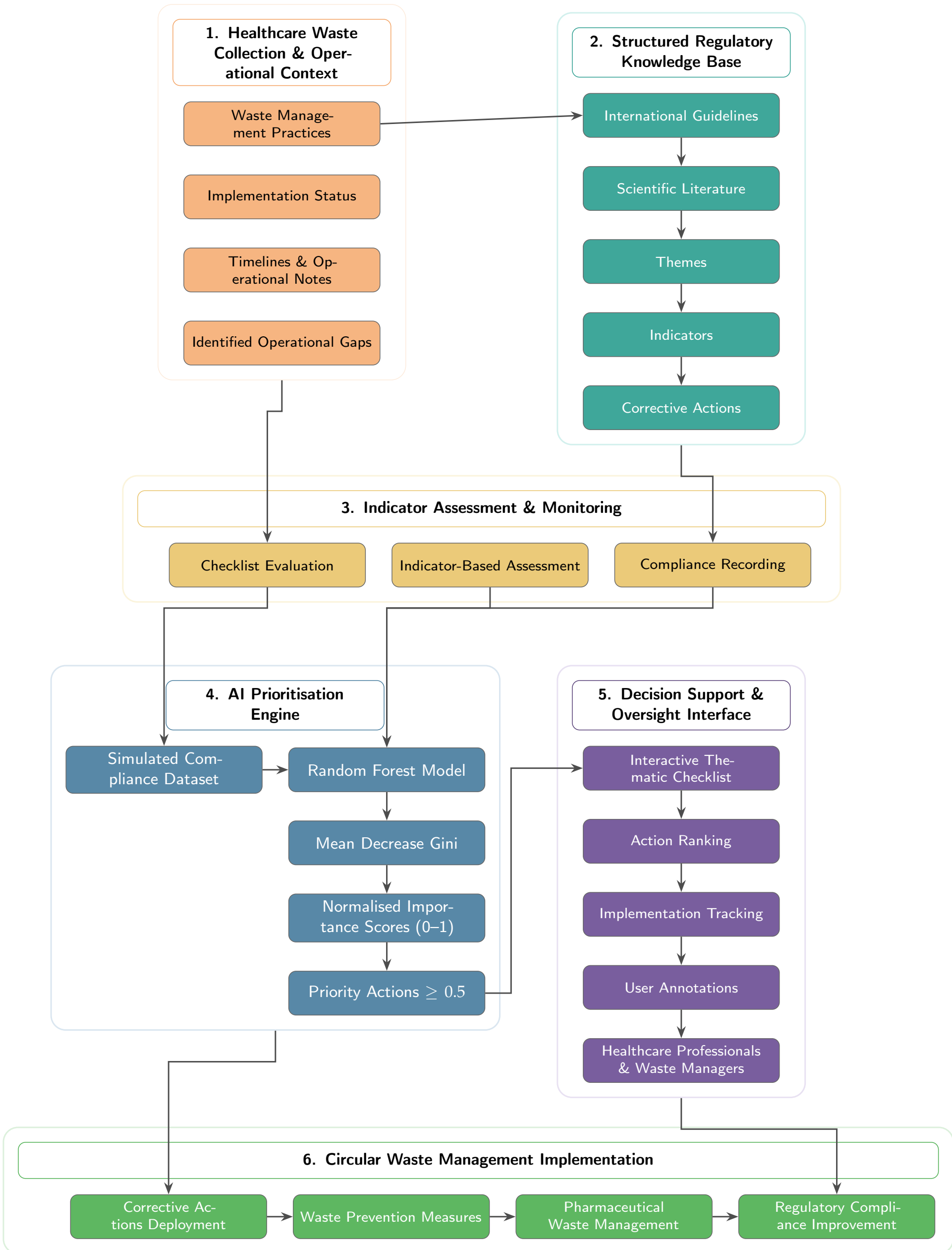

Figure 2. Development and operational framework of the AI-driven circular waste management tool.

3.2. Research Design

This study adopted a qualitative descriptive design to systematically and transparently capture the experiences and perceptions of the participants [34]. The research team conducted eleven semi-structured interviews and complemented them with descriptive quantitative analyses, including frequency calculations, distribution analyses, and importance indicators.

The analytical process initially examined interview data using the framework proposed by Lejeune [35], integrated with the analytical approach developed by Miles and Huberman [36]. Subsequently, the analysis mapped emerging themes onto operational areas, indicators, and priority levels embedded within the AI-based digital tool for hospital waste management.

The study adhered to and reported findings according to the Standards for Reporting Qualitative Research (SRQR) [37].

- **Sampling**
  The study adopted purpose-orientated and snowball sampling strategies [38] to identify settings and participants capable of meaningfully representing the diversity of practices and perspectives involved in waste management. We selected participants according to predefined inclusion criteria: (a) direct involvement in healthcare waste management processes; (b) at east one year of professional experience in the field; and (c) representation of different organisational levels (clinical, technical, managerial, and regulatory). The research team selected participants from a range of professional roles—including healthcare professionals, technical and administrative personnel, medical managers, safety officers, maintenance personnel, and an environmental legal expert—to obtain a broad multilevel perspective on the healthcare waste management process.
  The selection of participants and contexts followed a progressive and adaptive approach consistent with theoretical sampling principles [39,40]. Throughout data collection, researchers continuously monitored information saturation. When observations and interviews ceased to generate new or relevant insights, the team considered the sample sufficient and completed the fieldwork phase, in accordance with established methodological recommendations [39,40]. Two researchers with expertise in qualitative research and healthcare organisations conducted semi-structured interviews in Italian. We also diversified the sample to include participants with different levels of responsibility, years of experience, and exposure to circular waste management practices. This strategy allowed us to capture a broader range of operational perspectives and reduced the risk of over-representing a single organisational viewpoint. Throughout the study, we held regular reflexive meetings in which we explicitly examined our assumptions, disciplinary lenses, and prior expectations. By openly questioning how our background in healthcare management might shape coding choices or thematic emphasis, we aimed to maintain analytical distance from the data. We further strengthened credibility by comparing interpretations across researchers and by revisiting original transcripts when themes appeared ambiguous or potentially overex-tended. This iterative verification process helped ensure that the findings remained grounded in participants' accounts rather than in preconceived conceptual frameworks [32]. The interviews spanned approximately one month, during which the team collected and analysed data iteratively until saturation [39]. The sample demonstrates heterogeneity in both professional roles and geographical distribution, including participants from multiple Italian regions and various organisational contexts of hospitals. Specifically, the study involved four nurses, two physicians, two technicians (one administrative technician and one environmental technician), one medical physicist, one legal

professional, and two additional technical profiles with operational or managerial responsibilities. From a territorial perspective, the participants originated from six Italian regions (Veneto, Lazio, Friuli Venezia Giulia, Emilia-Romagna, Tuscany, and Lombardy), thus representing healthcare settings that vary in size and organisational structure. We summarise the participant characteristics in Table A1, which reports anonymised demographic and professional information (role, region, institution type, and years of experience) to enhance methodological transparency and reproducibility. The researchers conducted interviews in person or remotely, depending on the availability of the participants (see Table A1).

- **Data collection**
  Data collection focused on predefined topics that served as entry points to initiate and guide interviews. The research team developed a semi-structured interview guide consisting of open-ended questions and probing prompts. The interviewers did not follow a fixed question order throughout the interviews, as they aimed to establish a flexible flow that facilitated a natural and coherent conversation. The guide supported the real-time adaptation of the questions to the context of the interview and its progression [41].
  The interview guide comprised several sections: an initial exploratory section that addressed the organisation of work within the participant's healthcare setting and their professional role in healthcare waste management; a second section focussing on types of healthcare waste and related management processes; a third section that examined regulatory compliance and staff training; a fourth section that addressed sustainability and innovation, including principles of circular economy and emerging technologies; and a final section dedicated to operational challenges and future perspectives.
  Before data collection, researchers provided participants with written information detailing study objectives, interview procedures, and data management practices. All participants received the information sheet prior to interviews and gave their written informed consent by signing the document, in accordance with the principles of the Declaration of Helsinki [42].
  The researchers conducted interviews in Italian, according to the participant's preference, with durations ranging from 60 min to 2 h. Each interview began with a brief introduction to the study, followed by questions addressing the topics described in the interview guide. Throughout the interviews, the interviewers posed additional questions in response to the ongoing dialogue and the responses of the participants. The interviews maintained a conversational tone, allowing questions and themes to emerge organically through interaction with the interviewees.
- **Data Analysis**
  We analyse the data derived from the eleven interviews using Lejeune's analytical approach [35], which structures data coding into three sequential stages: open, axial, and selective coding applied to all interview transcripts. During the open coding phase, the researchers manually examined each transcript line by line to identify recurring concepts and patterns related to healthcare waste management. This process generated approximately ninety initial labels, which the team subsequently organised into preliminary categories that reflect the logical relationships between concepts.
  Through axial coding, the researchers examined the relationships between labels by constructing a co-mention matrix (see Table A5) and analysing how their properties varied in relation to each other [35]. Building on this step, selective coding enabled the integration of the relationships identified during axial coding, leading to the construction of five main themes and twenty subthemes that directly address the research questions. Each theme represents a coherent scenario that links expert perceptions to

operational priorities. For example, the theme *"Regulation and Staff Training"* emerged from the convergence of labels related to regulatory frameworks, training requirements, and compliance monitoring (see Tables A2 and A3, and Figure A1, which illustrate an example of thematic analysis applied to a single interview).

Throughout the analytical process, the researchers adopted a circular and retrospective approach consistent with the Miles and Huberman model [36], continuously revising categories and themes as the depth of data interpretation increased. For example, the analysis initially treated *"digital technologies"* and *"traceability"* as separate categories; however, the researchers merged them after recognising their systematic co-mention in the accounts of the participants [29].

Subsequently, the research team compared the results of the interview analysis with the components of the AI-driven circular waste management tool, focussing in particular on the importance indicators used to define the operational priorities of the tool. To this end, the team developed a structured mapping framework that systematically relates the content derived from the interviews to the operational elements defined in the AI tool checklist.

For each subtheme emerging from the interviews, the researchers identified a corresponding key concept. For example, within the subtheme *"Hospital Waste Classification"*, the analysis extracted key concepts such as *classification*, *segregation*, *EWC codes*, and *hazardous/non-hazardous waste*. The researchers then searched for semantic correspondences between these key concepts and the thirteen thematic areas of the AI tool that contained conceptually similar elements. This procedure relied on semantic rather than purely lexical matching. As illustrated by the example, the concept *"classification"* mapped onto two AI tool areas—*"Segregation of Hazardous and Non-Hazardous Waste"* and *"Regulatory Compliance"*—because classification constitutes both a regulatory obligation and an operational practice.

For each identified AI tool area, the researchers examined all associated actions (1.1–13.6) to determine whether: (a) the action directly addresses the interview subtheme (e.g., the subtheme *"Training"* corresponds to action 10.1 *"Create training programs"*); (b) the action provides a solution to the issue raised in the subtheme (e.g., *"Difficulties in regulatory compliance"* corresponds to action 1.2 *"Conduct audits"*); or (c) the action functions as an enabling instrument for the subtheme (e.g., *"Traceability"* corresponds to action 11.3 *"Blockchain"*). The researchers excluded actions from the mapping when they lacked semantic relevance to the subtheme, belonged to distinct operational contexts, or never appeared in the interviews within that context. For instance, the subtheme *"Circular economy"* did not map onto the *"Emergency Management"* area (Area 9), as no logical or empirical relationship emerged between the two domains. Finally, the team identified AI tool actions that participants never mentioned and that did not correspond to any emergent subtheme.

Table A4 presents the results of this mapping process. The first column lists the themes and subthemes identified across the eleven interviews; the second links each theme to the corresponding thematic area of the AI checklist; the third specifies the concrete operational actions associated with each theme; the fourth reports the number of interviews in which each theme appears (e.g., 9 out of 11), thereby indicating empirical relevance; the fifth column shows the specific frequency with which each action was mentioned in the interviews (e.g., action 5.3 cited in 9 out of 11 interviews); and the sixth column reports the action's importance score (ranging from 0 to 1) as defined within the AI tool based on previous case studies. Colour coding facilitates interpretation of the table. Green highlights indicate the three universally shared themes (present in 100% of the interviews) along with their associated high-importance actions. Blue highlights mark the headings of the five main themes, allowing rapid identification of the thematic architecture. Grey shading denotes actions with importance scores above 0.8, which represent the highest strategic priorities identified by the AI system. Red shading identifies actions included in the AI tool that did not find autonomous correspondence within the interviews.

Overall, this mapping enabled the researchers to assess whether: (a) the interviews comprehensively cover all critical operational areas of healthcare waste management; (b) intervention priorities emerge through the integration of empirical evidence and operational relevance; and (c) thematic gaps appear that warrant further investigation in future research.

To address potential bias in the mapping process, we implemented a structured verification protocol. Two members of the research team (the first and second authors) independently conducted the initial mapping of interview subthemes to AI tool actions for a randomly selected subset of three interviews (approximately 27% of the sample). They followed the semantic matching criteria described in the Data Analysis section: (a) direct correspondence between subtheme and action, (b) the action providing a solution to the issue raised in the subtheme, or (c) the action functioning as an enabling instrument. We documented all mapping decisions in a shared protocol matrix that recorded: the subtheme identifier, the proposed AI tool area(s), the specific action(s) selected, and the rationale for inclusion or exclusion. For example, when mapping the subtheme "Traceability," one coder initially proposed only action 11.3 (Blockchain), while the other included both 11.3 and actions 1.4 (Adopt protocols for traceability) and 8.1 (Implement software for waste tracking). Through discussion, we agreed that all three actions represented valid mappings because they addressed traceability through different operational mechanisms—regulatory protocols, digital infrastructure, and emerging technology, respectively. Discrepancies were resolved through consensus discussion, during which coders reviewed the original interview excerpts together and applied the semantic matching criteria systematically. When disagreement persisted, we consulted the co-mention matrix from the axial coding phase (Table A5) to verify whether the relationship between concepts had empirical support in the data. After establishing consensus on the subset, the first author completed the mapping for all remaining interviews following the agreed protocol. The second author then conducted a verification audit on 100% of the final mapping table, flagging any entries that appeared inconsistent with the established criteria. This resulted in minor adjustments to six mappings (approximately 3% of total theme–action pairs), primarily involving the removal of actions that lacked sufficient semantic relevance to the subtheme.

4. Results

In this section, we present the results of the analysis of the data collected through the interviews, together with the outcomes of the mapping process obtained by comparing the interview findings with the actions and thematic areas defined in the checklist.

4.1. Outcomes of the Interview Data Analysis

Table A5 (see Appendix C for the complete co-mention matrix) illustrates the relationships among the identified sub-themes.

The co-mention analysis conducted across the 11 interviews first confirms the presence of a central triad composed of the sub-themes *"Difficult-to-manage waste"* (11/11), *"Mandatory training"* (11/11), and *"Daily operational problems"* (11/11), which consistently co-occurred in all interviews. The co-mention levels among these three dimensions show perfect alignment: *Difficult-to-manage waste–Mandatory training* = 11/11, *Difficult-to-manage waste–Daily operational problems* = 11/11, and *Mandatory training–Daily operational problems* = 11/11. This pattern indicates that hazardous healthcare waste management requires continuously updated competencies and systematically generates operational challenges that directly affect daily work practices. These findings demonstrate that the intrinsic difficulty associated with managing specific categories of healthcare waste does not represent an episodic issue but rather a structural characteristic of routine operations. In this context, professional training does not merely function as a regulatory requirement; instead, it constitutes a necessary response to a persistent level of managerial complexity that directly shapes work processes and organisational routines.

Alongside this core nucleus, the analysis identifies a thematic cluster labelled *"Regulation–Training–Operations"*, characterised by very high co-mention values ranging from 9 to 10 cases out of 11. Specifically, *"Difficulties in regulatory application"* co-occurs with *"Mandatory training"* in 9/11 interviews (81.8%) and with *"Daily operational problems"* in 9/11 interviews (81.8%). Similarly, the relationship between *"Mandatory training"* (11/11) and *"Awareness-raising initiatives"* remains strong, with co-mention in 10/11 interviews (90.9%), as does the association between *"Awareness-raising initiatives"* and *"Daily operational problems"*, which also appears in 10/11 interviews (90.9%). This configuration shows that experts perceive regulatory frameworks as elements that directly shape organisational practices and therefore require both structured training processes and continuous awareness-raising actions.

These patterns suggest that professionals do not perceive regulation as a clear and readily applicable guide but rather as a complex and fragmented system that demands ongoing mediation between legal requirements and operational reality. Within this context, training and awareness initiatives assume a compensatory and adaptive function, equipping healthcare workers with shared cognitive frameworks and practical routines to manage regulatory uncertainty. In other words, organisations tend to privilege an accommodation-based approach grounded in individual capabilities and internal culture rather than pursuing systemic redesigns of waste management processes.

A further thematic group emerges around the cluster *"Sustainability and Innovation"*, although the empirical data indicate slightly lower levels of integration compared with the previously described clusters. *"Circular economy"* co-occurs with *"Difficult-to-manage waste"* in 8/11 interviews (72.7%) and with *"Mandatory training"* in 9/11 interviews (81.8%). *"Innovative technologies"* show meaningful but more moderate co-mention levels: 7/11 interviews (63.6%) with *"Difficult-to-manage waste"* and 6/11 interviews (54.5%) with *"Awareness-raising initiatives"*. These findings indicate that sustainability and innovation represent relevant themes and maintain clear links to managerial challenges; however, they do not reach the same level of operational integration observed in the core clusters. The lower co-mention with themes related to everyday operations suggests that these concepts largely remain at a strategic or planning level and do not consistently translate into concrete interventions embedded within routine healthcare waste management workflows.

Conversely, several sub-themes appear weakly integrated into the overall discourse. *"Cost and outcome evaluation"* appears in only 2/11 interviews (18.2%) and shows limited co-mention with all other sub-themes. *"Evolution of the role of sustainability"* emerges in just 1/11 interviews (9.1%), with isolated and fragmented associations. *"Collaborative projects"* appear in 2/11 interviews (18.2%), also displaying low levels of integration. These elements indicate domains that participants recognise but have not yet incorporated into operational thinking. This pattern suggests that systematic reflection on economic impacts, outcome assessment, and inter-organisational collaboration has not yet become fully embedded in daily decision-making processes, likely because the operational management of critical issues absorbs most cognitive and organisational resources. The absence of structured organisational policies and integrated performance indicators reinforces this dynamic. Without explicit mandates and dedicated resources, strategic reflection and the development of collaborative networks remain voluntary and marginal activities rather than becoming systemic components of sustainable healthcare waste management.

An intermediate case emerges with the sub-theme *"Difficulties in recycling hazardous waste"*, which appears in 4/11 interviews (36.4%), making it less frequent than other operational themes. When present, it co-occurs with *"Mandatory training"*, *"Difficult-to-manage waste"*, and *"Daily operational problems"* in 4/11 interviews each. However, associations with themes representing potential solutions remain weak: 2/11 interviews with *"Circular economy"* and 3/11 interviews with *"Innovative technologies"*. These findings indicate that participants recognise hazardous waste recycling as a critical issue but do not yet integrate it into broader discussions on systemic sustainability and technological innovation. This pattern confirms the presence of a structural gap: professionals acknowledge the problem, but they do not fully connect it to the tools and strategies capable of addressing it. Consequently, organisations predominantly frame hazardous waste recycling as an issue to be managed rather than as a strategic domain for investment in organisational and technological innovation.

Table 2 reports the final sub-themes together with their absolute and relative frequencies, indicating the number of interviews in which each sub-theme was mentioned. The sub-themes are grouped into three frequency levels: very high, high, and low.

Table 2. Absolute and relative frequency of sub-themes across the 11 interviews.

Category	Sub-Theme	Frequency
Sub-themes present in all 11 interviews (100%)	Difficult-to-manage waste (infectious, sharps, cytotoxic, chemical)	100%
	Training and continuing education of healthcare personnel (formal and informal)	100%
	Daily operational problems (space, costs, staffing, regulation)	100%
High-frequency sub-themes (>70%)	Awareness-raising initiatives and good management practices	90.9%
	Classification of healthcare waste	81.8%
	Difficulties in the application of regulations	81.8%
	Examples of circular economy practices in healthcare	81.8%
	Staff or institutional engagement	81.8%
	Innovative technologies	72.7%
Low-frequency sub-themes (<30%)	Evaluation of outcomes in terms of environmental sustainability and costs	18.2%
	Organisational projects or external collaborations	18.2%
	Evolution of the role of sustainability in public healthcare	9.1%

The sub-themes identified in the interviews confirm the existence of a central triad around which the experts' discourse consistently revolves, encompassing challenges related to waste management, healthcare personnel training, and daily operational issues. Beyond this core, several sub-clusters emerge, reflecting the operational and strategic priorities that complement the central triad. Overall, these findings support the conceptualisation of two main clusters: the "Regulation–Training–Operations" cluster, which captures the core aspects of interviewees' concerns, and the "Sustainability and Innovation" cluster, which highlights opportunities for improvement and forward-looking practices. Marginal sub-themes define peripheral areas of the discourse that, while less frequently mentioned, provide additional context to the broader narrative.

4.2. Outcomes of the Mapping Analysis Between Themes Emerging from the 11 Interviews and the Operational Areas of the Checklist

- **Analysis of the results reported in the theme-to-action mapping table**
  Before discussing the results, it is important to clarify a conceptual point. In this section, the term "frequency" does not represent "importance" per se, but rather operational relevance, that is, the extent to which a theme or action is explicitly discussed in the interviews. Frequency therefore captures what interviewees talk about most, but it does not necessarily reflect the level of risk, impact, cost, or strategic value associated with a given action. To avoid conceptual overlap, we therefore distinguish three analytical dimensions: (i) operational relevance (high frequency in interviews), (ii) risk/impact criticality (what may be dangerous, costly, or legally sensitive even if rarely mentioned), and (iii) strategic innovation potential (actions highlighted by the AI tool that may not yet be culturally or organisationally embedded).
  The analysis of Table A4 identifies three fully convergent themes, all mentioned in the 11 interviews.

  "Difficult-to-manage waste" appears in 11 out of 11 interviews (100%) and links to 10 operational actions, with an average importance score of 0.379. The most relevant actions include *"Conduct periodic drills"* (Action 13.2; importance score 0.645), *"Implement technologies for hazardous waste treatment"* (Action 13.6; importance score 0.591), and *"Monitor chemical waste"* (Action 4.3; importance score 0.585). This theme demonstrates that experts universally recognise the managerial complexity of hazardous healthcare waste (infectious, sharps, cytotoxic, and chemical), and that this complexity corresponds to actions with medium-to-high importance scores (0.15–0.64). Its universal frequency indicates very high operational relevance, meaning that hazardous waste management constitutes a consolidated and shared concern in daily practice. However, frequency alone does not exhaust its risk/impact criticality, which may be even higher than what discourse intensity suggests.

  "Mandatory training" appears in all interviews (11/11; 100%), with an average importance score of associated actions equal to 0.463. This theme primarily connects to *"Continuous staff training"* (Action 10.1; importance score 0.732; mentioned in 11/11 interviews), *"Raising staff awareness on sustainable waste management"* (Action 10.2; importance score 0.660; 11/11 interviews), and *"Training on waste segregation"* (Action 5.2; importance score 0.532; 7/11 interviews). The universal presence of this theme confirms that respondents perceive training as a fundamental operational lever for improving healthcare waste management. Here again, high frequency reflects operational centrality, while the importance scores also signal medium-to-high criticality in terms of compliance, safety, and organisational performance.

"Daily operational issues" (space, costs, staffing) also emerge in all interviews (11/11; 100%), with an average importance score of 0.529 for the related actions. Key actions include *"Conduct periodic drills to test emergency plans"* (Action 9.2; importance score 0.790; 3/11 interviews), *"Continuous staff training"* (Action 10.1; importance score 0.732; 11/11 interviews), *"Ensure additional resources to manage waste surges"* (Action 9.3; importance score 0.701; 7/11 interviews), and *"Develop an emergency management plan"* (Action 9.1; importance score 0.691; 2/11 interviews). This theme highlights how experts perceive daily operational constraints as priority issues that require both emergency-oriented and routine management actions. In this case, frequency clearly captures operational relevance, i.e., what practitioners experience as immediate and tangible constraints.

Beyond this universal core, several highly frequent but non-universal themes emerge, all of which hold substantial strategic relevance.

"Innovative technologies" appear in 8 out of 11 interviews (72.7%) and associate with seven actions, with an average importance score of 0.431. Notably, *"Assess emerging technologies such as blockchain for waste traceability"* (Action 11.3) reaches the maximum possible importance score of 1.000, despite being explicitly mentioned in only 1 out of 11 interviews (9.1%). Other relevant actions include *"Conduct feasibility studies for adopting new technologies"* (Action 11.4; importance score 0.909; 5/11 interviews), *"Implement technologies for hazardous waste treatment"* (Action 13.6; importance score 0.591; 4/11 interviews), *"Implement waste tracking software"* (Action 8.1; importance score 0.489; 7/11 interviews), and *"Adopt new treatment methods"* (Action 11.2; importance score 0.469; 4/11 interviews). The low frequency of Action 11.3 (1/11) should therefore not be interpreted as marginal importance. It may reflect outsourcing practices, the specific professional roles interviewed, the structure of the interview guide, or low perceived salience. From a risk/impact perspective, pharmaceutical waste may still represent a significant environmental and regulatory criticality despite its limited discursive presence.

"Circular economy" emerges in 9 out of 11 interviews (81.8%), with an average importance score of the related actions equal to 0.394. The most strategic action is *"Plan the reuse of sterilizable medical devices"* (Action 7.4; importance score 0.841; 7/11 interviews), followed by *"Establish practices for energy recovery from waste"* (Action 7.2; importance score 0.656; 4/11 interviews), *"Collaborate on the recovery of expired pharmaceuticals"* (Action 3.4; importance score 0.412; 1/11 interviews), *"Implement a collection system for recycling non-hazardous waste"* (Action 7.3; importance score 0.277; 9/11 interviews), and *"Identify solutions for recycling used materials"* (Action 7.1; importance score 0.179; 5/11 interviews).

"Difficulties in regulatory implementation" appear in 9 out of 11 interviews (81.8%), with an average importance score of 0.463 and a maximum value of 0.863 linked to *"Establish a non-compliance reporting system"* (Action 1.5; importance score 0.863; 7/11 interviews). Additional relevant actions include *"Conduct periodic audits"* (Action 1.2; importance score 0.723; 8/11 interviews), *"Adopt protocols for hazardous waste traceability"* (Action 1.4; importance score 0.537; 8/11 interviews), *"Define key performance indicators"* (Action 8.3; importance score 0.526; 4/11 interviews), and *"Implement waste tracking software"* (Action 8.1; importance score 0.489; 7/11 interviews). Here, operational relevance and risk/impact criticality appear more closely aligned, as regulatory compliance has both high discursive presence and high theoretical importance.

"Staff or institutional engagement" emerges in 9 out of 11 interviews (81.8%), with an average importance score of 0.584. This theme links to *"Engage community representatives"* (Action 12.2; importance score 0.844; 8/11 interviews), *"Continuous staff training"* (Action 10.1; importance score 0.732; 11/11 interviews), *"Organise community awareness programs"* (Action 12.1; importance score 0.732; 3/11 interviews), and *"Raise staff awareness"* (Action 10.2; importance score 0.660; 11/11 interviews). This theme combines high operational relevance with medium-to-high strategic value, suggesting a relatively mature organisational awareness.

Conversely, convergence decreases sharply for several areas that remain weakly represented in professional discourse.

"Sustainability performance evaluation" appears in only 2 out of 11 interviews (18.2%), despite an average importance score of 0.452 for the associated actions. These actions include *"Define key indicators to monitor effectiveness"* (Action 8.3; importance score 0.526; 4/11 interviews), *"Implement tracking software"* (Action 8.1; importance score 0.489; 7/11 interviews), *"Establish a periodic reporting system"* (Action 8.4; importance score 0.438; 4/11 interviews), and *"Collect data to assess environmental performance"* (Action 8.2; importance score 0.364; 2/11 interviews). The low thematic frequency (18.2%) contrasted with a moderate average importance score (0.452) highlights a clear misalignment between measurement practices and their perceived operational relevance.

"Difficulties in recycling hazardous waste" emerge in 4 out of 11 interviews (36.4%), with an average importance score of 0.541. The related actions include *"Ensure the safe treatment of hazardous materials"* (Action 6.2; importance score 0.446; 4/11 interviews), *"Establish practices for energy recovery"* (Action 7.2; importance score 0.656; 4/11 interviews), *"Implement technologies for hazardous waste treatment"* (Action 13.6; importance score 0.591; 4/11 interviews), and *"Adopt new treatment methods"* (Action 11.2; importance score 0.469; 4/11 interviews). Despite its medium-to-high importance (0.541), only 36.4% of respondents discuss this theme, suggesting an underestimation of technological opportunities for the circular management of hazardous waste.

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"Evolution of the role of sustainability" appears in only 1 out of 11 interviews (9.1%), although the associated actions reach an average importance score of 0.539. These actions include *"Engage community representatives"* (Action 12.2; importance score 0.844; 8/11 interviews), *"Organise awareness programs"* (Action 12.1; importance score 0.732; 3/11 interviews), *"Raise staff awareness"* (Action 10.2; importance score 0.660; 11/11 interviews), *"Collect data to assess environmental performance"* (Action 8.2; importance score 0.364; 2/11 interviews), and *"Create partnerships for sustainability"* (Action 12.4; importance score 0.292; 1/11 interview). The near absence of this theme from expert discourse highlights a lack of strategic vision regarding sustainability as a driver of systemic change in public healthcare. This is a typical example of low operational relevance combined with potentially high strategic transformation value.

"Collaborative projects" also show limited presence (2/11 interviews; 18.2%), with an average importance score of 0.413. Their marginal frequency may reflect organisational boundaries or externalised responsibilities, rather than low intrinsic importance. The associated actions include *"Collaborate with suppliers to reduce packaging use"* (Action 2.4; importance score 0.608; 5/11 interviews), *"Collaborate with specialised entities for the recovery of unused pharmaceuticals"* (Action 3.4; importance score 0.412; 1/11 interview), *"Create partnerships with local organisations"* (Action 12.4; importance score 0.292; 1/11 interview), and *"Establish a stakeholder feedback system"* (Action 12.3; importance score 0.270; 3/11 interviews).

Finally, four actions (7.3% of the total)—two belonging to the *"Management of Pharmaceutical Waste"* area and two to the *"Management of Infectious Emergencies/Pandemics"* area—did not find any autonomous correspondence in the 11 interviews. These actions include Action 3.1 *"Implement protocols for the safe management of expired pharmaceuticals"* (importance score 0.537; frequency 0/11), Action 3.2 *"Train staff on the correct management of pharmaceutical waste"* (importance score 0.450; frequency 0/11), Action 13.1 *"Develop specific emergency plans for healthcare waste management"* (importance score 0.784; frequency 0/11), and Action 13.4 *"Train staff on infectious waste management procedures during pandemics"* (importance score 0.161; frequency 0/11). Their absence from interview discourse should therefore be interpreted cautiously: it may indicate routinised practices taken for granted, strong regulatory standardisation, outsourcing dynamics, or cognitive blind spots, rather than true lack of importance.

- **Thematic coherence, alignment of action priorities, and discrepancy assessment**
In light of the conceptual clarification above, the following quantitative comparison does not interpret frequency as a proxy for intrinsic importance, but as an indicator of operational relevance. The comparison between relative frequencies and AI-derived importance scores therefore reflects the alignment (or misalignment) between what is culturally salient in practice and what is assessed as theoretically or strategically critical by the AI tool. The assessment focuses on three main aspects:
  - Action classification: grouping actions into three levels (low, medium, high) based on the frequency distribution derived from the interview data.
  - Priority comparison: identifying actions shared between the groups defined by the AI tool through importance scores and those defined by the relative frequencies observed in the interviews.

– Discrepancy assessment: quantifying, on average, the differences between the evaluations produced by the AI tool and those derived from the interview data across the different action groups.

The *action classification* step is required to assess the overall level of agreement between actions identified through the two approaches. Figure 3 illustrates the distribution of actions across three classes based on the relative frequencies observed in the interviews. The classification relies on the first and third quartiles of the frequency distribution to define classes based on importance scores. This approach represents a standard quartile-based statistical approach and was chosen because it provides objective thresholds that reflect the distribution of the observed data rather than relying on arbitrary cut-offs. Specifically, we consider:

– *High Class*: actions with frequencies above the third quartile, indicating a contribution significantly above the average.
– *Medium Class*: actions with frequencies between the first and third quartiles, indicating a moderate contribution.
– *Low Class*: actions with frequencies below the first quartile, indicating low occurrence.

This approach assigns empirical relevance to each action based on the number of times interviewees mentioned it, thereby associating each action with a quantitative measure of observed importance.

Figure 3 presents the actions ranked according to the relative frequencies observed in the interviews. Of a total of 55 actions, the analysis did not detect 4 actions in the empirical investigation (relative frequency equal to zero). The adopted categorisation distinguishes 18 highly frequent actions, 25 moderately frequent actions, and 12 low-frequency actions, thus clearly highlighting the main aspects emerging from the empirical context under analysis.

Alignment of action priorities. We conducted a qualitative analysis of the actions shared among the groups identified by the AI-based tool through importance scores and those defined by the relative frequencies derived from the interview data. Both measures—importance scores and relative frequencies—were normalised within the $[0,1]$ interval, allowing a direct and straightforward comparison. Figure 4 shows that, for the shared actions, the importance scores and relative frequencies exhibit a high degree of coherence, uniformly distributed across all three classes.

Discrepancy assessment. We perform a quantitative comparison between the two measures. Specifically, for actions shared across the three classes, we quantified the distance using the *normalised mean absolute error (NMAE)*. This metric captures the mean absolute difference between relative frequencies (x_i) and importance scores (y_i), normalised by the mean of the reference values. Let n denote the sample size (i.e., the number of observations). The NMAE index is computed as:

$$\mathrm{NMAE} = \frac{\frac{1}{n}\sum_{i=1}^{n}|x_i - y_i|}{\frac{1}{n}\sum_{i=1}^{n} x_i} \tag{1}$$

The NMAE represents a dimensionless indicator that expresses the discrepancy between the two measures as a relative proportion, enabling comparisons across different categories. This normalisation proves particularly suitable in contexts characterised by heterogeneous data, such as actions simultaneously classified according to empirical frequency and theoretical importance.

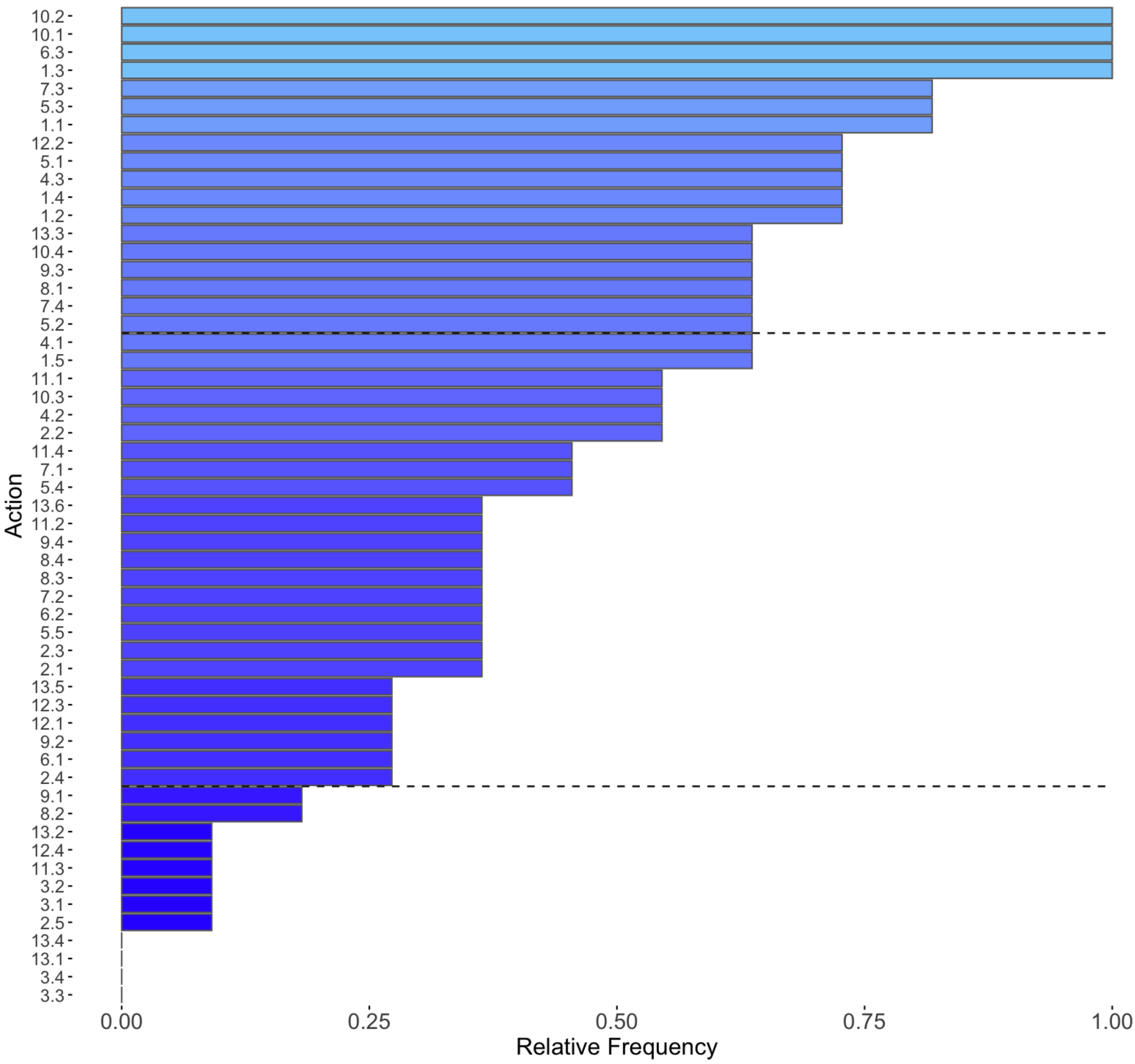

Figure 3. Relative frequencies of actions identified in the interviews, ordered in descending order. Dashed vertical lines indicate the three categories: highly frequent, moderately frequent, and low-frequency actions. The colour gradient from light blue to dark blue reflects the level of occurrence, with lighter shades corresponding to higher frequencies.

The results show that actions belonging to the *high class* display strong agreement between the two measures, with an average difference of 21%. The discrepancy increases for the *Medium Class* (31%) and reaches its highest level for the *Low Class* (33%), indicating lower coherence for less frequently mentioned actions (Table 3).

To obtain an overall assessment of the agreement between relative frequencies and importance scores regardless of class membership, we calculated NMAE index (Equation (1)) for all actions. The resulting value of 0.648 indicates a relatively high overall discrepancy, suggesting that the importance scores do not fully align with the empirical evidence emerging from the interviews.

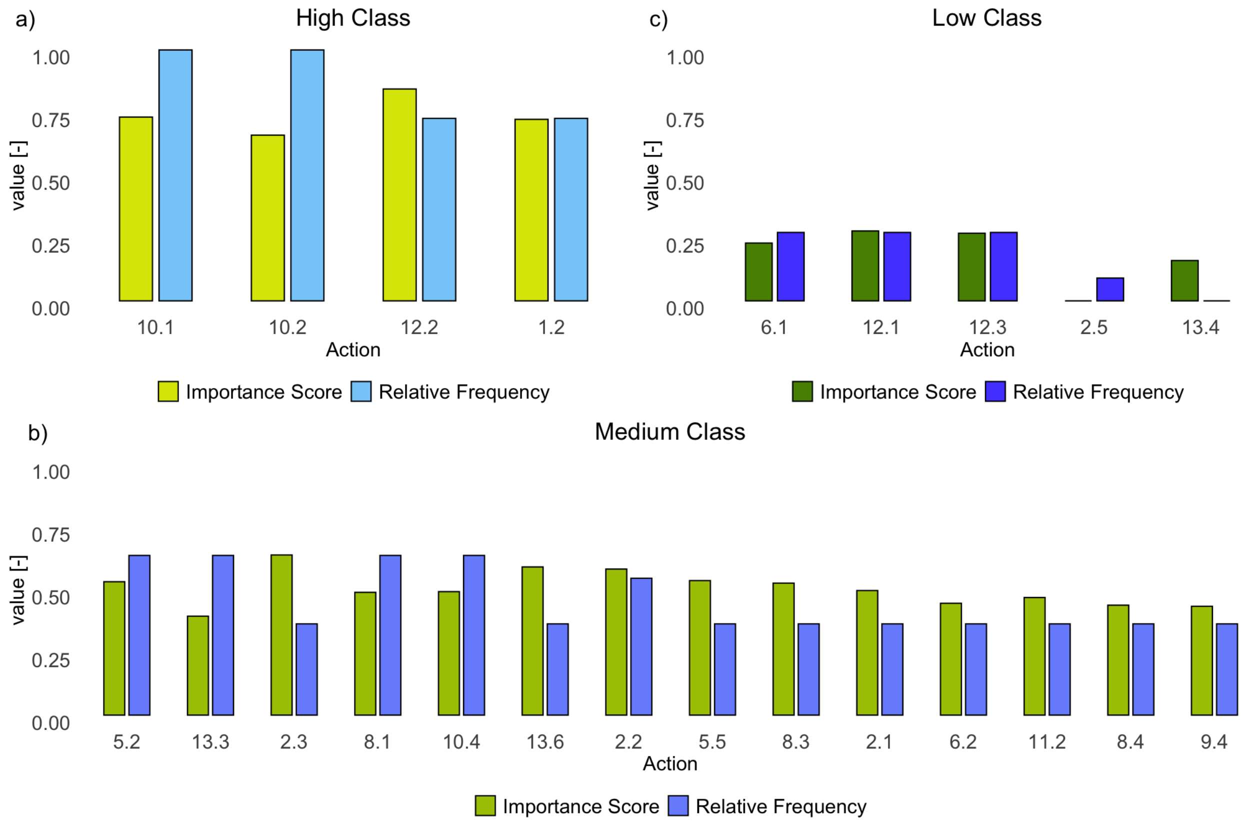

Figure 4. Comparison between importance scores and relative frequencies for shared actions across the three classes: (**a**) low, (**b**) medium, and (**c**) high.

This outcome likely reflects the limited sample size analysed. Nevertheless, it highlights the need to update the previously computed importance scores by integrating them with empirically derived relative frequencies through a linear combination of the following form:

$$w_i^{\text{new}} = \alpha\, w_i^{\text{RelFreq}} + (1-\alpha)\, w_i^{\text{ImpScore}} \tag{2}$$

By setting $\alpha = 0.70$, the model assigns greater weight to the empirical evidence collected through interviews.

In summary, the analysis reveals a high level of thematic coverage: out of the 55 actions proposed by the tool, 51 (93%) show direct correspondence with interview data, while only 4 actions (7%) lack empirical support. This percentage (93%) reflects the actual proportion of evidence-backed actions within the sample ($n = 11$), rather than a predefined threshold. We describe this alignment as 'high' due to the broad coverage and few exceptions found. This finding indicates a strong structural coherence between the AI-supported theoretical framework and the reality observed through expert interviews. The presence of three themes mentioned in 100% of the interviews, together with four actions cited by all 11 respondents, further supports the existence of a core set of transversal and shared actions that emerge as central regardless of the specific context.

At the same time, the analysis identifies six actions with importance scores greater than 0.8, indicating that the AI tool focusses on a relatively small subset of actions with high theoretical relevance. We quantitatively assessed the level of alignment between the relative frequencies derived from the interviews and the importance scores produced by the tool using NMAE index (Equation (1)) for each frequency class (high, medium, and low). The results show a coherent and informative pattern, indicating (a) a strong correspondence between empirical evidence and tool-based assessment for the most frequently mentioned shared actions, (b) a moderate discrepancy for moderately frequent actions, and (c) a greater divergence for less frequently mentioned actions. These findings indicate that agreement between interview data and the AI-based tool is highest for actions perceived as most relevant by respondents, while it progressively decreases for less frequently mentioned actions. This pattern aligns with the assumption that high-frequency actions reflect consolidated and shared operational dynamics, whereas low-frequency actions remain more sensitive to contextual factors and sample-specific characteristics.

Table 3. NMAE values between relative frequencies and importance scores for the shared actions across the three classes.

Category	NMAE
High class	0.211
Medium class	0.310
Low class	0.333

Table 4 provides an overall synthesis of the main results emerging from the study.

Table 4. Summary of the quantitative coherence assessment.

Element	Count/Value
Interview themes/subtopics	20
Tool thematic areas	13
Total tool actions	55
Actions mapped to interviews	51
Actions with no correspondence	4
Universal interview themes (100% frequency)	3
Actions with importance score $\geq$ 0.8	6
Actions mentioned in all 11 interviews	4
NMAE–high class	0.21
NMAE–medium class	0.31
NMAE–low class	0.33

4.3. Role-Based Differences in Perceptions of Circular Economy

Participants broadly recognised the strategic relevance of the CE, but they expressed different perspectives depending on their professional roles.

- Managerial Perspective: CE as Institutional Strategy
  Managers framed CE as a long-term governance strategy embedded within organisational planning, resource optimisation, and sustainability objectives. They emphasised formal validation, cross-functional coordination, and measurement of outcomes. Illustrative quotes:

  > *"My role is to identify potential waste, propose actions to reduce it, and report to the director."* (Int. V)
  >
  > *"If it is not measured, it may work or be useless. A monitoring plan is necessary."* (Int. I)

- Clinical Perspective: CE as Operational Governance
  Clinicians focused on operational feasibility, workflow integration, and patient safety. They highlighted the importance of clear protocols, continuous supervision, and recognition of good practices:

> *"It is not only about training, but also about continuous monitoring."* (Int. VI)

> *"We had a medical director attentive to waste management, which allowed us to develop this area effectively."* (Int. XI)

Thus, whereas managers emphasised strategic coordination and institutional redesign, clinicians focused on procedural compliance, supervision, and integration into everyday clinical workflows.

5. Discussion

The results allow us to systematically address the research questions formulated in the Introduction by integrating the empirical evidence derived from the interviews with the outputs generated by the AI-based tool. This approach aligns with the methodological framework proposed by previous studies that emphasise the necessity of integrating quantitative methods with qualitative user-centred evaluations to ensure that DSS are not only effective in principle, but also usable in routine clinical practice [15,16,28]. We clarify that interview frequency is interpreted as an indicator of operational relevance (i.e., discursive salience in daily practice) and not as a direct proxy for intrinsic importance. The AI-based importance scores, instead, reflect a structured assessment that may capture dimensions of risk/impact criticality and strategic innovation potential, even when these are weakly represented in practitioners' narratives.

Regarding RQ1 (*How do the themes emerging from the interviews correspond to the thematic areas, indicators, and operational actions included in the AI tool?*), the mapping analysis reveals a high level of structural coherence between the interview content and the AI tool framework. Specifically, all 20 subtopics identified through thematic analysis are directly mapped to thematic areas and operational actions included in the tool checklist (see Table A4). In general, 51 out of 55 actions (93%) find empirical support in interviews, indicating that the system effectively captures the majority of the practices, critical issues, and priorities expressed by the experts interviewed. This result is consistent with the growing body of empirical research demonstrating that qualitative approaches based on interviews are essential for the validation of CDSS, as they help uncover latent needs and explain why technically sound systems may fail to be adopted [24–27]. Further validation emerges from the identification of a universal triad—*"Difficult-to-manage waste"*, *"Mandatory training"*, and *"Everyday operational issues"*—mentioned in 100% of the interviews. These themes consistently align with high-relevance areas of the AI tool, confirming its ability to capture the core and cross-cutting operational dimensions of healthcare waste management. However, structural coherence alone does not guarantee operational effectiveness. As highlighted in recent literature [10], adoption challenges have frequently been attributed not to deficiencies in predictive accuracy, but to design choices that do not adequately account for work routines, organisational constraints, and the distribution of decision-making responsibilities among healthcare operators. Indeed, both effectiveness and user acceptance are dependent on coherence with everyday practices and seamless integration into existing decision-making processes [12]. In general, these findings indicate that the AI tool faithfully reflects the structure of problems and operational priorities as experienced by healthcare professionals and environmental managers. We note that the strong overlap between high-frequency themes and high-importance actions suggests alignment in terms of operational relevance. However, this coherence should not be interpreted as full equivalence between what is frequently discussed and what is objectively critical. Rather, it indicates that the AI tool successfully captures the stabilised and institutionally embedded dimensions of practice.

In relation to RQ2 (*Which practitioner-relevant aspects are not adequately represented or supported by the AI tool?*), the analysis highlights areas of partial misalignment. Some subtopics emerging from the interviews appear weakly represented or absent in the tool checklist, particularly those related to (a) systematic evaluation of outcomes and costs associated with implemented actions, (b) development of inter-organisational collaborative projects, and (c) the strategic evolution of sustainability within healthcare organisations. Although these dimensions show a low interview frequency (<30%), their marginal presence in both interviews and the tool design raises critical questions about the capacity of current DSS to support the transition to circular economy models in the healthcare sector. Previous research has emphasised the potential of DSS and AI to enable material recovery, optimise logistical flows, and foster integrated digital ecosystems across the value chain [1,14], yet the empirical evidence from this study suggests that these strategic dimensions remain weakly institutionalised in operational contexts. Moreover, as observed by Rauwerdink et al. [16], DSS assessments often prioritise randomised controlled trials and performance metrics, overlooking critical stages of planning, development, and implementation. The limited integration of outcome evaluation, inter-organisational collaboration, and sustainability evolution within the tool may therefore reflect not merely weak institutionalisation, but a more fundamental design gap that mirrors broader limitations in current DSS development approaches.

Their limited integration within the tool reflects both a weak institutionalisation of these practices in operational contexts—often associated with the absence of structured organisational policies, shared performance indicators, and dedicated resources—and the tendency of model-driven approaches to inadequately capture the complexity of real clinical environments [15]. As demonstrated by Guo et al., predictive models and simulations achieve practical effectiveness only when complemented by the experiential knowledge of operators, suggesting that the marginal presence of these strategic dimensions in both tool design and practitioner discourse may represent a structural limitation for long-term sustainability objectives.

From the perspective of the three analytical dimensions introduced above, these areas appear characterised by relatively low immediate operational relevance, yet potentially high-risk-impact criticality (e.g., performance measurement and accountability) and significant strategic innovation potential (e.g., inter-organisational collaboration and long-term sustainability governance). Their limited visibility within practitioners' narratives may therefore indicate constrained organisational readiness, reliance on outsourcing arrangements, or broader processes of institutional underdevelopment, rather than a lack of intrinsic importance. In this sense, the observed gap should be interpreted less as a design deficiency of the tool itself and more as an expression of the current maturity level of organisational practices within healthcare waste management contexts.

Regarding RQ3 (*Do the operational priorities expressed by interviewees coincide with those calculated by the system through importance scores?*), the results reveal a selective and non-uniform alignment. Quantitative comparison using NMAE index (Equation (1)) for actions shared across the three frequency classes (high, medium, low) shows: (a) strong agreement between interviews and the AI tool for high-frequency actions perceived as central by respondents; (b) moderate discrepancy for medium-frequency actions; and (c) more pronounced divergence for low-frequency actions. This methodological approach is supported by previous studies [28,33] that demonstrate how the integration of descriptive techniques—such as frequency counts—and non-parametric analyses supports the assessment of the relative importance of emergent themes, allowing for the mapping of alignment or misalignment between discursive prominence and strategic relevance as perceived by the involved actors.

The used pattern indicates that the AI tool effectively identifies and prioritises consolidated and widely shared actions, while it tends to overestimate or underestimate the less frequent actions that strongly depend on organisational context and sample-specific characteristics. This finding aligns with a critical concern raised in the literature regarding advanced DSS: if the parameters that define importance scores fail to adequately represent real operational constraints—such as limited resources, fluctuating waste volumes, or procedural complexity—the resulting recommendations may prove impractical or applicable only at the design stage, diverging from actual waste management requirements [20]. This misalignment between algorithmic rationales and operational practice represents one of the principal risks associated with advanced DSS: despite generating theoretically optimal outputs, such systems may produce recommendations that require substantial human mediation to be implemented [10,18].

The observed behaviour aligns with the assumption that recurrent operational priorities reflect stabilised practices, whereas marginal actions remain more context-sensitive. At the same time, the AI tool appears capable of signalling emerging or under-recognised domains that may require anticipatory governance even in the absence of a strong discursive presence. The discrepancies can be attributed to two complementary mechanisms. First, the AI tool's importance scores derive from aggregated case study data across multiple healthcare contexts, potentially overestimating actions that prove critical in specific settings (e.g., pandemic preparedness in hospitals with infectious disease units) but remain peripheral in routine operations at the interviewed facilities. Second, low-frequency actions in interviews may reflect underestimation by practitioners rather than lack of operational relevance—these actions often concern emerging practices (e.g., blockchain for traceability, drug recovery programs) that have not yet been institutionalised in daily workflows despite their strategic potential. This dual interpretation suggests that alignment between AI-based priorities and practitioner-reported frequencies is strongest for established, consolidated practices, while divergence emerges in areas characterised by either context-specific criticality or insufficient organisational maturity.

Finally, with respect to RQ4 (*Which factors facilitate or hinder the integration of the AI tool into hospital workflows?*), the analysis of the eleven interviews reveals a clear predominance of barriers over facilitators in integrating the digital tool into hospital settings. The main challenges fall into three categories—(a) structural, (b) organisational, and (c) cultural—while the enabling factors appear limited and context-specific. These findings are consistent with the observation that the introduction of DSS and AI-based tools alone does not ensure operational effectiveness, nor does it guarantee alignment between model-embedded priorities and those that are practically relevant to healthcare professionals and environmental managers [10]. Moreover, this gap extends beyond technical considerations, including organisational, procedural, and contextual factors that can hinder the integration of DSS into established workflows and ultimately undermine their practical utility [19].

The most critical barrier concerns logistical constraints and the lack of physical space, which directly hinders the implementation of recommended operational actions.

"The issue is logistics; we simply do not have space in ecological islands and storage areas." (Int. VII)

A second major obstacle involves staff shortages and workload pressure, which lead professionals to prioritise clinical activities over practices perceived as additional:

"There is always less staff and more work to do." (Int. I)

Limited awareness and participation among healthcare professionals—particularly physicians—emerges as another critical issue, as waste management often appears marginal to clinical priorities.

"It is the last of healthcare problems." (Int. IX)

This statement highlights how low perceived salience at the operational level may coexist with high systemic importance, underscoring the need for decision-support tools capable of reframing sustainability and healthcare waste management as strategic rather than ancillary domains. This perception also reflects the broader difficulty of embedding waste management practices within healthcare environments characterised by high regulatory complexity, stringent compliance requirements, and significant environmental and public health risks in cases of non-compliance [17,18]. Consistent with previous research identifying a persistent gap between regulatory prescriptions and the capacity of digital tools to support realistic operational decision making in dynamic hospital contexts [19], our findings confirm that this misalignment remains a critical challenge.

Additional recurring barriers include staff turnover, weak leadership and governance structures, economic constraints and misaligned tariff systems, and discontinuous training, all of which hinder the long-term consolidation of correct practices.

"Training needs to be continuous, and this is not always guaranteed." (Int. III)

Among facilitators, interviewees less frequently mention access to qualified external expertise and the presence of motivated internal actors capable of locally promoting tool adoption.

"We rely on the support of an expert consultant." (Int. IV)

Training plays an ambivalent role: when insufficient, it acts as a barrier, whereas structured and continuous training generates tangible operational and economic benefits.

"We achieved almost a 15% reduction in infectious waste." (Int. I)

The interviews revealed that the strategic relevance of CE is interpreted differently depending on professional role [43]. Managers emphasised long-term institutional planning, resource governance, and alignment with sustainability objectives, while clinicians focused on operational feasibility, workflow integration, and patient safety. These role-specific perspectives highlight the need for both strategic alignment at the managerial level and operational adaptability at the clinical level. Embedding CE principles effectively thus requires bridging these viewpoints to ensure that institutional strategies translate into practical, everyday practices. This distinction complements the broader RQ1 findings, showing that while the AI tool captures strategic and operational practices, its effective integration into hospital workflows must account for these role-specific interpretations of CE principles.

The results indicate that the integration of the digital tool into hospital workflows is highly dependent on structural, organisational, and cultural constraints. Ultimately, the effectiveness of the tool depends on its capacity to bridge operational relevance (what practitioners recognise and enact), risk/impact criticality (what is objectively significant), and strategic innovation potential (what anticipates future regulatory, technological, and sustainability challenges). The effectiveness of the tool, therefore, relies on the practical feasibility of the actions it supports, its adaptability to infrastructure limitations, and its embedding within broader strategies addressing training, governance, and resource allocation [30].

Table 5 summarises the main barriers and facilitators identified in all interviews, together with their corresponding frequencies.

Beyond operational alignment, the findings raise an important question concerning whether AI-based sustainable healthcare waste management systems may contribute to reducing the risk of regulatory non-compliance across heterogeneous healthcare environments. The findings suggest that the system has the potential to reduce regulatory non-compliance by enhancing procedural standardisation and decision support; however, their effectiveness is contingent upon organisational readiness, workforce engagement, and integration into existing hospital workflows rather than technological performance alone.

Table 5. Summary of identified barriers and facilitators with corresponding frequency.

Sub-Theme	Frequency %
Barriers	
Logistical constraints and lack of space	63.7%
Staff shortages and operational workload	54.5%
Low awareness and limited staff engagement	100%
Staff turnover and discontinuity of skills	45.5%
Insufficient training	45.5%
Weak leadership and governance	45.5%
Economic constraints and misaligned tariff systems	45.5%
Regulatory and contractual fragmentation	27.3%
Facilitators	
Availability of qualified external expertise	18.2%
Motivated internal actors sensitive to environmental issues	18.2%
Structured and effective training	9.1%

6. Conclusions

This study confirms that the AI-driven circular waste management tool is generally well aligned with the operational needs and perceived priorities of healthcare professionals and environmental managers, showing a high degree of correspondence between the tool's actions and the themes emerging from the interviews. In particular, the shared core—*difficult-to-manage waste*, *mandatory training*, and *everyday operational issues*—demonstrates the tool's ability to capture the most relevant operational priorities, while circular economy practices are acknowledged but mainly framed at a strategic rather than an operational level. Discrepancies emerge primarily for less frequent or context-dependent actions, highlighting the importance of integrating empirical evidence to improve alignment between the digital tool and real-world operational settings.

To enhance the value of field-derived information and reduce the risk of relying exclusively on AI-model-driven assessments, we proposed updating the relevance weights assigned to actions by combining empirical evidence—represented by observed relative frequencies—with importance scores, assigning a higher weight to the former (Equation (2)). This hybrid weighting approach strengthens the contextual grounding of the tool and improves its practical relevance.

An important avenue for future research involves analysing the actual use of the AI tool within hospital departments, comparing observed performance with interview data and simulation results. Experimental implementation would allow the identification of strengths and critical issues, providing concrete guidance for further refinement of the tool.

The main limitations of this study relate to its qualitative validation design and the relatively small sample ($n = 11$), which may limit transferability to other hospital settings. However, the objective was not to achieve statistical generalisation, but to evaluate the correspondence between the most relevant actions identified by the AI-supported tool and the most frequently recurring actions emerging from expert interviews. In this context, sample adequacy is linked to the stability and consistency of the observed alignment patterns rather than to statistical power. Nevertheless, broader multi-site studies involving heterogeneous hospital contexts will be necessary to strengthen external validity and assess the robustness of the alignment across different organisational settings.

The findings are based on participants' declarative perceptions and do not include direct observation of the tool's operational implementation. Consequently, performance assessment is currently limited to interview-based evidence and prior simulation results rather than real-world application.

Although the AI-supported tool is grounded in a structured theoretical framework and domain-informed inputs, potential biases related to model design, embedded assumptions, or underlying training logic cannot be entirely excluded. Continuous validation across diverse contexts and iterative refinement through systematic expert feedback are therefore essential to mitigate potential AI-related biases and enhance methodological robustness.

This choice reflects the primary objective of the present study, namely to evaluate the correspondence between the actions most frequently emerging from expert interviews and those prioritised by the AI-based importance scores. In this phase, empirical evidence represents the main reference for alignment; therefore, a higher weight was intentionally assigned to interview-derived relative frequencies.

Finally, validation on a larger and more heterogeneous sample will be crucial to enhance the reliability, robustness, and generalisability of the tool. Future research should include experimental implementation within hospital departments, enabling systematic comparison between observed operational performance, interview insights, and simulation outputs. Such multi-site validation would facilitate the identification of strengths and critical issues while supporting progressive refinement and empirical consolidation of the tool. With a larger dataset, ML models can be trained more effectively, allowing the application of model-agnostic interpretability techniques (e.g., SHAP values, permutation importance) to complement the current alignment-based evaluation and provide deeper insights into both global and local patterns of action relevance.

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Abbreviations

The following abbreviations are used in this manuscript:

CDSS	Clinical decision support system
CER	Catalogo Europeo dei Rifiuti
DSS	Decision support systems
EU	European Union
HCWH	Health Care Without Harm
IA	Artificial intelligence
IoT	Internet of things
IPC	Infection prevention control
ML	Machine learning
NMAE	Normalised mean absolute error
PE	Polyethylene
PET	Polyethylene terephthalate

RFID	Radio frequency identification
SDGs	Sustainable Development Goals
SRQR	Standards for Reporting Qualitative Research
UN	United Nations
WASH	Water sanitation and hygiene
WHO	World Health Organization

Appendix A. Research Design

Appendix A.1. Interviewers

Table A1 reports the main characteristics of the eleven participants involved in the qualitative study. It provides an overview of the sample analysed by highlighting, for each interviewee: the identification code (to ensure anonymity), the interview date, the professional role, the type of healthcare institution (hospital, university, or research institute), total years of professional experience, direct involvement in hospital waste management, and the region of operation.

Table A1 shows that the sample is heterogeneous in terms of professional roles (physicians, nurses, technicians, medical physicists, legal experts, and administrative staff) as well as in the organisational context and geographical distribution. The participants represent healthcare institutions from six Italian regions (Veneto, Lazio, Friuli Venezia Giulia, Emilia-Romagna, Tuscany, and Lombardy), ensuring a diversified perspective on hospital waste management practices.

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Table A1. Interviews conducted for the study on healthcare waste management.

Code	Date	Role	Expertise	Experience	Region	Institution	Target Audience
I-1	25 March 2025	Administrative officer	Healthcare waste management, professional development, continuing education	30 years	Veneto	University hospital	Healthcare professionals
I-2	1 April 2025	Nursing coordinator	Infection control, healthcare waste management, continuing education	20 years	Lazio	University hospital	Healthcare professionals
I-3	4 April 2025	Nurse	Infection control, healthcare waste management, continuing and academic education	3 years	Friuli Venezia Giulia	Research institute	Healthcare professionals and students
I-4	8 April 2025	Medical director	Coordination of hospital and territorial waste management, continuing education	14 years	Emilia-Romagna	Hospital trust	Healthcare professionals, managers, health authorities
I-5	10 April 2025	Medical physicist	Environmental management, hospital procurement consulting, healthcare waste management	6 years	Emilia-Romagna	Hospital trust	Healthcare professionals, managers, health authorities
I-6	17 April 2025	Nursing coordinator	Hospital and territorial waste management, environmental sanitation, pest control services	11 years	Tuscany	Hospital trust	Healthcare and technical staff, managers
I-7	22 April 2025	Environmental prevention technician	Healthcare environmental management, healthcare waste management, healthcare sustainability, continuing education	22 years	Emilia-Romagna	Hospital trust	Healthcare professionals, administrators, managers, health authorities
I-8	23 April 2025	Occupational health and safety technician	Healthcare waste management, academic education	4 years	Friuli Venezia Giulia	University hospital	Healthcare and technical staff, administrators, health authorities
I-9	24 April 2025	Medical director	Hospital and territorial waste management, continuing education	1 year	Lombardy	Hospital trust	Healthcare professionals, managers, health authorities
I-10	28 April 2025	Environmental legal expert	Waste safety, continuing and academic education	36 years	Friuli Venezia Giulia	Consultancy	Companies, healthcare institutions, healthcare professionals, managers
I-11	30 April 2025	Nursing coordinator	Healthcare waste management, infection control, pest control	3 years	Emilia-Romagna	University hospital	Technical services, healthcare professionals, managers

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Appendix A.2. Example of Open, Axial, and Selective Analysis Applied to Data from a Single Interview

Table A2. Examples of labels extracted during open coding based on a single interview.

Theme/Subtheme	Interview Excerpt	Assigned Label
Waste classification	"Special waste and waste assimilated to municipal waste. Among special waste, we certainly have infectious waste, which has its own EWC code 18.01.03"	`EWC_classification`
Hard-to-manage waste	"Infectious waste: within the organisation we produce about 1.2 million kilograms across the two hospitals, also because disposal costs are calculated per kilogram"	`infectious_waste_volume` `disposal_cost`
Chemical waste	"Then we have chemical waste produced by laboratories. The effluent, with EWC code 18.01.06, contains chemical, biological, and aqueous components"	`laboratory_effluents` `container_management`
Regulations	"The same regulation currently constrains you, rightly so, because regulations not only provide guidance but also specify prevention, protection, and container requirements"	`regulatory_constraints` `container_specifications`
Training	"When I talk about training, I mean in-person training, where people meet and discuss. It is somewhat mandatory, but waste management training is not"	`in_person_training` `partial_mandatory`
Circular economy	"If we talk about waste assimilated to municipal waste, then yes: our glass goes to glass recycling plants, paper as well, plastic as well"	`municipal_recycling` `separate_streams`
Difficulties in hazardous waste recycling	"I already struggle to get my colleagues to separate plastic, glass, and paper; how can I ask them to separate types of plastic like PET or PE? It is extremely difficult"	`staff_resistance` `sorting_complexity`
Innovative technologies	"I do not want to talk about sterilisation plants, because that enters a sensitive area—but I am strongly opposed, because I have seen them and they are not viable"	`sterilization_skepticism`
Cost–benefit	"The training we carried out in 2017 was widespread [. . .] we calculated that, in terms of reducing infectious waste, we achieved more than 10%, almost 15%"	`training_effectiveness` `quantitative_reduction`
Spatial constraints	"Chemical waste: we do not have space for tanks [. . .] instead, we use 10-liter containers. Do the math: how many containers replace one tank"	`spatial_constraints` `suboptimal_solution`
Staff shortages	"Staff numbers keep decreasing while workload increases, so if you must choose where to throw a gown, you use the first available bin"	`staff_shortage` `operational_priorities`

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Table A3. Relationships among labels identified during axial coding based on a single interview.

Label A	Relation Type	Label B	Evidence
Infectious waste volume	→	Disposal cost	"disposal costs are calculated per kilogram" (positive causal)
Staff shortage	→	Reduced compliance	"if you must choose where to throw a gown, you use the first available bin" (negative causal)
Spatial constraints	→	Suboptimal solutions	"we do not have space for tanks [. . .] we use 10-liter containers" (causal)
Effective training	→	Waste reduction	"reduction of infectious waste [. . .] more than 10%, almost 15%" (positive causal)
Sorting complexity	↔	Staff resistance	"how can I ask them to separate types of plastic?" (bidirectional)
Regulation	→	Container specifications	"regulations [. . .] specify containers" (prescriptive)
Municipal-type waste	→	Circular economy	"our glass goes to glass recycling plants" (enabling condition)
Hazardous waste	↛	Recycling	"It is extremely difficult" to separate (barrier)

Legend: → = unidirectional causal relationship; ↔ = bidirectional relationship; ↛ = absence of relationship/barrier.

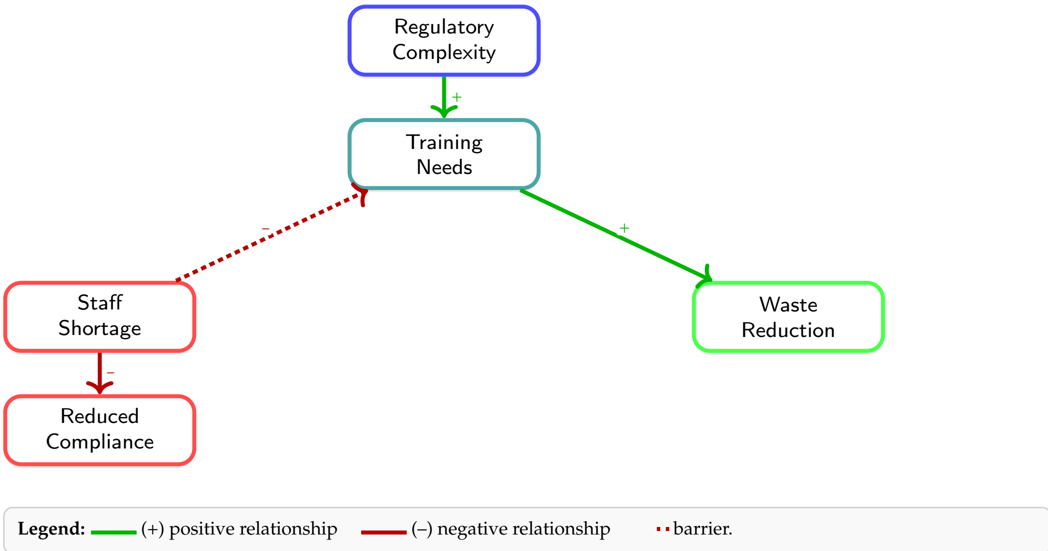

Figure A1. Scenario 1: Relationship between regulation, training, and operational outcomes.

Appendix B. Theme-to-Action Mapping Table

Table A4. Complete mapping: interview themes ($n = 11$) to AI tool actions ($n = 55$).

Interview Theme/Subtopic	Tool Thematic Area	Actions in Tool	Theme Freq.	Action Freq.	Import. Score
MAIN THEME 1: Waste typology and management					
1. Classification of hospital waste	Segregation of Hazardous/Non-Hazardous Waste	5.1 Implement operational instructions for waste separation	9/11	8/11	0.343
		5.2 Train staff on waste separation		7/11	0.532
		5.3 Provide containers distinguished by color code		9/11	0.490
		5.4 Define monitoring system for correct separation		5/11	0.724
		5.5 Implement feedback system to improve practices		4/11	0.536
	Regulatory Compliance	1.1 Implement all local and national regulations		9/11	0.047
		1.4 Adopt protocols for traceability of hazardous waste		8/11	0.537
2. Difficult-to-manage waste	Management of Cytotoxic/Chemotherapy Waste	4.1 Implement specific protocols for cytotoxic waste	**11/11**	7/11	0.150
		4.2 Train staff on safe use/disposal of chemical waste		6/11	0.195
		4.3 Monitor and track chemical waste		8/11	0.585
	Safety in Waste Management	6.1 Adopt technologies to monitor waste flows		3/11	0.230
		6.2 Ensure safe treatment of hazardous materials		4/11	0.446
		6.3 Implement protocols for infectious waste		11/11	0.175
	Management of Infectious Emergencies	13.1 Develop specific emergency plans		0/11	0.784
		13.2 Conduct periodic exercises		1/11	0.645
		13.3 Provide additional resources		7/11	0.394
		13.4 Train staff on infectious waste (pandemics)		0/11	0.161
		13.5 Implement communication system		3/11	0.382
		13.6 Implement technologies for hazardous treatment		4/11	0.591
3. Source reduction strategies	Waste Prevention	2.1 Prefer reusable medical devices	6/11	4/11	0.497
		2.2 Reduce single-use materials		6/11	0.582
		2.3 Use low environmental impact materials		4/11	0.638
		2.4 Collaborate with suppliers to reduce packaging		5/11	0.608
		2.5 Implement material recovery programs [a]		1/11	0.000

Table A4. *Cont.*

Interview Theme/Subtopic	Tool Thematic Area	Actions in Tool	Theme Freq.	Action Freq.	Import. Score
MAIN THEME 2: Regulation and personnel training					
4. Difficulties in applying regulations	Regulatory Compliance	1.1 Implement all local and national regulations	9/11	9/11	0.047
		1.2 Conduct periodic audits		8/11	0.723
		1.3 Provide materials and spaces for storage		11/11	0.123
		1.4 Adopt protocols for traceability		8/11	0.537
		1.5 Establish reporting system for non-compliance		7/11	0.863
	Monitoring and Evaluation	8.1 Implement software for waste tracking		7/11	0.489
		8.3 Define key indicators		4/11	0.526
		8.4 Establish periodic reporting system		4/11	0.438
	Technological Innovation	11.1 Implement digital technologies for monitoring		6/11	0.237
		11.3 Evaluate blockchain for traceability		1/11	**1.000**
5. Mandatory training	Training and Awareness	10.1 Create continuous training programs	**11/11**	11/11	0.732
		10.2 Raise staff awareness		11/11	0.660
		10.3 Organise multidisciplinary workshops		6/11	0.178
		10.4 Implement feedback system		7/11	0.492
	Segregation at Source	5.2 Train staff on waste separation		7/11	0.532
	Management of Pharmaceutical Waste [b]	3.2 Train staff on pharmaceutical waste		1/11	0.450
	Management of Cytotoxic Waste	4.2 Train staff on chemical waste		6/11	0.195
	Management of Infectious Emergencies	13.4 Train staff on infectious waste		0/11	0.161
6. Awareness initiatives	Training and Awareness	10.2 Raise staff awareness	10/11	11/11	0.660
		10.4 Implement feedback system		7/11	0.492
	Community and Stakeholder Engagement	12.1 Organise awareness programs for community		3/11	0.732
		12.2 Involve community representatives		8/11	0.844
		12.3 Establish feedback from stakeholders		3/11	0.270
7. Responsibility and internal controls	Regulatory Compliance	1.2 Conduct periodic audits	7/11	8/11	0.723
		1.5 Establish reporting system		7/11	0.863
	Monitoring and Evaluation	8.1 Implement software for tracking		7/11	0.489
		8.2 Collect data for environmental performance		2/11	0.364
		8.3 Define key indicators		4/11	0.526
		8.4 Establish periodic reporting		4/11	0.438
	Segregation at Source	5.4 Define monitoring system for separation		5/11	0.724
		5.5 Implement feedback system		4/11	0.536

Table A4. *Cont.*

Interview Theme/Subtopic	Tool Thematic Area	Actions in Tool	Theme Freq.	Action Freq.	Import. Score
MAIN THEME 3: Sustainable transition in waste management					
8. Waste cycle reduction measures	Waste Prevention	2.1 Prefer reusable devices	7/11	4/11	0.497
		2.2 Reduce single-use materials		6/11	0.582
		2.3 Use low impact materials		4/11	0.638
		2.4 Collaborate with suppliers		5/11	0.608
		2.5 Material recovery programs [a]		0/11	0.000
	Management of Pharmaceutical Waste [b]	3.3 Reduce pharmaceutical waste		1/11	0.461
		3.4 Collaborate for drug recovery		0/11	0.412
	Segregation at Source	5.5 Implement feedback system		4/11	0.536
9. Circular economy examples	Recycling and Recovery	7.1 Identify recycling solutions	9/11	5/11	0.179
		7.2 Arrange energy recovery from waste		4/11	0.656
		7.3 Implement collection system for recycling		9/11	0.277
		7.4 Schedule reuse of sterilizable devices		7/11	0.841
	Waste Prevention	2.5 Material recovery programs [a]		0/11	0.000
	Management of Pharmaceutical Waste [b]	3.4 Collaborate for drug recovery		1/11	0.412
		3.1 Implement protocols for the safe management of expired drugs		0/11	0.537
10. Difficulties recycling hazardous waste	Safety in Waste Management	6.2 Ensure safe treatment of hazardous materials	4/11	4/11	0.446
	Recycling and Recovery	7.2 Arrange energy recovery (incineration)		4/11	0.656
	Technological Innovation	11.2 Adopt new treatment methods		4/11	0.469
	Management of Infectious Emergencies	13.6 Technologies for hazardous treatment		4/11	0.591
11. Innovative technologies	Technological Innovation	11.1 Implement digital technologies	8/11	6/11	0.237
		11.2 Adopt new treatment methods		4/11	0.469
		11.3 Evaluate blockchain for traceability		1/11	**1.000**
		11.4 Conduct feasibility studies		5/11	0.909
	Monitoring and Evaluation	8.1 Implement software for tracking		7/11	0.489
	Safety in Waste Management	6.1 Adopt technologies to monitor flows		3/11	0.230
	Management of Infectious Emergencies	13.6 Technologies for hazardous treatment		4/11	0.591
12. Sustainability results evaluation	Monitoring and Evaluation	8.1 Implement software for tracking	2/11	7/11	0.489
		8.2 Collect data for environmental performance		2/11	0.364
		8.3 Define key indicators		4/11	0.526
		8.4 Establish periodic reporting		4/11	0.438

Table A4. *Cont.*

Interview Theme/Subtopic	Tool Thematic Area	Actions in Tool	Theme Freq.	Action Freq.	Import. Score
MAIN THEME 4: Operational criticalities and strategic vision					
13. Daily problems (space, costs, staff)	Regulatory Compliance	1.3 Provide materials and spaces for storage	**11/11**	11/11	0.123
	Emergency Management	9.1 Develop emergency plan		2/11	0.691
		9.2 Conduct periodic exercises		3/11	0.790
		9.3 Additional resources during emergencies		7/11	0.701
		9.4 Implement communication system		4/11	0.434
	Management of Infectious Emergencies	13.3 Provide additional resources		7/11	0.394
	Training and Awareness	10.1 Continuous training		11/11	0.732
	Monitoring and Evaluation	8.2 Collect data (costs)		2/11	0.364
14. Improvement priorities	Technological Innovation	11.1 Digital technologies	7/11	6/11	0.237
		11.3 Blockchain for traceability		1/11	**1.000**
		11.4 Feasibility studies		5/11	0.909
	Monitoring and Evaluation	8.1 Software for tracking		7/11	0.489
		8.3 Define key indicators		4/11	0.526
	Regulatory Compliance	1.4 Protocols for traceability		8/11	0.537
	Waste Prevention	2.2 Reduce single-use		6/11	0.582
	Training and Awareness	10.4 Feedback system		7/11	0.492
	Segregation at Source	5.5 Feedback system		4/11	0.536
	Community Engagement	12.3 Stakeholder feedback		3/11	0.270
15. Future projects	Technological Innovation	11.2 New treatment methods	6/11	4/11	0.469
		11.3 Blockchain		1/11	**1.000**
		11.4 Feasibility studies		5/11	0.909
	Recycling and Recovery	7.2 Energy recovery		4/11	0.656
		7.4 Reuse sterilizable devices		7/11	0.841
	Waste Prevention	2.3 Low impact materials		4/11	0.638
		2.4 Collaborate with suppliers		5/11	0.608
	Community Engagement	12.4 Create partnerships for sustainability		1/11	0.292
16. Evolution of sustainability role	Community and Stakeholder Engagement	12.1 Organise awareness programs	1/11	3/11	0.732
		12.2 Involve community representatives		8/11	0.844
		12.4 Create partnerships		1/11	0.292
	Training and Awareness	10.2 Raise awareness (sustainable)		11/11	0.660
	Monitoring and Evaluation	8.2 Collect environmental performance data		2/11	0.364

Table A4. *Cont.*

Interview Theme/Subtopic	Tool Thematic Area	Actions in Tool	Theme Freq.	Action Freq.	Import. Score
MAIN THEME 5: Comprehensive vision and support network					
17. Additional relevant aspects	Training and Awareness	10.1 Continuous training	7/11	11/11	0.732
		10.3 Multidisciplinary workshops		6/11	0.178
	Community Engagement	12.1 Awareness programs for community		3/11	0.732
	Waste Prevention	2.4 Collaborate with suppliers		5/11	0.608
18. Knowledge of entities and associations	Community and Stakeholder Engagement	12.1 Organise awareness programs	6/11	3/11	0.732
		12.2 Involve community representatives		8/11	0.844
		12.3 Establish stakeholder feedback		3/11	0.270
		12.4 Create partnerships with organisations		1/11	0.292
	Training and Awareness	10.3 Multidisciplinary workshops		6/11	0.178
19. Collaborative projects	Community and Stakeholder Engagement	12.3 Establish stakeholder feedback	2/11	3/11	0.270
		12.4 Create partnerships		1/11	0.292
	Waste Prevention	2.4 Collaborate with suppliers		5/11	0.608
	Management of Pharmaceutical Waste [b]	3.4 Collaborate for drug recovery		0/11	0.412
20. Personal/institutional involvement	Community and Stakeholder Engagement	12.1 Organise awareness programs	9/11	3/11	0.732
		12.2 Involve community representatives		8/11	0.844
		12.3 Establish feedback system		3/11	0.270
		12.4 Create partnerships		1/11	0.292
	Training and Awareness	10.1 Continuous training		11/11	0.732
		10.2 Raise staff awareness		11/11	0.660
		10.4 Feedback system		7/11	0.492

Table A4. *Cont.*

Interview Theme/Subtopic	Tool Thematic Area	Actions in Tool	Theme Freq.	Action Freq.	Import. Score
TOOL ACTIONS WITH NO DIRECT CORRESPONDENCE IN INTERVIEWS					
No corresponding interview theme [b]	Management of Pharmaceutical Waste	3.1 Protocols for expired drugs	—	0/11	0.537
		3.2 Train staff on pharmaceutical waste	—	0/11	0.450
		3.4 Collaborate for drug recovery	—	0/11	0.412
No corresponding interview theme [c]	Management of Infectious Emergencies/Pandemics	13.1 Develop specific emergency plans for healthcare waste management	—	0/11	0.784
		13.4 Train staff on procedures for managing infectious waste during pandemics	—	0/11	0.161

[a] Action 2.5 (Material recovery programs): This action has an importance score of 0.000, indicating that it was not prioritised in previous case studies. [b] Management of Pharmaceutical Waste (Area 3): This thematic area is completely absent as an autonomous theme in the interviews. None of the 11 interviewees spontaneously discussed pharmaceutical waste management as a distinct topic, despite the tool assigning moderate-to-high importance (0.412–0.537) to related actions. Individual actions from this area were mapped only when mentioned in other contexts (e.g., 3.2 mapped under "Mandatory training" when training on pharmaceuticals was discussed). This represents a critical blind spot: experts do not perceive pharmaceutical waste as a priority area despite its operational relevance. [c] Actions 13.1 and 13.4 with zero importance: These first actions have an importance score of 0.784, indicating that they were not prioritised. Their absence from all 11 interviews highlights the disconnect between emergency preparedness frameworks and everyday operational concerns in hospital settings. Legend: Theme Freq.: number of interviews (out of 11) where the theme/subtopic appeared; Action Freq.: number of interviews (out of 11) where the specific action was explicitly or implicitly mentioned; Import. Score: importance weight (0–1) calculated by the AI tool based on previous case studies; green highlighting : themes present in 100% of interviews (11/11); gray highlighting : high-importance actions (score $\geq$ 0.8); Blue headers : main thematic categories; red section : tool actions with no interview correspondence (blind spots).

Appendix C. Co-Mention Matrix of Sub-Themes

Table A5. Co-mention matrix of sub-themes identified across the 11 interviews.

	1. Classification	2. Separate Collection	3. Waste Reduction	4. Regulatory Differences	5. Training	6. Initiatives	7. Responsibility	8. Reduction Measures	9. Circular Economy	10. Recycling Barriers	11. Technology	12. Evaluation	13. Problems	14. Prioritisation	15. Future Projects	16. Evolution	17. Additional Aspects	18. Knowledge	19. Current Projects	20. Stakeholder Involvement
1. Classification (9/11)	–	9	5	7	9	7	5	5	7	3	6	2	9	5	5	1	5	4	1	7
2. Separate collection (11/11)	9	–	6	8	11	9	6	6	8	4	7	2	11	6	6	1	6	5	2	8
3. Waste reduction (6/11)	5	6	–	5	6	6	4	5	5	1	5	1	6	5	5	0	4	3	1	5
4. Regulatory differences (9/11)	7	8	5	–	9	8	5	5	8	2	6	2	9	5	5	0	6	4	1	7
5. Training (11/11)	9	11	6	9	–	10	6	6	9	4	7	2	11	6	6	1	6	5	2	8
6. Initiatives (10/11)	7	9	6	8	10	–	5	6	8	2	6	1	10	6	5	0	5	5	2	7
7. Responsibility (7/11)	5	6	4	5	6	5	–	4	5	1	4	1	7	4	4	0	4	3	1	5
8. Reduction measures (7/11)	5	6	5	5	6	6	4	–	5	2	5	1	7	5	4	0	4	3	1	5
9. Circular economy (9/11)	7	8	5	8	9	8	5	5	–	2	6	2	9	5	5	1	6	4	1	7
10. Recycling barriers (4/11)	3	4	1	2	4	2	1	2	2	–	3	1	4	2	2	1	2	1	0	3
11. Technology (8/11)	6	7	5	6	7	6	4	5	6	3	–	2	8	5	5	0	5	4	1	6
12. Evaluation (2/11)	2	2	1	2	2	1	1	1	2	1	2	–	2	1	1	0	1	1	0	2
13. Problems (11/11)	9	11	6	9	11	10	7	7	9	4	8	2	–	7	6	1	7	6	2	8
14. Prioritisation (7/11)	5	6	5	5	6	6	4	5	5	2	5	1	7	–	5	0	5	4	1	5
15. Future projects (6/11)	5	6	5	5	6	5	4	4	5	2	5	1	6	5	–	0	4	3	1	5
16. Evolution (1/11)	1	1	0	0	1	0	0	0	1	1	0	0	1	0	0	–	1	1	0	1
17. Additional aspects (7/11)	5	6	4	6	6	5	4	4	6	2	5	1	7	5	4	1	–	5	1	6
18. Knowledge (6/11)	4	5	3	4	5	5	3	3	4	1	4	1	6	4	3	1	5	–	2	5
19. Current projects (2/11)	1	2	1	1	2	2	1	1	1	0	1	0	2	1	1	0	1	2	–	1
20. Stakeholder involvement (8/11)	7	8	5	7	8	7	5	5	7	3	6	2	8	5	5	1	6	5	1	–

Note: Values indicate the number of interviews (out of 11 total) in which both sub-themes were mentioned together. Values cannot exceed 11 as this represents the total number of interviews conducted. Dark blue indicates universal co-mention (11/11 interviews, 100%); light blue indicates very high co-mention (10/11 interviews, 90.9%); grey indicates high co-mention (8–9/11 interviews, 72.7–81.8%); white indicates moderate co-mention (6–7/11 interviews, 54.5–63.6%).

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