Periodica Polytechnica Social and Management Sciences

An Integrated Fuzzy-FMEA and DEMATEL Framework with Waste Priority Categorisation for Sustainable Higher Education Institutions

Lusia Permata Sari Hartanti[1,2*], Ivan Gunawan[1,2], Ig. Jaka Mulyana[1], Atanasius Gunanda[1]

[1] Department of Industrial Engineering, Faculty of Engineering, Widya Mandala Surabaya Catholic University, Kalijudan 37, 60114 Surabaya, East Java, Indonesia
[2] Department of Engineer Profession Education, Faculty of Engineering, Widya Mandala Surabaya Catholic University, Kalijudan 37, 60114 Surabaya, East Java, Indonesia
[*] Corresponding author, e-mail: lusia.hartanti@ukwms.ac.id

Received: 23 October 2025, Accepted: 03 May 2026, Published online: 11 June 2026

Abstract
Higher education institutions (HEIs) are increasingly required to improve service quality while addressing sustainability challenges. However, inefficiencies and waste within academic and administrative processes often undermine institutional performance. This study proposes an integrated approach combining Fuzzy Failure Mode and Effect Analysis (fuzzy-FMEA), the Decision-Making Trial and Evaluation Laboratory (DEMATEL), and Waste Priority Categories (WPC) systematically to evaluate and prioritise critical waste occurrences in a private HEI in Indonesia. Fuzzy-FMEA was employed to address the uncertainty inherent in expert assessments and to generate a Fuzzy Waste Priority Number for ranking purposes. DEMATEL was then applied to map causal–effect relationships among the nine most critical waste occurrences, while WPC translated these results into actionable categories: eliminate, option, or acceptance. The analysis revealed that delayed campus facility repairs (C5) represent the most influential causal form of waste, while lecturer-task misalignment (D1), administrative overload (B6), and teaching preparation inefficiencies (A10) also emerged as critical issues. By prioritising the elimination of these waste occurrences, HEIs can simultaneously improve resource efficiency, enhance staff wellbeing, and strengthen student learning outcomes. The findings demonstrate that integrating fuzzy-FMEA, DEMATEL, and WPC provides a robust decision-support framework for aligning risk management with institutional sustainability strategies.

Keywords
higher education, waste, fuzzy-FMEA, DEMATEL, sustainability

1 Introduction

Higher education institutions (HEIs) operate in increasingly complex environments, facing the dual challenge of meeting rising stakeholder demands while maintaining competitiveness and improving organisational performance. Pressures related to student recruitment, research funding, and quality rankings often compel HEIs to seek cost-effective strategies without compromising service quality. In this context, aligning strategic and operational processes with sustainability performance, particularly in terms of resource consumption, is crucial for supporting the achievement of the Sustainable Development Goals (SDGs). Beyond their educational mission, HEIs play a pivotal role in fostering societal development by cultivating awareness, developing skills, supporting technological advancements, and disseminating research outcomes (Ankareddy et al., 2025)

Lean management, originating from the Toyota Production System, provides a systematic approach to enhancing productivity and cultivating a culture of continuous improvement through waste reduction and value creation. In lean management, waste is defined as any non–value-adding activity that consumes time and resources without contributing to process outcomes (Mulyana et al., 2022). Its adoption in HEIs, commonly referred to as Lean in Higher Education (LHE), has gained traction as a means to enhance service quality, operational efficiency, and stakeholder satisfaction (Hartanti et al., 2022a; Helmold et al., 2022). From an educational perspective, lean facilitates the delivery of teaching and administrative services more effectively by eliminating non-value-adding activities. Previous studies have demonstrated

Cite this article as: Hartanti, L. P. S., Gunawan, I., Mulyana, I. J., Gunanda, A. (2026) "An Integrated Fuzzy-FMEA and DEMATEL Framework with Waste Priority Categorisation for Sustainable Higher Education Institutions", Periodica Polytechnica Social and Management Sciences. https://doi.org/10.3311/PPso.42606

that lean practices have a positive impact on sustainability performance across environmental, economic, institutional, and social dimensions (Klein et al., 2022; Nawanir et al., 2019). However, challenges remain in embedding lean thinking within HEIs, particularly in communicating its value, fostering staff engagement, and integrating it into human resource systems (Hartanti et al., 2020). The study identified key factors for planning and implementing quality management in HEIs, including quality, business, and expert orientation contexts (Vnoučková et al., 2019). As complex organisations, HEIs encompass both academic processes, such as teaching, research, community engagement, and curriculum design, and administrative processes, such as admissions, faculty recruitment, finance, and maintenance (Shamsuzzaman et al., 2023). Inefficiencies in these processes often manifest as waste, including excessive documentation, unnecessary movement of people and information, workload imbalances, delays in administrative approvals, and underutilised talent (Hartanti et al., 2022a; Lima et al., 2023). The literature identifies eight categories of waste in HEIs, such as overproduction, overprocessing, waiting, motion, transportation, inventory, defects, and underutilised talent (Hariyani et al., 2025; Mulyana et al., 2023). Reducing such waste is central to improving workflow and service delivery.

From a risk management perspective, identifying and assessing waste represents a proactive strategy to mitigate procedural failures that may compromise institutional effectiveness and sustainability. Failure Mode and Effect Analysis (FMEA) remains one of the most widely adopted tools for risk assessment, offering a systematic framework for identifying, evaluating, and prioritising failure modes in a system, assessing their impact, and planning corrective actions (Cardiel-Ortega and Baeza-Serrato, 2023; Liu et al., 2020). Reliability methods can be classified into four main categories: reliability prediction techniques, qualitative methods, quantitative methods, and analytical models. Among these, qualitative methods emphasise systematic and proactive evaluation approaches, such as FMEA, to identify and mitigate potential failures (Jónás et al., 2018). However, the classical FMEA approach is constrained by its inability to effectively address uncertainty in failure data, particularly when expert assessments are subjective; its lack of weighting mechanisms for risk parameters; and its omission of potential interdependencies among failure events among failure modes (Yucesan et al., 2021).

To address these shortcomings, fuzzy logic has been introduced into FMEA, enabling the use of linguistic variables and fuzzy membership functions to model subjective uncertainty and heterogeneity in expert assessments, leading to more refined and reliable risk prioritisation (Chang et al., 2022). Nevertheless, while fuzzy-FMEA is effective in identifying and ranking critical waste factors, it does not inherently capture the causal interdependencies among them. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method addresses this limitation by modelling and quantifying cause–and–effect relationships, thereby enabling more profound insights into the systemic dynamics of waste (Si et al., 2018). Consequently, integrating fuzzy-FMEA with DEMATEL provides a comprehensive and robust framework not only for prioritising critical waste factors but also for understanding their interconnectivity, thereby enhancing decision-making in sustainability initiatives in higher education.

Despite the increasing interest in lean applications within HEIs, existing literature offers limited empirical evidence on waste assessment that simultaneously integrates risk prioritisation and causal relationship analysis, particularly in the context of improving both academic and administrative service quality. Only a few studies have employed a combined fuzzy-based FMEA and DEMATEL approach, to prioritise critical waste factors while mapping their interdependencies.

The objective of this study is to develop and apply an integrated decision-support framework that combines fuzzy-FMEA, DEMATEL, and Waste Priority Categories (WPC) to systematically identify, prioritise, and categorise critical waste occurrences in HEIs. By simultaneously addressing uncertainty in expert evaluations, mapping causal–effect relationships, and translating analytical insights into actionable categories, the study aims to provide a structured methodology that enhances institutional performance while advancing environmental, social, and economic sustainability.

The paucity of literature employing such an approach highlights the need for a hybrid analytical framework capable of accurately identifying and ranking waste factors under conditions of uncertainty, while also revealing their structural influence, thereby enabling more effective and sustainable operational improvements. Addressing this gap, this study investigates the types of waste prevalent in private HEIs in Indonesia, analyses the causal interdependencies among the most critical waste factors, and develops targeted recommendations to eliminate or minimise these inefficiencies, with a view to enhancing sustainable lean practices in higher education.

2 Methods

2.1 Waste identification

Waste identification in this study was conducted through a combination of literature review and direct field observation at a private higher education institution (HEI) in Indonesia. The authors systematically explored non-value-added activities (waste) within a private HEI in a previous study (Hartanti et al., 2022a). This process involved analysing institutional practices and operational inefficiencies, which were validated through on-site observations. The study's results showed that waste was categorised into eight types: defects, overproduction, waiting, underutilised talent, transportation, inventory, motion, and extra processing (Table 1).

2.2 Classical FMEA application

Following the waste identification phase, a classical FMEA was implemented to systematically assess and prioritise each identified waste based on three key risk factors: severity (S), occurrence (O), and detection (D). In line with the study by Hartanti et al. (2022a), FMEA was used to evaluate the risks associated with each waste, thereby enabling a structured, quantitative analysis of their criticality and potential impact on institutional performance. The Waste Priority Number (WPN) was computed by multiplying the respective values of S, O, and D, serving as an index to rank waste types by relative risk. For this purpose, a ten-point scale is commonly employed. The severity of each identified effect is assessed on a numerical scale from 1 (minimal risk) to 10 (highest severity). Subsequently, potential causes of failure are identified, and their likelihood of occurrence is evaluated on a scale from 1 (rare) to 10 (very high). The ability to detect each failure mode is then rated on a scale from 1 (highly effective detection) to 10 (extremely ineffective detection). The scoring of the S, O, and D parameters was performed by sixteen department heads, who were asked to complete a structured questionnaire.

Table 1 Definition of waste in HEI (Hartanti et al., 2022a)

Waste type	Definition
Defect	Errors or inaccuracies occurring within service delivery or support processes that compromise quality.
Overproduction	Performing services that are not yet required or delivering them earlier than scheduled, leading to inefficiencies.
Waiting	Involves idle time or process delays caused by bottlenecks or a lack of coordination in service activities.
Non-utilised talent represents	Occurs when the competencies, expertise, or potential of lecturers and staff are underutilised or misallocated.
Extra transportation	Entails unnecessary movement or transportation within the HEI that does not add value.
Excess inventory	The presence of surplus materials, supplies, or outputs that exceed the actual demand or current requirements.
Extra motion or unnecessary movement	Involves inefficient physical movement by lecturers or staff that leads to wasted effort in delivering services
Over-processing	Conducting more tasks or procedures than necessary, often without contributing to improved outcomes or value

2.3 Fuzzy-FMEA application

A mixed qualitative–quantitative approach is designed to evaluate the waste. To derive the waste ranking, a fuzzy method is applied that integrates expert discussion and subsequent validation. The WPN obtained from the classical FMEA is subsequently processed using fuzzy logic to address uncertainties inherent in expert evaluations. The fuzzy-FMEA procedure consists of three sequential stages: fuzzification, application of fuzzy inference rules, and defuzzification, resulting in the Fuzzy Waste Priority Number (FWPN).

In this study, the fuzzification stage uses the Mamdani (Max–Min) method within the fuzzy inference system framework. This method enables the derivation of conclusions or optimal decisions under uncertain conditions. In the Mamdani approach, the system output is expressed as a fuzzy set, which is subsequently mapped to the corresponding linguistic variables via predefined membership functions.

The S, O, and D, each defined over a numerical range of 1–10 and categorised into five linguistic terms: Very Low (VL), Low (L), Moderate (M), High (H), and Very High (VH) (Puente et al., 2002). The categories are shown in Table 2, while the curves and input parameters for Fuzzy-FMEA are provided in Table 3. Then, the output of the variable Fuzzy-FMEA, FWPN, is defined over a broader numerical range of 1–1000 and represented by nine linguistic terms: VL, VL–L, L, L–M, M, M–H, H, H–VH, and VH. The parameters of the FWPN membership Function are presented in Table 4. The inference process employs the minimum operator for rule implication,

Table 2 Categories for S, O, and D indexes (Puente et al., 2002)

Categories	Scores		
	S	O	D
VL	1	1	1
L	2–3	2–3	2–3
M	4–6	4–6	4–6
H	7–8	7–8	7–8
VH	9–10	9–10	9–10

Table 3 Types of curves and parameters input

Category	Curve type	Parameters
VL	Trapezoid	[0; 0; 1; 2,5]
L	Triangle	[1; 2,5; 4,5]
M	Trapezoid	[2,5; 4,5; 5,5; 7,5]
H	Triangle	[5,5; 7,5; 9]
VH	Trapezoid	[7,5; 9; 10; 10]

Table 4 Types of curves and parameters output

Category	Curve type	Parameters
VL	Trapezoid	[0; 0; 25; 75]
VL-L	Triangle	[25; 75; 125]
L	Triangle	[75; 125; 200]
L-M	Triangle	[125; 200; 300]
M	Triangle	[200; 300; 400]
M-H	Triangle	[300; 400; 500]
H	Triangle	[400; 500; 700]
H-VH	Triangle	[500; 700; 900]
VH	Trapezoid	[700; 900; 1000; 1000]

which determines the degree of fulfilment for each fuzzy rule before aggregation. This step is followed by defuzzification to obtain a crisp FWPN value, enabling prioritisation of waste factors.

2.4 Decision making trial and evaluation laboratory

Applying Decision Making Trial and Evaluation Laboratory (DEMATEL) in the context of higher education waste enables us to uncover pathways for strategically targeting improvement by focusing on systemic causality rather than isolated symptoms. In this study, the DEMATEL approach determines and measures the interdependencies among criteria, categorising them into causal factors (drivers) and effect factors (dependents). The results of the DEMATEL method reveal reciprocal relationships among several components, enabling the identification of which factors influence one another. The DEMATEL methodology comprises a series of structured procedures, such as expert assessment of factor interrelationships, construction and normalisation of the average direct-relation matrix, derivation of the total-relation matrix capturing both direct and indirect effects, calculation of prominence and relation scores to determine importance and influence direction, and visualisation of the causal structure via an influence diagram (Chi et al., 2025).

2.5 Waste priority categories

The Waste Priority Categories (WPC) framework was employed to translate the analytical outputs of fuzzy-FMEA and DEMATEL into actionable improvement strategies. WPC functions as a structured decision-support mechanism that classifies identified waste occurrences into three categories: eliminate, option, and acceptance. The process begins with fuzzy-FMEA, which generates FWPN for each waste occurrence, reflecting its relative S, O, and D ratings under uncertainty. Subsequently, DEMATEL analysis is used to determine the causal–effect structure among the critical waste occurrences, thereby identifying which wastes primarily act as systemic drivers and which emerge as downstream effects.

These two analytical inputs, fuzzy-FMEA and DEMATEL, are then synthesised through the WPC framework. Waste occurrences with high FWPN scores and a causal role in the DEMATEL structure are classified as the eliminate category, indicating they must be prioritised for immediate intervention. Waste occurrences categorised as options have moderate influence or criticality and may be handled contingent on available resources or institutional priorities. Finally, waste occurrences in the acceptance category are those deemed to have minimal systemic impact, for which intervention is not urgent and monitoring is considered sufficient. By integrating risk prioritisation via fuzzy-FMEA with causal mapping via DEMATEL, WPC enables a transparent, systematic approach to determine which waste occurrences should be addressed first, ensuring that improvement efforts in HEIs are both resource-efficient and aligned with sustainability objectives.

3 Results and discussion

3.1 Waste identification and Failure Mode and Effect Analysis (FMEA)

The results of waste identification in HEI are shown in Table 5. The data in Table 5 reveal a broad spectrum of waste occurrences across HEI, spanning various operational domains, including teaching, administration, facility management, and communication. From a frequency perspective, human-related procedural inefficiencies dominate the dataset, particularly those associated with lecturer's time management and preparedness, such as A1, A8, B6, and C2. Such inefficiencies directly contribute to delays, reduced teaching effectiveness, and diminished institutional productivity.

The presence of overproduction-related waste occurrences such as B1, F3, and F4 highlights weaknesses in resource planning and demand forecasting. These issues not only escalate operational costs but also contradict sustainability objectives in academic environments. Another significant cluster involves waiting waste occurrences, such as C7, C8, C9, and C6. These indicate scheduling

Table 5 Waste in HEI (Hartanti et al., 2022a)

No	Waste types	Waste codes
1	The lecturer is experiencing difficulty locating the necessary files	A1
2	The lecturer enters the incorrect classroom by mistake	A2
3	The lecturer does not inform students of class cancellations or absences on time	A3
4	The course schedule is changed unexpectedly by the lecturer	A4
5	Errors occur when the lecturer inputs grades into the academic system	A5
6	The lecturer needs to administer a make-up exam for students	A6
7	The lecturer is unable to access the required documents	A7
8	The lecturer encounters issues opening teaching materials	A8
9	There is a typographical error in the content	A9
10	Errors are made during the preparation of learning material.	A10
11	The projector connection cable is damaged	A11
12	There are not enough exam papers provided	A12
13	The lecturer prints excessive quantities of teaching materials and handouts	B1
14	The teaching workload each semester is unmanageable	B2
15	Lecturers extend teaching hours beyond the scheduled time	B3
16	Too many announcements or pieces of information are circulated	B4
17	There are more lecturers employed in the department than necessary	B5
18	Lecturers work beyond official hours to complete administrative tasks	B6
19	Students wait too long for lecturers to respond to their questions	C1
20	Lecturers miss the deadline for report submissions	C2
21	Lecturers arrive late to scheduled meetings	C3
22	Rescheduled classes are postponed to the following week	C4
23	Repairs to classroom facilities often take a considerable amount of time to complete	C5
24	Lecturers await the outcomes of teaching evaluations during meetings	C6
25	Lecturers wait for students to arrive before starting class	C7
26	Lecturers wait for students to submit their exam papers	C8
27	Students' delay in submitting their assignments	C9
28	Lecturers are assigned tasks outside their field of expertise	D1
29	Lecturers do not engage in research activities each semester.	D2
30	Lecturers do not participate in community service each semester	D3
31	Mistakes are made when lecturers distribute documents between departments	E
32	Emails remain in draft form and are not sent	F1
33	The lecturer reuses exam questions from previous years	F2
34	The lecturer has too many documents stored	F3
35	Lecturers accumulate an excess of office supplies	F4
36	Classroom facilities are left unused during teaching hours	F5
37	There is a long walking distance between the classrooms and the faculty offices	G1
38	The lecturer's workspace is consistently cluttered	G2
39	Lecturers spend excessive time searching for academic resources	H1
40	Lecturers must re-enter student grades into multiple systems	H2
41	Information is received through multiple inconsistent communication channels	H3
42	The same announcements are distributed repeatedly	H4
43	Files like exam answers or theses are reviewed multiple times	H5
44	Teaching materials are frequently double-checked	H6
45	The lecturer repeatedly covers identical topics in class	H7
46	The same discussion topics are created or attended multiple times	H8

inefficiencies and a lack of synchronisation between different stakeholders, which rigid academic calendars and ineffective communication channels may exacerbate. Furthermore, the data reveals defects and rework as recurring issues, such as A5, H5, and H6. This indicates gaps in quality control mechanisms, a lack of standardised work processes, and insufficient verification protocols before task completion. From a systemic perspective, several waste occurrence items point to structural and organisational shortcomings within HEIs, such as G1, H3, and H2. These systemic inefficiencies hinder collaboration, lengthen process cycles, and weaken student service delivery.

3.2 Classical FMEA

After identifying the types of waste, the next step is to determine the risk weighting for each type. This risk assessment is essential for prioritising corrective actions based on the S, O, and D of each waste-related failure mode. The risk weighting process is grounded in the principles of classical FMEA, a structured, systematic methodology for evaluating and ranking potential failure modes in both products and processes. FMEA facilitates proactive decision-making by highlighting critical areas that may impact performance, efficiency, or customer satisfaction. As emphasised by Paciarotti et al. (2014), FMEA enables organisations to systematically identify, assess, and prioritise risks, thereby ensuring that resources for improvement are allocated to the most impactful areas. The integration of FMEA into waste analysis aligns with lean management and continuous improvement principles, supporting the development of more resilient, efficient operational systems in HEIs. The WPN score is shown in Table 6. The classical FMEA results, expressed as the WPN, reveal a clear prioritisation of waste factors based on their S, O, and D scores. The WPN ranges from 2 (lowest) to 70 (highest), indicating significant variation in perceived risk across identified wastes.

B6 has the highest WPN of 70, indicating substantial operational strain and inefficiency due to faculty overload and poor time allocation. C5 follows closely with a WPN of 64, reflecting the high impact of inadequate maintenance on service continuity. D1 scores 28, indicating a critical misalignment between qualifications and job assignments that may impair academic quality. Several waste occurrences, such as C1, C2, and H1, with WPNs ranging from 18 to 24, represent notable inefficiencies involving waiting times, communication delays, and repetitive work. These mid-tier risks suggest systemic bottlenecks that, while less severe than top-ranked wastes, still require targeted interventions.

Table 6 WPN and FWPN scores

Codes	S	O	D	WPN	FWPN	WPN rank	FWPN rank
Defect							
A1	2	3	3	18	203	6	10
A2	2	1	1	2	103	40	30
A3	2	1	2	4	103	31	30
A4	2	3	2	12	155	12	13
A5	2	1	1	2	103	40	30
A6	2	3	2	12	155	12	13
A7	2	2	2	8	155	19	13
A8	2	1	2	4	103	31	30
A9	2	1	1	2	103	40	30
A10	7	1	1	7	479	29	2
A11	4	2	2	16	318	10	5
A12	2	1	2	4	103	31	30
Over production							
B1	2	2	2	8	155	19	13
B2	3	3	2	18	258	6	8
B3	2	1	2	4	103	31	30
B4	1	2	2	4	61,6	31	46
B5	2	1	1	2	103	40	30
B6	5	7	2	70	471	1	3
Waiting							
C1	2	4	3	24	203	4	9
C2	2	3	3	18	203	6	10
C3	2	2	2	8	155	19	13
C4	2	1	2	4	103	31	30
C5	4	8	2	64	443	2	4
C6	5	2	1	10	300	18	6
C7	2	2	2	8	155	19	13
C8	2	3	1	6	103	30	30
C9	2	3	2	12	155	12	13
Non-utilised talent							
D1	7	2	2	28	595	3	1
D2	2	1	2	4	103	31	30
D3	2	5	2	20	155	5	13
Transportation							
E	2	1	2	4	103	31	30
Inventory							
F1	3	2	2	12	258	12	7
F2	2	2	2	8	155	19	13
F3	2	2	3	12	155	12	13
F4	2	1	1	2	103	40	30
F5	2	1	1	2	103	40	30
Motion							
G1	2	2	1	4	103	31	30
G2	2	3	2	12	155	12	13

Table 6 WPN and FWPN scores (continued)

Codes	S	O	D	WPN	FWPN	WPN rank	FWPN rank
Extra processing							
H1	2	3	3	18	203	6	10
H2	2	2	2	8	155	19	13
H3	2	4	2	16	155	10	13
H4	2	2	2	8	155	19	13
H5	2	2	2	8	155	19	13
H6	2	2	2	8	155	19	13
H7	2	2	2	8	155	19	13
H8	2	1	1	2	103	40	30

Many items, including A2, A5, B5, H8, and others, scored the minimum WPN of 2–4, suggesting either low frequency, low severity, or ease of detection. These issues may still warrant process improvements but are less critical compared to higher-ranked wastes. Overall, the classical FMEA prioritisation indicates that workload imbalance, facility maintenance delays, and skill-job mismatches are the most pressing operational risks in the HEI context.

3.3 Fuzzy-FMEA

The fuzzy-FMEA methodology begins with the fuzzification stage, in which numerical values from the assessment criteria (S, O, D) are transformed into linguistic variables using membership functions. The weighted scores for S, O, and D are used to define the membership functions of the input variables in the fuzzy inference system. These input variables are categorised into five linguistic categories, such as VH, H, M, L, and VL (Table 2). Subsequently, fuzzy inference rules are developed to establish relationships between the input and output fuzzy sets, ultimately yielding the FWPN. According to Puente et al. (2002), there are 125 possible combinations of fuzzy rule bases. The following are examples of fuzzy rule base combinations used in the FMEA framework:

1. IF Severity is VL and Occurrence is VL and Detection is VL THEN FWPN is VL,
2. IF Severity is L and Occurrence is M and Detection is VL THEN FWPN is L,
3. IF Severity is M and Occurrence is H and Detection is M THEN FWPN is H,
4. IF Severity is H and Occurrence is L and Detection is VH THEN FWPN is VH,
5. IF Severity is M and Occurrence is M and Detection is VL THEN FWPN is M.

The constructed fuzzy rule base serves as the foundation for determining the membership function of the output variable. The output of the FWPN is classified into nine linguistic levels: VH, H–VH, H, M–H, M, L–M, L, VL–L, and VL (Table 4). The membership function and its parameters for the output variable are defined based on the type of curve applied. The resulting FWPN value reflects the level of risk prioritisation required, with a higher FWPN indicating a greater need for mitigation. The FWPN calculation is performed in MATLAB (The MathWorks, Inc., online). The complete FWPN results are summarised in Table 6.

One notable limitation of conventional FMEA is the implicit assumption that the three parameters (S, O, and D) are of equal importance. It assumes linear relationships and equal weighting among these factors, often oversimplifying complex expert judgments. However, in practical applications, these parameters usually differ in their relative significance (Mandal and Maiti, 2014). In contrast, fuzzy-FMEA integrates linguistic variables and fuzzy inference rules better to capture the inherent uncertainty and subjectivity in expert evaluations. As a result, several wastes experienced significant shifts in their priority ranking, some moving substantially higher due to the recognition of indirect or compounded impacts.

In contrast, others dropped in perceived criticality when assessed under more nuanced conditions. This recalibration ensures a more representative and context-sensitive prioritisation for decision-making in higher education waste management. This discrepancy is evident in the case of A10, where the conventional WPN value is merely 7, resulting from the direct multiplication of S, O, and D values. In contrast, the corresponding FWPN reaches a significantly higher value of 479.2. Therefore, the FWPN is utilised as a more appropriate reference for identifying critical waste occurrences in higher education service processes. The use of FWPN is considered more accurate for failure evaluation, aligning with the findings of Keskin and Özkan (2009), who concluded that studies employing fuzzy logic tend to yield more precise results than traditional FMEA approaches. As presented in Table 2, D1 recorded the highest FWPN, indicating it as the most critical waste in the context of higher education service delivery.

Based on the fuzzy-FMEA analysis results, nine wastes with the highest FWPN scores were identified as the most critical (Table 7). The prioritisation of these wastes follows the Pareto principle, which posits that addressing the most significant 20% of non-value-added activities

Table 7 The critical waste types in HEI

Rank	Waste description	Code
1	Lecturers assigned teaching or duties outside their field of expertise	D1
2	Lecturers making errors when preparing teaching materials	A10
3	Lecturers completing administrative tasks outside of regular working hours	B6
4	Prolonged delays in repairing campus facilities	C5
5	LCD projectors unavailable or non-functional	A11
6	Lecturers delaying the delivery of teaching materials for lectures	C6
7	Lecturers retaining messages or emails in drafts rather than sending	F1
8	Excessive teaching workloads for lecturers each semester	B2
9	Lecturers taking extended time to respond to student inquiries	C1

(wastes) can yield approximately 80% of the overall performance improvement. From the 46 wastes identified in total, 20% corresponds to nine waste categories. A cumulative FWPN analysis confirms this Pareto effect: the top nine wastes collectively account for 78.4% of the total FWPN, indicating that a relatively small subset of issues contributes disproportionately to the overall waste burden. Consequently, focusing improvement efforts on these high-impact wastes offers the greatest potential for enhancing institutional performance. These nine wastes, ranked according to their FWPN scores, serve as the basis for subsequent causal relationship analysis using DEMATEL and for the formulation of targeted corrective actions.

3.4 DEMATEL analysis

The nine wastes with the highest FWPN scores (Table 7) were selected as the focal set for causal analysis and targeted improvement. These wastes were selected as the focus for improvement initiatives aimed at mitigating and preventing their root causes, given their significant impact on the efficiency and quality of higher education service processes. The DEMATEL method was applied to elucidate both direct and indirect interdependencies among these forms of waste and to distinguish upstream (cause) factors from downstream (effect) factors, thereby informing strategic allocation of improvement resources (Beiranvand, 2024).

The DEMATEL method provides a systematic approach to uncovering both direct and indirect relationships among complex factors. It not only quantifies the degree of interconnection but also distinguishes between causal (cause) and resultant (effect) elements, thus providing a clearer picture of the systemic dynamics underlying waste in higher education. The methodological stages include a direct-relation matrix, normalisation, a total relation matrix, an impact diagram, and causal analysis.

3.4.1 Direct relation matrix and normalisation

The direct-relation matrix serves as the initial input in the DEMATEL method, capturing the direct influence one waste exerts on another based on expert evaluations. This matrix serves as the foundation for analysing the structure of interdependencies among the identified critical wastes. To examine the relationships among the identified waste factors, a questionnaire survey was administered to the five department heads at a HEI. The questionnaire employed a scale of 0, 1, 2, 3, and 4, representing no influence, low influence, moderate influence, high influence, and very high influence, respectively. Based on these responses, the average values were subsequently calculated. Table 8 presents the obtained direct-relation matrix.

Following the construction of the direct-relation matrix, the next step is to normalise it to ensure that all

Table 8 Direct relation matrix (***X***)

Waste codes	D1	A10	B6	C5	A11	C6	F1	B2	C1	Total
D1	0	2.8	2.6	1.4	1.2	2	1.4	2	1	14.4
A10	2.8	0	2.4	1.2	1.2	2.8	1	2	1.4	14.8
B6	1.2	1.6	0	1.2	1	1.8	1.8	1.6	2	12.2
C5	2.2	2.2	1.8	0	2.6	1.8	1	1.8	1.4	14.8
A11	2	2	2	2	0	1.6	1.4	1.4	1.6	14
C6	2.2	1.8	2.8	1.6	2	0	1.4	2	1.6	15.4
F1	1.4	1.6	1.6	1.4	1	2	0	1.6	1.4	12
B2	1.6	2.4	2.4	1.4	1.4	2.6	1.2	0	2.2	15.2
C1	2	2.2	1.8	1.2	1	1.8	2	2	0	14
Total	15.4	16.6	17.4	11.4	11.4	16.4	11.2	14.4	12.6	

influence values fall within a standardised scale, typically 0 to 1. This normalisation process is essential for enabling valid comparisons and further mathematical operations in the DEMATEL analysis. Normalisation is standard practice in DEMATEL workflows and is necessary to compute the total influence matrix reliably (Shooshtarian et al., 2024). The normalised direct-relation matrix is presented in Table 9.

3.4.2 Direct relation matrix and normalisation

The total-relation matrix was computed by applying Eq. (1). This matrix captures both the direct and indirect influences among factors, providing a comprehensive view of the interrelationships within the system.

$$\boldsymbol{T} = \left[\boldsymbol{Y} \left(\boldsymbol{I} - \boldsymbol{Y} \right)^{-1} \right] \tag{1}$$

Where:

- $\boldsymbol{Y}$ is the normalised direct-relation matrix (Table 9),
- $\boldsymbol{I}$ is the identity matrix (presented in Table 10),
- $\boldsymbol{T}$ is the total relation matrix.

To translate the continuous total matrix into an impact diagram, a threshold must be chosen to retain only substantively meaningful influences. While mean-based thresholding is widely used, recent methodological work emphasises that threshold selection can materially affect network density and interpretations and therefore recommends reporting sensitivity checks and/or alternative mathematically driven thresholds. Researchers should consequently document how alternative thresholds influence the cause–and–effect partition (Ebrahimi, 2023).

As shown in the total relation matrix in Table 11, a threshold value is determined to identify relationships among the nine critical wastes. The threshold value is calculated as the average of all values within the total relation matrix. Based on the analysis, the threshold value obtained is 0.476. Each entry in the total relation matrix is then compared against this threshold. If a value exceeds 0.476, it indicates that a significant influence exists between the two corresponding waste occurrences. Conversely, if the value is below 0.476, it implies that there is no substantial influence or interrelation between them.

Based on the total relation matrix results, the interrelationships among waste factors can be identified, as presented in Table 12, which serves as an indicator of the presence or absence of influence between waste factors. This influence is represented as a binary value: 0 indicates no influence, and 1 denotes its presence.

Table 9 Normalised direct influence matrix (***Y***)

Waste codes	D1	A10	B6	C5	A11	C6	F1	B2	C1
D1	0.000	0.161	0.149	0.080	0.069	0.115	0.080	0.115	0.057
A10	0.161	0.000	0.138	0.069	0.069	0.161	0.057	0.115	0.080
B6	0.069	0.092	0.000	0.069	0.057	0,103	0.103	0.092	0.115
C5	0.126	0.126	0.103	0.000	0.149	0.103	0.057	0.103	0.080
A11	0.115	0.115	0.115	0.115	0.000	0.092	0.080	0.080	0.092
C6	0.126	0.103	0.161	0.092	0.115	0.000	0.080	0.115	0.092
F1	0.080	0.092	0.092	0.080	0.057	0.115	0.000	0.092	0.080
B2	0.092	0.138	0.138	0.080	0.080	0.149	0.069	0.000	0.126
C1	0.115	0.126	0.103	0.069	0.057	0.103	0.115	0.115	0.000

Table 10 Identity matrix (***I***)

Waste codes	D1	A10	B6	C5	A11	C6	F1	B2	C1
D1	1	0	0	0	0	0	0	0	0
A10	0	1	0	0	0	0	0	0	0
B6	0	0	1	0	0	0	0	0	0
C5	0	0	0	1	0	0	0	0	0
A11	0	0	0	0	1	0	0	0	0
C6	0	0	0	0	0	1	0	0	0
F1	0	0	0	0	0	0	1	0	0
B2	0	0	0	0	0	0	0	1	0
C1	0	0	0	0	0	0	0	0	1

Table 11 Total relationship matrix

Waste codes	D1	A10	B6	C5	A11	C 6	F1	B2	C1	D
D1	0.437	0.605	0.628	0.401	0.391	0.572	0.400	0.516	0.422	4.373
A10	0.590	0.481	0.636	0.402	0.402	0.621	0.392	0.530	0.451	4.506
B6	0.439	0.482	0.424	0.345	0.334	0.493	0.375	0.438	0.417	3.748
	0.564	0.594	0.605	0.339	0.471	0.574	0.391	0.519	0.451	4.508
A11	0.529	0.557	0.585	0.423	0.320	0.538	0.392	0.477	0.439	4.260
C6	0.573	0.587	0.665	0.431	0.449	0.493	0.421	0.540	0.472	4.630
F1	0.444	0.478	0.504	0.352	0.333	0.499	0.277	0.434	0.384	3.706
B2	0.545	0.611	0.645	0.419	0.419	0.623	0.410	0.436	0.499	4.605
C1	0.527	0.566	0.576	0.382	0.372	0.549	0.421	0.506	0.355	4.255
R	4.648	4.961	5.269	3.494	3.490	4.962	3.479	4.396	3.890	
Threshold value						0.476				

Table 12 The binary influence matrix

Waste codes	D1	A10	B6	C5	A11	C6	F1	B2	C1
D1	0	1	1	0	0	1	0	1	0
A10	1	0	1	0	0	1	0	1	0
B6	0	1	0	0	0	1	0	0	0
C5	1	1	1	0	0	1	0	1	0
A11	1	1	1	0	0	1	0	1	0
C6	1	1	1	0	0	0	0	1	0
F1	0	1	1	0	0	1	0	0	0
B2	1	1	1	0	0	1	0	0	1
C1	1	1	1	0	0	1	0	1	0

3.4.3 Causal diagram of wastes

The results of the DEMATEL analysis, which reveal the influence and interrelationships among all identified wastes, are illustrated in the causal diagram of waste shown in Fig. 1. This diagram visualises the directional relationships between waste occurrences, where arrows indicate that one waste exerts influence on another in the direction the arrow points. Red bidirectional arrows represent mutual influence between two waste occurrences. A series of focus group discussions is conducted to validate the causal diagram and the interrelationships among waste occurrences. Accordingly, experts are engaged to support the validation of the causal diagram.

As depicted in Fig. 1, C5 influences five other waste occurrences. This suggests that prolonged repair times for campus facilities significantly affect other waste categories, such as delaying lecturers' ability to deliver course materials.

In contrast, B6 only influences two other waste codes. These patterns show that infrastructural and process level deficiencies act as upstream drivers that ripple through teaching and administrative activities, an observation consistent with recent DEMATEL applications that identify structural/process factors as root causes in service and project

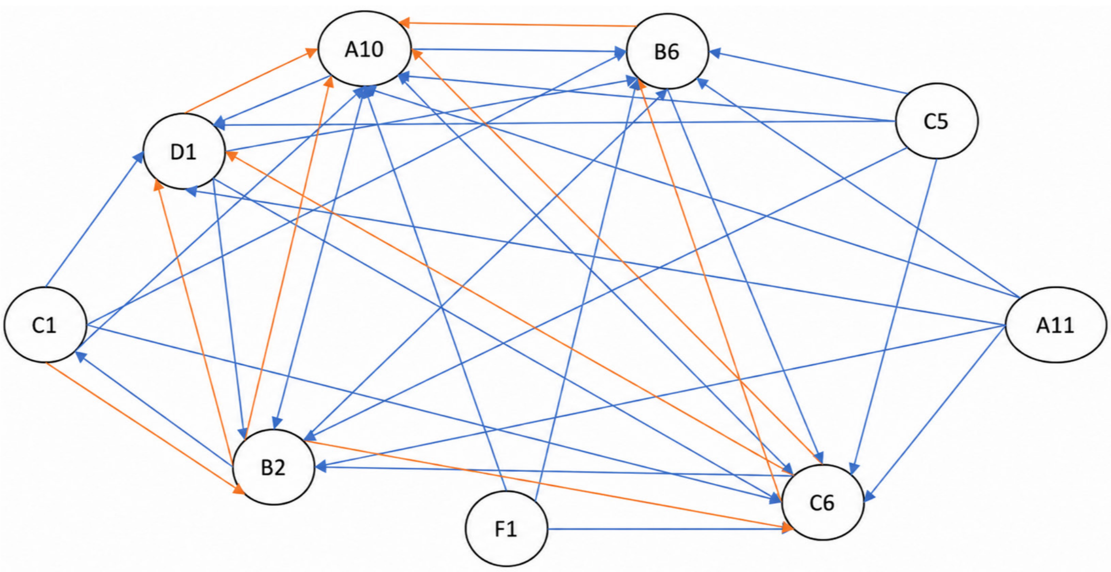

Fig. 1 Causal diagram of wastes

contexts. Targeting such upstream causes is thus likely to produce broader systemic benefits than addressing effect-side symptoms alone (Shooshtarian et al., 2024; Ye, 2024).

3.4.4 Causal analysis of waste occurrences

In addition to identifying the relationships among waste occurrences, the DEMATEL method also facilitates the assessment of the relative importance of each waste occurrence, as presented in Table 13. The level of importance is determined through the calculation of the ($\boldsymbol{D} + \boldsymbol{R}$) vector, which represents the degree to which a waste occurrence both influences and is influenced by others. Meanwhile, the ($\boldsymbol{D} - \boldsymbol{R}$) value reflects a waste occurrence's tendency to act as either a cause or an effect. A positive ($\boldsymbol{D} - \boldsymbol{R}$) value indicates that the waste primarily influences other criteria and is therefore categorised as a cause. Conversely, a negative ($\boldsymbol{D} - \boldsymbol{R}$) value signifies that others predominantly influence the waste and is thus classified as an effect.

In Table 13, C5 exhibits the largest positive ($\boldsymbol{D} - \boldsymbol{R}$) value of +1.014, indicating it is a principal driver with multiple outgoing effects; conversely, B6 shows the most negative ($\boldsymbol{D} - \boldsymbol{R}$) value at −1.521, suggesting it is predominantly a consequence rather than a driver. D1, A10, and C6 also fall on the effect side, whereas A11, F1, B2, and C1 sit in the cause set. Substantively, the prominence of C5 suggests that campus infrastructure reliability is a leverage point: delays in facility maintenance propagate downstream, for example, into delayed material delivery by lecturers, ultimately degrading instructional quality. This interpretation is consistent with prior higher education decision analytics, which have shown that structural and process factors often sit upstream of instructional outcomes and should be targeted first.

The waste related to prolonged campus facility repairs (C5) exhibits the highest ($\boldsymbol{D} - \boldsymbol{R}$) value, at 1.014, indicating that this waste occurrence exerts the greatest influence on other waste occurrences and contributes significantly to the decline in overall institutional quality. In contrast, the waste concerning lecturers performing administrative tasks outside working hours (B6) has the lowest negative ($\boldsymbol{D} - \boldsymbol{R}$) value at –1.521, suggesting that it is predominantly affected by other waste occurrences rather than being a source of influence. Similarly, waste occurrences coded D1, A10, and C6 also tend to function as effect criteria, being influenced by other factors. On the other hand, waste occurrences coded A11, F1, B2, and C1 are more inclined to act as causal factors, exerting influence on other waste occurrences.

3.5 Waste priority categories for managing critical waste occurrences in HEI

The Waste Priority Categories (WPC) framework translates the outputs of fuzzy-FMEA and DEMATEL into prioritised action categories, such as eliminate, option, and acceptance (Table 14), enabling HEI to systematically address the most critical waste occurrences first while ensuring sustainable process improvement. The outcomes of the fuzzy inference process are classified into predefined WPC, which range from Very High (VH) to Very Low (VL). Each category represents the degree of criticality of a waste factor and guides subsequent decision-making. This categorisation allows HEI to align corrective strategies with the criticality and systemic role of each waste. The eliminate category includes wastes that must be removed or reduced immediately through targeted intervention. The option category refers to wastes for which interventions remain discretionary, either because their systemic influence is less pronounced or because immediate removal is resource intensive. The acceptance category applies to wastes that are either unavoidable or negligible, where taking no immediate action is deemed a rational allocation of resources.

This tri-level classification reflects the broader principle of risk-informed prioritisation in higher education

Table 13 Prominence and relation values

Waste codes	$\boldsymbol{D}$	$\boldsymbol{R}$	$\boldsymbol{D} + \boldsymbol{R}$	$\boldsymbol{D} - \boldsymbol{R}$	Identify
D1	4.373	4.648	9.022	−0.275	Effect
A10	4.506	4.961	9.466	−0.455	Effect
B6	3.748	5.269	9.016	−1.521	Effect
C5	4.508	3.494	8.002	1.014	Cause
A11	4.260	3.490	7.750	0.769	Cause
C6	4.630	4.962	9.592	−0,332	Effect
F1	3.706	3.479	7.185	0.227	Cause
B2	4.605	4.396	9.001	0.209	Cause
C1	4.255	3.890	8.145	0.364	Cause

Table 14 Waste priority categories

WPC	Action
VH	
H-VH	Eliminate
H	
M-H	
M	Option
L-M	
L	
VL-L	Acceptance
VL	

process improvement, ensuring resources are allocated to actions that maximise systemic impact. Recent empirical work emphasises that hybrid models combining fuzzy-FMEA and DEMATEL with priority categorisation frameworks yield more effective risk mitigation strategies in complex service systems.

The WPC is determined by referring to the fuzzy inference rules. For example, in the case of waste occurrence D1, the input values S, O, and D are 7, 2, and 2, respectively. Based on Table 2, these values correspond to the linguistic categories H, L, and L. Consequently, by applying the fuzzy rule, the resulting WPC for waste occurrence D1 is classified as High–Very High (H–VH), thus requiring an elimination action. Table 15 presents the WPC results for all critical waste occurrences along with the corresponding recommended actions. Expert opinions from academia are collected via focus group discussions to gain in-depth insights for determining mitigation actions against critical waste occurrences. Four waste occurrences (D1, A10, B6, and C5) were prioritised under the eliminate category. These items are both high in FWPN and function as upstream causal factors in the DEMATEL model, underscoring their leverage for systemic improvement. By contrast, waste occurrences categorised under options such as A11, C6, F1, B2, and C1 can be deferred without compromising overall process stability, while acceptance applies to minor residuals.

The integration of WPC into the waste analysis framework, which bridges fuzzy-FMEA and DEMATEL, enables the conversion of multidimensional analytical insights into clear, actionable strategies. By categorising waste into elimination, option, and acceptance, WPC enables targeted, phased interventions that focus scarce resources on leverage points that yield systemic, long-lasting improvements to enhance institutional sustainability. This structured prioritisation aligns with sustainability principles in HEIs, which advocate evidence-based, tiered action planning to maximise impact across environmental, social, and economic dimensions.

Table 15 Actions for critical waste occurrences

Rank	Waste codes	S	O	D	WPC	Action
1	D1	H	L	L	H-VH	Eliminate
2	A10	H	VL	VL	H	Eliminate
3	B6	M	H	L	H	Eliminate
4	C5	M	H	L	H	Eliminate
5	A11	M	L	L	M-H	Option
6	C6	M	L	VL	M	Option
7	F1	L	L	L	L-M	Option
8	B2	L	L	L	L-M	Option
9	C1	L	M	L	L-M	Option

3.6 Implications for sustainability in HEIs

The integrated application of FWPN ranking, DEMATEL causal analysis, and WPC mapping provides a pragmatic decision framework for directing limited institutional resources toward interventions that deliver the greatest systemic and sustainability returns. The DEMATEL finding that C5 (delays in campus facility repairs) functions as a primary upstream driver implies that targeted investments in facilities management will generate cascading benefits by reducing multiple downstream wastes. Many studies support the finding that comprehensive reviews of university building maintenance emphasise prioritising preventive maintenance, integrating digital tools, and adopting data-driven maintenance strategies. These strategies materially reduce lifecycle costs and reactive work orders, outcomes that directly support environmental and economic sustainability. Grącki and Plebankiewicz (2024) highlight the strategic importance of prioritising maintenance and adopting technology to improve building performance in higher education. Standardised facility repair procedures, rationalised teaching assignments, integrated information systems, and enhanced learning management systems are proposed as key actions for waste (Hartanti et al., 2022b).

Investments that reduce reactive repairs (C5) also reduce avoidable resource consumption, temporary fixes, repeated material use, and emergency mobilisation, which increase energy use and material waste. Large, open datasets and analyses of campus maintenance work orders reinforce the potential for preventive programmes to improve asset longevity and reduce reactive expenditures (Pampana et al., 2024). These findings lend empirical support to the WPC recommendation to eliminate causal, high-FWPN forms of waste to achieve environmental and economic benefits.

Beyond infrastructure, the WPC and DEMATEL results highlight the socio-organisational dimensions of sustainability. The prioritisation of D1 (misaligned teaching assignments) and B6 (lecturers burdened with administrative tasks outside working hours) reflects threats to social sustainability – faculty wellbeing, pedagogical quality, and student outcomes. Recent open-access work on fuzzy-FMEA and risk prioritisation demonstrates that social and operational risks in service systems should be treated alongside technical risks, as their mitigation yields measurable improvements in service quality and stakeholder wellbeing (Beiranvand, 2024; Magableh et al., 2024). In higher education, reducing administrative burden and improving role alignment are associated with better teaching performance, higher job satisfaction, and enhanced student perceptions, outcomes that sustain institutional reputation and retention

Specifically, the DEMATEL classification of B6 and A10 as effect-type wastes (high FWPN but negative $\boldsymbol{D} - \boldsymbol{R}$) suggests that direct mitigation of these symptoms without addressing upstream causes (facility delays, coordination failures) will yield limited systemic improvement. Therefore, WPC's triage, giving eliminate status to forms of waste that are both high in FWPN and causal (C5, D1), while assigning option or acceptance to less systemic items, aligns with recent studies advocating an upstream-first strategy to achieve sustainable service improvement (Beiranvand, 2024; Magableh et al., 2024).

Operationalising WPC for sustainability requires embedding outputs into institutional governance and performance dashboards. HEIs that formalise maintenance key performance indicators (KPIs), faculty workload metrics, and student satisfaction indicators within multi-year planning cycles are better positioned to sustain improvements. The literature suggests concrete monitoring metrics, reduced reactive work orders, mean time to repair, proportion of faculty time on teaching versus administration, and student satisfaction scores, that map directly to the upstream and downstream wastes identified in this study (Grącki and Plebankiewicz, 2024; Pampana et al., 2024). Integrating these KPIs into governance supports transparency, enables evidence-based resource allocation, and helps demonstrate sustainability impact to stakeholders.

The integration FWPN, DEMATEL, and WPC approach produces actionable, sustainability-oriented recommendations that prioritise elimination of causal, high-FWPN wastes (especially C5) to maximise environmental and economic returns; concurrently, implement targeted short-term remedies for high-impact effect forms of waste (A10, B6) to protect service quality while upstream changes take effect; and embed performance monitoring to ensure that improvements persist and translate into measurable sustainability outcomes.

4 Conclusion

This study establishes an integrated framework combining fuzzy-FMEA, DEMATEL, and WPC systematically to identify and prioritise critical waste occurrences in HEIs. Fuzzy-FMEA analysis indicates nine types of critical waste. The most critical form of waste in HEI is the assignment of lecturers outside their field of expertise, indicating inefficient use of intellectual resources. Other waste is dominated by lecturer performance, including errors in teaching materials, excessive administrative burdens, and delayed responses to communication. Furthermore, operational obstacles arise from damaged facilities, such as LCDs, and from slow campus repairs.

DEMATEL analysis shows a strong interrelationship between nine critical wastes at HEI. Systemic factors, such as delayed facility repairs and equipment failures, are the primary drivers of other wastes, including errors in teaching preparation. Lecture's workload and misaligned teaching assignments also have a strong reciprocal influence. Intervening in the primary causal factors will effectively reduce other waste chains simultaneously. Systemically, these waste occurrences serve as the main triggers that drive the emergence of other derivative waste occurrences within the network of influence.

The main contribution of this study lies in translating complex risk assessments and causal mapping into actionable categories that directly support managerial decision-making. Beyond addressing inefficiencies, the framework advances the sustainability agenda in HEIs by promoting efficient use of resources, safeguarding staff wellbeing, and enhancing the quality of student learning.

From a sustainability standpoint, the implications are threefold. First, interventions targeting causal waste occurrences enhance environmental sustainability by reducing resource inefficiencies and preventing deferred maintenance backlogs. Second, eliminating the high-FWPN effect directly contributes to social sustainability by improving faculty workload balance, pedagogical quality, and student learning outcomes. Third, prioritising preventive strategies over reactive responses supports economic sustainability by mitigating hidden costs and ensuring long-term financial viability.

This study confirms that combining fuzzy-FMEA with DEMATEL and WPC provides a robust decision-support framework for HEIs. By systematically identifying critical waste occurrences, clarifying their causal–effect relationships, and aligning improvement strategies with sustainability goals, institutions can minimise inefficiencies, strengthen resilience, and improve the quality of educational services. This study has limitations in terms of its data collection scope, which focuses on one particular HEI and relies on expert assessment, thereby introducing a level of subjectivity in the scoring of fuzzy-FMEA and DEMATEL. Future studies may expand this approach by integrating quantitative performance metrics, such as sustainability-oriented key performance indicators, to evaluate the longitudinal impacts of waste elimination on institutional performance.

Acknowledgement

The authors acknowledge financial support for this research provided by Universitas Katolik Widya Mandala Surabaya in 2025, as well as the heads of the relevant departments of the case organiation. The authors are also thankful to all employees of the concerned departments for generously sharing their valuable time and information.

References

Ankareddy, S., Dorfleitner, G., Zhang, L., Ok, Y. S. (2025) "Embedding sustainability in higher education institutions: A review of practices and challenges", Cleaner Environmental Systems, 17, 100279. https://doi.org/10.1016/j.cesys.2025.100279

Beiranvand, B. (2024) "Development of modified fuzzy FMEA method in environmental risk assessment of earth dams", Scientific Reports, 14(1), 17585. https://doi.org/10.1038/s41598-024-68217-w

Cardiel-Ortega, J. J., Baeza-Serrato, R. (2023) "Failure Mode and Effect Analysis with a Fuzzy Logic Approach", Systems, 11(7), 348. https://doi.org/10.3390/systems11070348

Chang, J., Jang, S., Lalonde, R., Huq, S. M. (2022) "Fuzzy analytic hierarchy process-based risk priority number for risk assessments of commissioning process of a ring gantry LINAC", Journal of Applied Clinical Medical Physics, 23(11), e13760. https://doi.org/10.1002/acm2.13760

Chi, M., Ren, S., Xu, Y., Chen, Y., Wu, Y. (2025) "Critical success factors for metaverse implementation in the service industry: A hybrid ISM-DEMATEL approach", Journal of Retailing and Consumer Services, 87, 104424. https://doi.org/10.1016/j.jretconser.2025.104424

Ebrahimi, S. H. (2023) "Some equations to identify the threshold value in the DEMATEL method", Operations Research and Decisions, 33(2), pp. 1–22. https://doi.org/10.37190/ord230201

Grącki, J., Plebankiewicz, E. (2024) "Strategies of Public University Building Maintenance—A Literature Survey", Sustainability, 16(10), 4284. https://doi.org/10.3390/su16104284

Hariyani, D., Hariyani, P., Mishra, S., Sharma, M. K. (2025) "A literature review on lean tools for enhancing the quality in the outcome-based education system", Thinking Skills and Creativity, 57, 101793. https://doi.org/10.1016/j.tsc.2025.101793

Hartanti, L. P. S., Gunawan, I., Mulyana, I. J., Herwinarso, H. (2022a) "Identification of Waste Based on Lean Principles as the Way towards Sustainability of a Higher Education Institution: A Case Study from Indonesia", Sustainability, 14(7), 4348. https://doi.org/10.3390/su14074348

Hartanti, L. P. S., Mulyana, I. J., Gunawan, I., Herwinarso (2022b) "Managing the 8 Wastes of Lean at a Higher Education Institution: An ISM-MICMAC Approach", KnE Social Sciences, 7(17), pp. 130–138. https://doi.org/10.18502/kss.v0i0.12318

Hartanti, L. P. S., Mulyana, I. J., Hartiana, T. I. P. (2020) "Waste In Higher Education Institution: A Systematic Literature Review", International Journal of Scientific & Technology Research, 9(9), pp. 16–22.

Helmold, M., Küçük Yılmaz, A., Flouris, T., Winner, T., Cvetkoska, V., Dathe, T. (2022) "Lean Management in Higher Education (LHE)", In: Lean Management, Kaizen, Kata and Keiretsu: Best-Practice Examples and Industry Insights from Japanese Concepts, Springer, pp. 229–238. ISBN 978-3-031-10103-8 https://doi.org/10.1007/978-3-031-10104-5_17

Jónás, T., Árva, G., Tóth, Z. E. (2018) "Forecasting Failure Rates of Electronic Goods by Using Decomposition and Fuzzy Clustering of Empirical Failure Rate Curves", Periodica Polytechnica Social and Management Sciences, 26(1), pp. 10–18. https://doi.org/10.3311/PPso.9026

Keskin, G. A., Özkan, C. (2009) "An alternative evaluation of FMEA: Fuzzy ART algorithm", Quality and Reliability Engineering International, 25(6), pp. 647–661. https://doi.org/10.1002/qre.984

Klein, L. L., Alves, A. C., Abreu, M. F., Feltrin, T. S. (2022) "Lean management and sustainable practices in Higher Education Institutions of Brazil and Portugal: A cross country perspective", Journal of Cleaner Production, 342, 130868. https://doi.org/10.1016/J.JCLEPRO.2022.130868

Lima, E. de S., de Oliveira, U. R., Costa, M. de C., Fernandes, V. A., Teodoro, P. (2023) "Sustainability in public universities through lean evaluation and future improvement for administrative processes", Journal of Cleaner Production, 382, 135318. https://doi.org/10.1016/j.jclepro.2022.135318

Liu, H.-C., Zhang, L.-J., Ping, Y.-J., Wang, L. (2020) "Failure mode and effects analysis for proactive healthcare risk evaluation: A systematic literature review", Journal of Evaluation in Clinical Practice, 26(4), pp. 1320–1337. https://doi.org/10.1111/jep.13317

Magableh, G. M., Mumani, A. A., Obaidat, S. F., Mistarihi, M. Z. (2024) "Fuzzy-FMEA theory approach for prioritizing supply chain nervousness factors", Applied Sciences, 14(11), 4747. https://doi.org/10.3390/app14114747

Mandal, S., Maiti, J. (2014) "Risk analysis using FMEA: Fuzzy similarity value and possibility theory based approach", Expert Systems with Applications, 41(7), pp. 3527–3537. https://doi.org/10.1016/j.eswa.2013.10.058

Mulyana, I. J., Hartanti, L. P. S., Herdianto, V. A., Gunawan, I., Herwinarso, H. (2022) "Lean Waste Identification in Higher Education Institution Using Waste Assessment Model", Management Systems in Production Engineering, 30(3), pp. 200–206. https://doi.org/10.2478/mspe-2022-0025

Mulyana, I. J., Singgih, M. L., Partiwi, S. G., Hermanto, Y. B. (2023) "Identification and prioritization of lean waste in Higher Education Institutions (HEI): A proposed framework", Education Sciences, 13(2), 137. https://doi.org/10.3390/educsci13020137

Nawanir, G., Binalialhajj, M., Teong Lim, K., Hanafiah Ahmad, M. (2019) "Becoming Lean: The Way towards Sustainability of Higher Educations Institutions", KnE Social Sciences, 3(22), pp. 603–626. https://doi.org/10.18502/kss.v3i22.5078

Paciarotti, C., Mazzuto, G., D'Ettorre, D. (2014) "A revised FMEA application to the quality control management", International Journal of Quality & Reliability Management, 31(7), pp. 788–810. https://doi.org/10.1108/IJQRM-02-2013-0028

Pampana, A. K., Jeon, J., Yoon, S., Weidner, T. J. (2024) "Comprehensive maintenance dataset of building facilities for planned preventive and unplanned maintenance in North American universities", Data in Brief, 57, 110845. https://doi.org/10.1016/j.dib.2024.110845

Puente, J., Pino, R., Priore, P., de la Fuente, D. (2002) "A decision support system for applying failure mode and effects analysis", International Journal of Quality & Reliability Management, 19(2), pp. 137–150. https://doi.org/10.1108/02656710210413480

Shamsuzzaman, M., Khadem, M., Haridy, S., Shamsuzzoha, A., Abdalla, M., Al-Hanini, M., Almheiri, H., Masadeh, O. (2023) "Improving the admission process in a higher education institute using lean six sigma: a case study", International Journal of Lean Six Sigma, 14(7), pp. 1596–1625. https://doi.org/10.1108/IJLSS-05-2021-0098

Shooshtarian, S., Gurmu, A. T., Mahmood, M. N. (2024) "Application of the DEMATEL approach to analyse the root causes of building defects", Quality & Quantity, 58(5), pp. 4641–4660. https://doi.org/10.1007/s11135-024-01872-3

Si, S.-L., You, X.-Y., Liu, H.-C., Zhang, P. (2018) "DEMATEL technique: A systematic review of the state-of-the-art literature on methodologies and applications", Mathematical Problems in Engineering, 2018(1), 3696457. https://doi.org/10.1155/2018/3696457

The MathWorks, Inc. "MATLAB, (R2025a)", [computer program] Available at: https://www.mathworks.com/products/matlab.html [Accessed: 22 October 2025]

Vnoučková, L., Urbancová, H., Smolová, H. (2019) "Business and Management Higher Education Quality: A Case Study of a Czech Private University", Periodica Polytechnica Social and Management Sciences, 27(1), pp. 87–97. https://doi.org/10.3311/PPso.12145

Ye, Q. (2024) "Extended DEMATEL method with intuitionistic fuzzy information: A case of electric vehicles", PLoS ONE, 19(12), e0314650. https://doi.org/10.1371/journal.pone.0314650

Yucesan, M., Gul, M., Celik, E. (2021) "A holistic FMEA approach by fuzzy-based Bayesian network and best–worst method", Complex & Intelligent Systems, 7(3), pp. 1547–1564. https://doi.org/10.1007/s40747-021-00279-z