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Fostering cleaner production through the adoption of sustainable maintenance: An umbrella review with a questionnaire-based survey analysis

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A B S T R A C T

The global industrial sector accounts for about 26%, while manufacturing and construction accounts for about 13% of global CO_2 emissions, highlighting the need for sustainable operational strategies. Regulatory frameworks (e.g., GreenDeal, RePowerEU), have placed increasing pressure on manufacturing industries to align their economic productivity practices with sustainable business models. In this context, Sustainable Maintenance (SM) emerged as a strategic approach to reduce resource inefficiencies and minimise environmental waste. Hence, the research on SM is important for two reasons. Firstly, the impact of maintenance activities in reducing energy consumption can be considered one of the main determinants for enhancing the sustainability of manufacturing processes. Secondly, integrating SM practices within the context of Industry 4.0 offers a strategic move in achieving cleaner production and availability of manufacturing processes. However, the lack of research on investigating factors hindering the adoption of these practices within manufacturing entities has been reported. Leveraging Umbrella Review, contemporary research on SM prospects has been examined. Instead of focusing solely on the barriers and enablers, the study uses these factors to describe the existing body of SM research by performing network analysis. Secondly, given that digitalization is a barrier and an enabler, a questionnaire-based survey instrument has been developed. The data obtained from the survey is subjected to statistical testing using Bayes inferential statistics and Multiple Correspondence Analysis. The findings suggest strong to extreme evidence ($BF_{10} > 100$) in favour of the existence of a correlation between digitalization (and technology) and maintenance sustainability aspects.

List of Abbreviations

SMA	Sustainable Manufacturing
SM	Sustainable Maintenance
CP	Cleaner Production
MDM	Maintenance Decision-Making
PRISMA	Preferred Reporting of Items in Systematic Reviews and Meta-Analyses
IoT	Internet of Things
DT	Digital Twin
CPS	Cyber-Physical Systems
AI	Artificial Intelligence
UR	Umbrella Review
SLR	Systematic Literature Review
TB	Technological Barriers

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(*continued*)

OMB	Organisational and Management Barriers
KSB	Knowledge and Skills Barriers
FEB	Financial and Economic Barriers
SPC	Strategic and Planning Challenges
TOC	Technical and Operational Challenges
CBC	Cultural and Behavioural Challenges
FMC	Financial Management Challenges
TE	Technological Enablers
OME	Organisational and Management Enablers
KSE	Knowledge and Skills Enablers
FEE	Financial and Economic Enablers
SPF	Strategic and Planning Facilitators
TOF	Technical and Operational Facilitators

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(*continued*)

CBF	Cultural and Behavioural Facilitators
MCA	Multiple Correspondence Analysis
VS-MPR	Vovk-Sellke Maximum *p*-Ratio

1. Introduction

The industrial sector, responsible for about 26% of global CO_2 emission (IEA, 2023), stands at the forefront of the global sustainability crisis, highlighting the urgent need for industries to reconcile productivity with planetary boundaries. With the rise of regulatory frameworks and sustainability initiatives like Green Deal (Haines and Scheelbeek, 2020), sustainability has transformed from a voluntary initiative to a strategic imperative. Amid global environmentalism, industrial manufacturing faces a dual challenge: meeting escalating demand while decarbonising operations to meet net-zero targets. This challenge is significant since the manufacturing sector experiences an upward trend in medium-high and high-technology of a 1% quarterly increase with global manufacturing output growth of 0.4% (UNIDO, 2024)Within such contextual settings, sustainability is no longer a peripheral concern but rather a core operational prerequisite, requiring transformative strategies that balance economic growth with environmental and social responsibility.

Considering the global challenges, this suggests that the future of manufacturing is digital and green. Influenced by the advent of Industry 4.0 (I4.0) technological solutions—Cyber-Physical Systems, Digital Twinning, and the Internet of Things—while at the same time being committed to global sustainability initiatives—Paris Agreement (Lee et al., 2019) and United Nations' Sustainable Development Goals (United Nations, 2015)—manufacturing companies are constantly under pressure to transform their operational processes to achieve Cleaner Production (CP). The CP emerged as a cornerstone of industrial sustainability, serving as a proactive strategy aimed at reducing environmental footprints by optimising processes, material and energy (Srinivas, 2022). Nevertheless, achieving CP's complete potential demands more than simple technological upgrades, requiring systematic integration of sustainability principles into operational practices, particularly maintenance. Rhetorically, the contemporary technological landscape in which manufacturing companies find themselves offers a dual advantage: enhancing operational efficiency and increasing sustainable responsibility, making manufacturing not just smarter but eco-friendly (Lin and Chen, 2023).

Seizing the opportunity to go digital and green, Sustainable Maintenance (SM) emerged as a vital strategy for achieving such objectives (Zhao et al., 2022). Traditionally viewed as a "necessary evil" (Orosnjak, 2021), contemporary maintenance became a strategic lever in reducing costs associated with inefficient resource utilisation (Acerbi et al., 2020), environmental waste (Elia et al., 2017) and risks associated with poor operational practices (Anandakumar and Varughese, 2020). Given that sustainable manufacturing acts as a catalyst (Vrignat et al., 2022) in the global movement towards environmentalism, adopting SM practices represents both a challenge and an opportunity. While advancements in digital technologies offer a solution space for the adoption of SM practices (Jasiulewicz-Kaczmarek et al., 2020), the effective implementation of these practices remains underexplored. Although many conceptualise their definition of SM, we define SM as a strategic practice for managing assets and equipment by considering social, environmental and economic aspects to ensure long-term operational efficiency, resource conservation and minimal environmental waste. In addition, SM emphasises a data-driven approach that aligns with sustainability goals aimed at reducing energy consumption, waste generation and lifecycle costs while at the same time fostering a culture of continuous improvement.

While origins date back to 2000's (Ulrich and Eberhard, 2005) with more theoretical and opinion papers (Jasiulewicz-Kaczmarek, 2013), recent studies offered a valid rationale regarding the importance of SM (Franciosi et al., 2018). Acknowledging the sustainability role in maintenance (Saihi et al., 2023b), different concepts started emerging: Green Maintenance (Ajukumar and Gandhi, 2013), Energy-oriented maintenance (Xia et al., 2018), Energy-Based Maintenance (Orosnjak, 2021), Sustainable Cleaner Maintenance (Sari et al., 2021), Sustainable Predictive Maintenance (Karuppiah et al., 2021) and other typologies. Driven by the same underlying ideology—energy-efficient maintenance—the SM research agenda considers different domains: diagnostics/prognostics (Orošnjak et al., 2023), optimisation (Yildirim and Nezami, 2014) and decision-making (Do et al., 2018). Driven by the exponential rise of reviews on SM prospects, some have started summarising evidence on SM. In particular, Santos et al. (2023) surveyed prior reviews on SM research, concluding that there is a lack of systematic reviews specifically assessing maintenance policies for reusing and remanufacturing products. Vasić et al. (2024) were the first to conduct an Umbrella Review (UR), suggesting that research before 2021 is more profit-oriented while post-2021 reflects a more balanced approach considering social and environmental responsibility. Hence, several gaps were noticed in the prior body of knowledge: (i) there is a lack of summarised knowledge about factors affecting the adoption of SM practices; (ii) there is a lack of understanding of how these factors are perceived in the industry; and lastly (iii) there is a lack of clear empirical evidence from industrial and manufacturing entities. It is important to note that SM prospects for facility, offshore and building maintenance are studied elsewhere (Ighravwe and Oke, 2019).

The study's primary aim is to bridge the knowledge gap surrounding the adoption of SM by systematically analysing the key factors that influence the implementation of SM in industrial and manufacturing settings. To do so, the study performs dual analysis. Firstly, by integrating insights from prior systematic reviews, the study seeks to establish comprehensive and actionable recommendations highlighting barriers and enablers in adopting SM. Namely, barriers and enablers are stratified as items and subjected to multivariate statistical analysis to determine reasons for the slow adoption of SM practice. Consequently, the analysis's expected outcome is synthesised as the main determinants affecting the integration of SM within industrial settings. This study relies on empirical (practical) evidence generated from a questionnaire-based industrial survey analysis instead of expert opinion-based data to validate these factors. Leveraging Bayesian inferential statistics, the study investigates the association of digitalization and technology with the adoption of SM, ultimately offering actionable insights and recommendations for industry stakeholders and academicians.

The remainder of the article is structured as follows. Section 2 describes in-detail UR protocol, including transparent and replicable search strategy, synthesis of reviews and retrieval of evidence. Also, a complete description of the questionnaire-based survey design alongside preliminary data is provided. Section 3 provides an extensive summary of evidence and analysis of results, uncovering latent internal-organisational and external-industrial factors affecting the adoption of SM practices. For secondary (content) data in the corpus of reviews, the study performs Bayesian Network Analysis to determine the most important factors within prior systematic reviews about barriers and enablers in the SM body of knowledge. Section 4 provides an overview and discussion of secondary data and survey results, highlighting the most important results. Lastly, the conclusion provides an overall summary of the work, including limitations and implications of findings.

2. Research design

2.1. Umbrella review

2.1.1. Review protocol

In contrast to an SLR, a UR provides a broader picture of the findings (Aromataris et al., 2015). In this study, the UR was used to summarise the existing body of work and provide a general understanding of the main determinants in the SM research domain. The realisation of UR is performed using an OoRS (Overviews of Review Studies) (Bougioukas et al., 2018) workflow and PRIOR (Preferred Reporting in Overviews of Reviews) checklist (Pollock et al., 2019). Considering the nature of the review, the PCC (Population Concept Context) framework was used as a less restrictive alternative to PICO (Population Intervention Comparison Outcome) (Peters et al., 2015) for formulating Research Questions (RQs). The *Population* component comprises industrial organisations considering SM, the *concept* component represents factor items (e.g., barriers, enablers) affecting the adoption of SM, and the context component explains industrial settings in the manufacturing and service domain.

Although existing research considers barriers synonymous with challenges, to extract relevant information, the barrier is conceptualised "*… as an obstacle, rule or condition that prevents or hinders the movement, action or access*." This could include a physical (e.g., lack of infrastructure), systemic (e.g., bureaucratic rules), or immaterial (e.g., psychological or cultural constraint), typically external to an organisation (or individual) that makes it difficult or even impossible to achieve without a change or an intervention. A challenge, on the other hand, is referred to as "*… a task (or situation) requiring significant mental (or physical) effort to accomplish a specific goal*." In summary, barriers are impediments that need to be removed or overcome, while the challenge is a task that tests an individual' (or organisation') ability to grow. (Note: For a detailed description and conceptualisation of barriers and challenges, please see Supplementary File 2). Thus, the first RQ states:

RQ1: *Which barriers and challenges hinder the adoption of sustainable maintenance practices?*

Conversely, factors potentially aiding in adopting SM (enablers and facilitators) are also extracted. Thus, in SM research, enablers are conceptualised as "*… factors, conditions, and mechanisms that enable the adoption of a proposed practice or achievement of a specific goal*". In the same context, facilitators are "*… individuals, elements, techniques or apparatuses that ease or assist in implementing a particular process or change*". The difference between a facilitator and an enabler is that the facilitator does not make the process possible (like the enabler) but makes it smoother or more effective. For a detailed description of conceptualisation, please see Supplementary File 2. Thus, the following RQ states:

RQ2: *Which enablers and facilitators aid in adopting sustainable maintenance practices?*

The motivations behind the proposed RQs are twofold: (i) most prior reviews concerned with challenges and barriers lack an understanding of these items and their impact, hindering the adoption of SM, and (ii) many argue that KET (Key Enabling Technologies) of Industry 4.0 are commonly trusted features for resolving these issues; however, there is a lack of industrial and empirical evidence supporting such claims.

2.1.2. Search and retrieval process

The intent was not only to isolate reviews dealing with "*sustainable maintenance*" since it encompasses many variants (e.g., Energy-Based Maintenance, Green Maintenance) outside of the industrial and manufacturing sphere (e.g., facility maintenance). The OpenAlex and Google Scholar search is conducted through *Harzing's Publish or Perish* software (Windows GUI Edition, v.8.9.4554.8721). Since the software requires API from SCOPUS and Web of Science, the search strings and IES (Isolation-Exclusion-Selection) criteria are explained in detail and provided in Supplementary file 1. The isolation criteria consider full-text reviews written in English, sole or mixed-method reviews published between 2000 and 2023, and full-access papers corresponding to the proposed RQ. Two reviewers independently performed the selection, reaching an interrater agreement of Cohen's Kappa = 0.86 ($R_{N1} = 58$; $R_{N2} = 61$), with 67 reviews identified. The excluding reviews mainly did not deal with SM, were theoretical, or were unrelated to industrial and manufacturing domains (e.g., building and facility maintenance).

Finally, the OoSR protocol (Fig. 1) illustratively reports the method for retrieving reviews. Based on the performed search, $n = 1129$ papers were identified. After removing duplicate papers (n = 402), the remaining n = 727 papers were screened. The screening phase selects reviews based on titles, abstracts, and keywords. After screening, the final list included 67 papers for full-text analysis. The reviewers agreed to include 20 reviews for an in-depth analysis during this stage. The complete process of search strategy, identification of studies and evidence retrieval can be found in Supplementary File 1.

2.1.3. Data analysis

For the analysis of proposed RQs, we rely on BNA (Bayes Network Analysis) with GCGM (Gaussian Copula Graphical Model) estimator. Graphic network models have lately been favoured by researchers who explore the relationship between (edges) and variables (nodes) due to their ability to provide compelling understanding through visualisations. Nevertheless, traditional networks employ GGMs (Gaussian Graphical Models) in social and health sciences, and not many researchers consider GCGMs. Here, the choice of BNA is considered for two reasons. Firstly, the aim was to explore the probabilistic relationship between items. Secondly, unlike GGMs, requiring continuous data, the BNA-GCGM models supersede traditional GGMs since they can handle both linear and non-linear dependencies across continuous, ordinal, and count data (Adler et al., 2011).

For positioning nodes in the model, the Fruchterman-Reingold (FR) algorithm is used (Fruchterman and Reingold, 1991). The FR algorithm is understood as a force-directed measure visually represented by nodes (vertices) and lines (edges). For the edge-evidence network plot, inclusion criteria are set as BF_{10} (Bayes Factor) > 3, categorised as moderate evidence in favour of the alternative over the null hypothesis (van Doorn et al., 2021). The centrality indices considered Betweenness (the number of times a node lies within the shortest path between other nodes (Kalantari et al., 2022)), Strength (the sum of the absolute weights of connections between different nodes), and Expected Influence (the relative importance of a node considering both strength and direction of influence) (Robinaugh et al., 2016). An inclusion criterion, BF_{10}, with a credible interval of 95%, is used for the edge centrality plot. In Bayes' statistics, estimating credible intervals differs from frequentists' confidence intervals; please see Hespanhol et al. (2019). The network prior is set as edge inclusion (*g* prior) Gamma = 0.5 (Foygel and Drton, 2010) with G-Wishart prior (*df* prior) = 3. The initial configuration for prior edge inclusion is set as "empty". It is commonly used in practice because of the reduced complexity of connections. Finally, the node and edge estimation sampling options are based on the 5000 (burn-in) period with 10000 iterations (seed is set to 100). The analysis was performed in JASP (v.0.18.3).

2.2. Questionnaire-based survey analysis

2.2.1. Designing a survey

Given that we targeted West Balkan industrial companies, a previous study reports that up to 13.1% of companies outsource their maintenance activities (e.g., Maintenance as a Service), while as high as 50.4% rely on external experts for sophisticated infrequent failure analysis (Orošnjak and Šević, 2023). To collect practical (empirical) evidence, companies with indoor maintenance management were mainly targeted, and companies that outsource their maintenance activities were excluded. Next, the development of a survey is provoked by the lack of empirical evidence in previous studies, specifically analysing the role of digitalization (and technology) and the sustainability aspect of maintenance. For this reason, we identify TBL (Tripple Bottom Line) dimensions (e.g., social, environmental, economic) as the most important

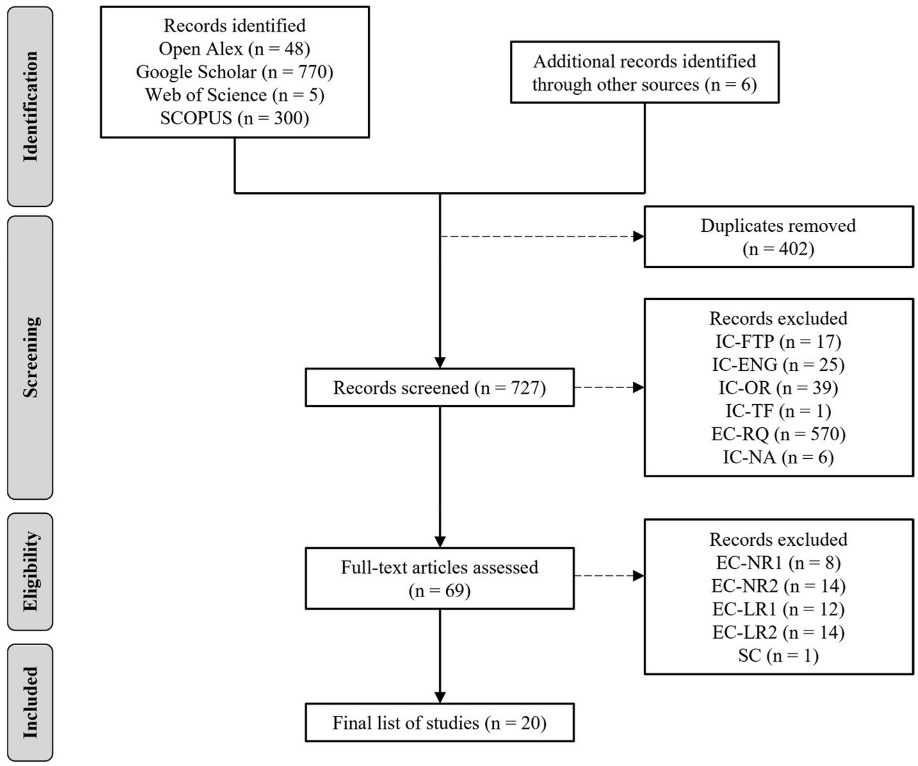

Fig. 1. OoSR flow diagram for synthesis of review studies.

aspects of SM practices (Campos and Simon, 2019; Hami et al., 2019; Roda et al., 2021; Saihi et al., 2023a; Sari et al., 2015; Sénéchal, 2018) from which we develop questionnaire-based survey items. Before constructing the items, contemporary surveys within the sustainable maintenance domain were reviewed. However, as a part of our in-depth analysis built on an evidence-based approach, only a few questionnaire-based surveys were found (see (Duque and El-Thalji, n.d.; Macchi and Fumagalli, 2013; Mehairjan et al., 2016; Saihi et al., 2022a; Schuh et al., 2010)). Still, there was no information about the role and impact of the aforementioned factors on sustainability. Specifically, only one study investigating maintenance maturity and sustainability models for manufacturing systems was identified (Franciosi et al., 2023), in which authors also suggest the lack of surveys. Even so, the model proposed by Franciosi et al. (2023) consist of a small sample size ($n = 3$) and was investigated on a case-study basis.

The survey proposed here comprises three segments: (1) demographic data, (2) maintenance factors, and (3) sustainable performance measures. The demographic information consists of company size (e.g., Small, Medium, Large), industry sector (e.g., processing industry; mining and quarrying), sector categories (e.g., production of plastic packaging, production of tyres, production of motor vehicle parts), and personnel responsible for filling out the survey. The items comprised nominal and ordinal data. The nominal items were coded as binary data – *Have you implemented ISO 9001 and associated procedures for your maintenance processes? Does your company manage waste (disposal and recycling) within maintenance practices? Does your company use renewable energy sources as a part of maintenance practices?* The ordinal variables are constructed as the following items: *How would you describe the maintenance technology level of your company*? *What is the digitalization level applied within your maintenance function*? *To what extent does your company care for environmental protection in industrial maintenance practice?* A 5-point ordinal scale (1-low level to 5-high level) was used for the first two items, and a 5-point ordinal scale (1-does do not consider to 5-considers to a large extent) was used for the last item. Finally, a design of sustainability maintenance performance metric was challenging to deliver, namely because there are no uniformly accepted SMPIs (Sustainable Maintenance Performance Indicators) (Franciosi et al., 2020; Saihi et al., 2022b; Sari et al., 2015; Sénéchal, 2018) for assessing maintenance performance. Therefore, the item was first constructed as a multiple-choice question based on the reported indicators in the literature. After completion, it was subjected to coding.

2.2.2. *Coding of Maintenance Sustainable Responsibility item*

Delphi meetings were conducted in person and online to code the item. The item was coded as ordinal, and an MSR (Maintenance Sustainable Responsibility) was conceptualised as a measurement scale to assess the level of sustainability considered by maintenance decision-makers. The scale was proposed with the following Levels: MSR-L1 – Basic Sustainable Responsibility; MSR-L2 – Basic Sustainable Responsibility; MSR-L3 – Moderate Sustainable Responsibility; MSR-L4 – High Sustainable Responsibility; and MSR-L5, defined as Comprehensive Sustainable Responsibility. All three authors participated in assessing the reliability of the scale. Cohen's kappa and Krippendorff's α are used to assess the interrater agreement of coders. In the first round,

Table 1
Interrater agreement of coders.

Delphi	Coding	Test statistic	SE	95% CI_{Lower}	95% CI_{Upper}
R1	OM-KR[b]	0.916 [a]	0.068	0.740	1.000
R1	OM-NB[b]	0.874 [a]	0.042	0.876	1.000
R1	KR-NB[b]	0.916 [a]	0.057	0.804	1.000
R1	AVG_Cohen	0.916	0.055	0.806	1.000
R1	AVG_Krippendorff	0.916	0.048	0.817	1.000
R2	AVG_Cohen	1.000	0.000	1.000	1.000
R2	AVG_Krippendorff	1.000	0.000	1.000	1.000

NOTE.
AVG = Average Cohen and Krippendorff. SE = Standard Error; CI = Confidence Interval.
[a] Cohen's alpha.
[b] authors initials.

both Cohen's κ = 0.916 ± 0.055 and Krippendorff's $\alpha = 0.916 \pm 0.048$ (Table 1) offered high but not complete agreement of coders. Thus, to assure the reliability of an item, round 2 was performed with a 100% agreement score.

The coding of MSR levels was performed as follows. The MSR-L1 considers one or more maintenance performance measures, but only in one TBL dimension, ignoring all others (e.g., ENV = energy consumption and/or CO_2 emissions, without considering any economic (e.g., maintenance costs) and social (e.g., employee satisfaction)). The MSR-L2 explains where a company considers at least one item in two of three TBL dimensions. For instance, it measures environmental (e.g., energy consumption) and social (e.g., health and safety) but ignores the economic dimension. The MSR-L3 explains where a company measures at least one item in all three dimensions but considers more than one item in only one dimension. The MSR-L4 suggests high responsibility with a minimum of two or more items in two dimensions. The MSR-L5 explains a fully sustainable, responsible maintenance function that measures at least two or more items in all three sustainability dimensions (e.g., social, environmental, and economic). The coded categories are then used to test the association with proposed items and for factor analysis utilising MCA (Multiple Correspondence Analysis).

2.2.3. Sample size and test statistics

Estimating a priori survey sample size required for test statistic was performed in G*Power (v.3.1.9.7). Given that it was difficult to estimate the required sample size for a non-parametric correlation test (e.g., Spearman, Kendall), Exact family of tests, specifically Bivariate regular model for sample determination was used. Although the bivariate model was more closely aligned with Pearson's statistic, it can still be used to estimate the required sample size for Spearman's rank since both measures often require similar sample sizes and are used interchangeably in cases of normality violation. Hence, given that both Spearman's ρ and Kendall's τ-b are used as non-parametric correlation tests, we considered Kendall's τ more appropriate measure for evaluating the association between two ordinal variables mainly because the test provides both the strength and direction of association between the ranks of ordinal data. The total required sample size of $n = 29$ was determined (r critical = 0.3673, actual Power = 0.814), given the parameters of obtaining at least $\rho = 0.5$ correlation (effect), with $\alpha = 0.05$, and Power $(1\text{-}\beta) = 0.8$ for a two-tailed test. Note that there is currently no methodological study for computing the g prior. Thus, the minimum required sample size was determined per the frequentists approach.

For testing the association between categorical variables, the contingency model with inferences from Bayes Factors (Gûnel and Dickey, 1974) was used. In cases of comparison using bivariate ordinal data, Kendall's τ-b statistic per Bayes Factors (Zhang et al., 2023) was reported. For reporting the strength of evidence of competing hypotheses, the following metrics were used: $BF_{10} = 1$–3 (anecdotal and weak evidence), $BF_{10} = 3$–10 (moderate evidence), $BF_{10} = 10$–30 (strong evidence), $BF_{10} = 30$–100 (very strong), and $BF_{10} > 100$ (extreme) evidence in favour of the alternative over the null hypothesis. Thus, for an in-depth analytical description of performing Bayes inferential analysis, the reader is referred to (Kelter, 2020; van Doorn et al., 2021; Zhang et al., 2023).

2.2.4. Preliminary survey data

The survey was disseminated in September 2023, and the final questionnaire was collected in June 2024. The survey was emailed to 347 companies with a 32% response rate. Immediately after obtaining data, the first question about whether the company outsources maintenance activities eliminated 44 respondents. A sample of $n = 67$ companies remained. However, 15 respondents were excluded due to missing and incomplete data. A final list of $n = 52$ (14.98%) companies was identified as valid. Descriptives (Fig. 2a) show that most companies were within the process (82%) industry, where primary activities include – manufacturing parts of vehicles (12%) and production of plastic packaging (10%), followed by others. Company sizes comprised of large (42%), followed by medium (33%), small (17%) and micro (8%). The personnel responsible for filling out the survey are mostly Directors (19.6%), followed by Quality Managers (15.7%), Head of Maintenance (9.8%) and Head of Production (9.8%). The data (Fig. 2b) show that 75% of companies have an ISO 9001 system, 18% do not carry out waste disposal practices, and only 27% use renewable resources.

As for the survey items (Fig. 2c) 31% of companies care for environmental protection and sustainability substantially. The technology level is skewed slightly towards higher levels. Two companies reported that their maintenance activities are manually performed without software solutions, and two reported some technological and software solutions. As for the MSR levels, most companies fall under MSR-L3 (27%), followed by MSR-L4 (21%) and MSR-L5 (21%). Overall, the coded item suggests a balanced approach and normal probability distribution. In answering the question about the role of digitalization, most companies report none to the minor (31%), followed by low (25%), medium (23%), and high (21%). It is important to note that none of the companies reported level 5 ("*Fully digitalized – Complete infrastructure enables digital exchange of data …*"). For details about the survey, see Appendix 1.

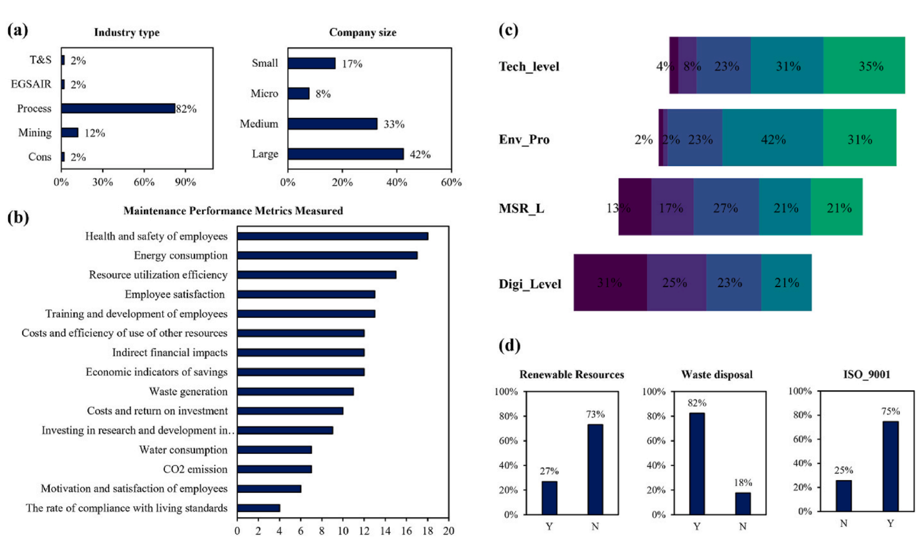

Fig. 2. Descriptive results of (a) demographics, (b) indicators, (c) investigated survey items, and (d) organisational data.

3. Umbrella review results

3.1. Descriptive summary

From the preliminary analysis regarding the corpus of review studies on SM (Fig. 3), the overall evidence suggests that Organisational and Management Barriers (13.39%) were mainly reported items affecting the adoption of SM, followed by Technological Barriers (12.5%) and Technological Enablers (12.5%). A separate analysis of the barriers/challenges domain suggests that Organisation and Management (19.9%), followed by Technology (18.5%) and Knowledge and Skills (15.2%) items are mainly reported in this domain (Fig. 3). The analysis of the enabler/facilitator domain suggests that Technology (38.4%), followed by Knowledge and Skills (17.8%) and Organisation and Management (16.4%) items, are mostly reported enablers aiding the adoption of SM. Lastly, the overall focus of existing reviews seems more situated and focused on barriers/challenges (67.41%, 151/224) domain rather than enablers/facilitators (32.59%, 73/224).

In response to the RQ1, 151 items (barriers and challenges) were identified from retrieved reviews. The items were used as count data and stratified into eight categories – four categories of barriers and four categories of challenges (Fig. 4). The most commonly reported barriers were Organisational and Management Barriers (19.9%), while Strategic and Planning Challenges (13.9%) and Technical and Operational Challenges (11.9%) account for most of the challenges. Considering the specifics of the RQ1, Hallioui et al. (2023) and Karuppiah et al. (2021) explicitly addressed the barriers affecting the adoption of SM, both of which advocate that OMB acts as the main barrier to the adoption of SM, followed by KSB and TB. Interestingly, among all of the prior work, Karuppiah et al. (2021) identify FEB items (e.g., shortage of financial resources, high cost of implementing SM, high cost of sustaining SM measures), second to OMB, as main financial constraints causing slow adoption of SM by manufacturing entities.

Regarding the RQ2, the items that are mostly reported (Fig. 5) fall under Technological Enablers (38.4%), followed by Knowledge and Skill Enablers (17.8%) and Organisational and Management Enablers (16.4%). The Technical and Operational (9.6%), followed by Strategic and Planning (5.5%) and Cultural and Behavioral (5.5%) are the most reported facilitators. Although reviews do not specifically delve into enablers and facilitators, the work of Franciosi et al. (2018), Jasiulewicz-Kaczmarek et al. (2020) and Ramiya and Suresh (2021; Suresh and Dharunanand, 2023), primarily argued that technology is a key enabler for aiding the adoption of SM practice.

3.2. Network analysis of barriers and challenges

The edge evidence probability plot (Fig. 6a) shows that only the relationship between OMB and CBC (r = 0.316, BF10 = 4.882) and between TB and FEB (r = 0.298, BF_{10} = 4.556) suggest moderate evidence (BF_{10} > 3). The plots (Fig. 6b) highlight network uncertainty obtained via posterior structure probability and complexity plot. The posterior structure probability indicates the probabilities of visited structures, sorted from the most to the least probable, where each dot in the plot indicates one complete structure. This, in turn, implies that the more structures there are, the less confident the true plot structure is. Given that one structure separates from the rest of the structure (Fig. 6b top) one can be sure about the true structure. Ultimately, this allows to identify dominant dependencies where high posterior probability (close to 1) is strongly supported by the data, while low posterior probability (close to 0) is unlikely to be a true dependency. Observing the plot, this suggest simple underlying structure, small number of dependent edges given the existence of only few high-probability edges. The posterior complexity plot (Fig. 6b bottom) indicates the true number of present edges in a network, whereas the posterior probabilities of all structures with the same complexity are aggregated into one plot. If the posterior distribution is centred and narrow around a particular number of edges (which was the case), this suggests the model is confident about its structural complexity. The resulting network shows 0.607 sparsity (11/28 non-zero edges). The centrality plot (Fig. 6c) show shared connections between multiple nodes. The connectedness quantified by strength centrality suggests that OMB (0.397), CBC (0.373), and FEB (0.321) have the highest impact on the network structure. Looking at the

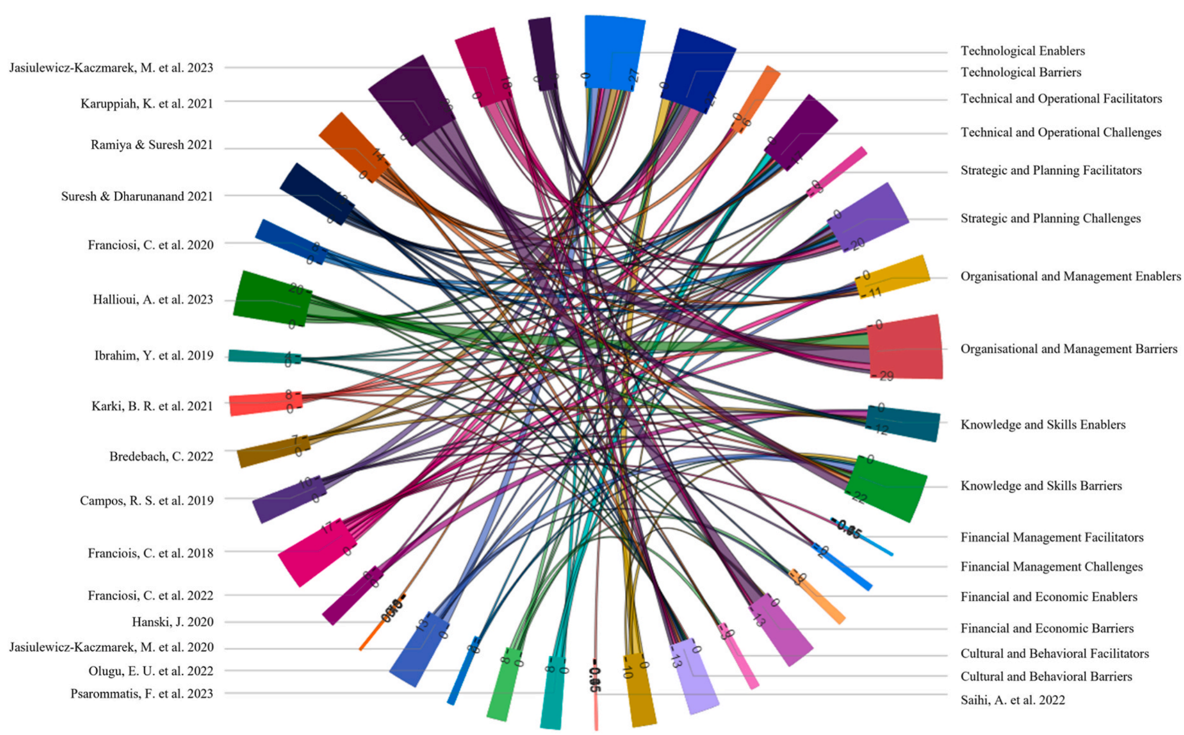

Fig. 3. The chord diagram describes systematic reviews (first author and year) and content data comprising barriers/challenges and enablers/facilitators domain (items).

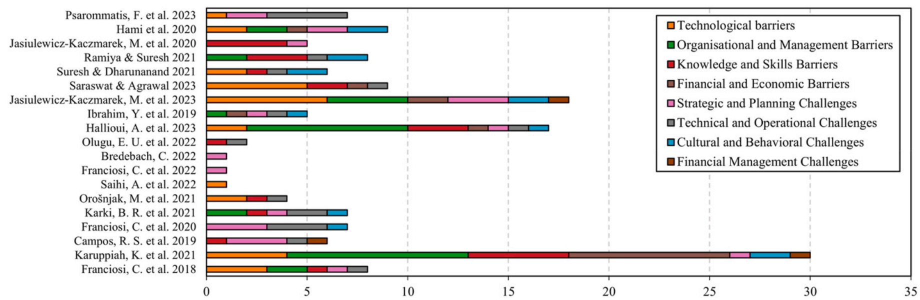

Fig. 4. Barriers and Challenges reported in previous studies.

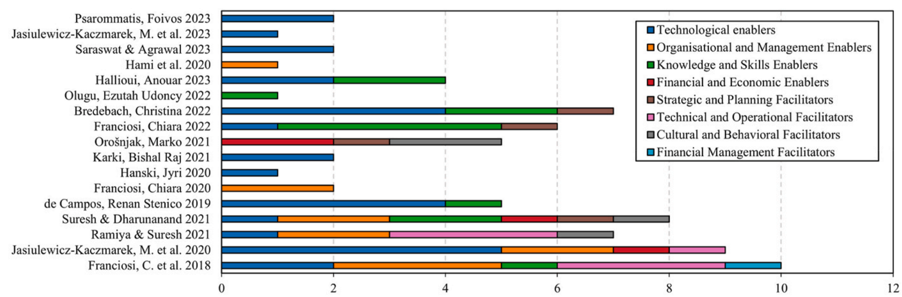

Fig. 5. Enablers and Facilitators reported in previous studies.

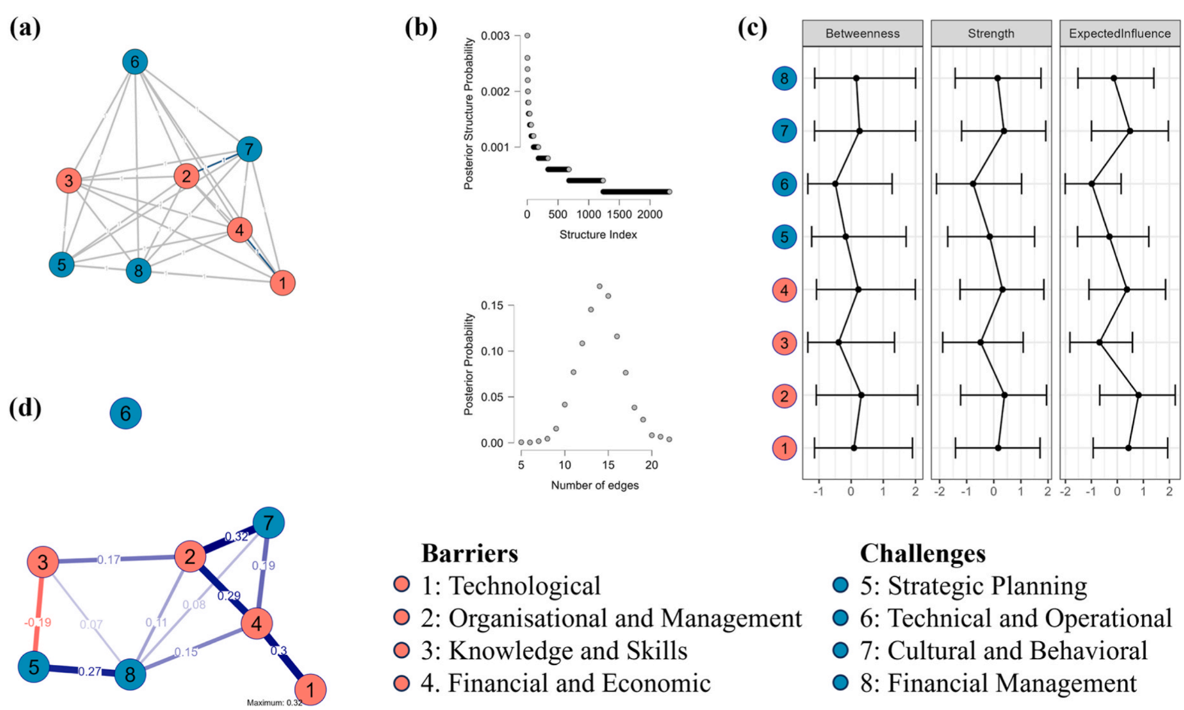

Fig. 6. The BNA-GCGM analysis of barriers and challenges is reported through: (**a**) Edge evidence plot such that grey edges indicate the absence of evidence and blue edges indicate presence of evidence (e.g., conditional dependence). (**b**) Posterior structure plot (top) – focuses on the specific dependencies (edges) between variables and their probabilities. The *y*-axis represents the probability that a particular network structure is true underlying dependency structure, given the data. The *x*-axis represent different possible graphical structures sampled from the posterior distribution. Each (structure) index represent a unique network structure encountered via Bayesian inference. Posterior complexity plot (bottom) indicates the overall complexity of the model, e.g., number of edges. The *x*-axis represent number of edges in the graph, while *y*-axis represent posterior probability of having a given number of edges. (**c**) Centrality measures of betweenness, strength and expected influence (note that credible intervals are determined by calculating centrality indices for each sample of posterior distribution); and (**d**) BNA network plot where edges indicate strength of partial association between two nodes. The line thickness and saturation represent the strength of the association, while blue and red indicate positive and negative association, respectively.

expected influence, which considers both the direction and sign of the relationship, this indicates that OMB (0.815), CBC (0.486), and FEB (0.371) have the highest expected influence.

The network (Fig. 6d) suggests the existence of conditional dependencies between nodes. Although the network shows multiple non-zero edges, the evidence suggests that only OMB-CBC and TB-FEB have true conditional dependencies ($BF_{10} > 3$). At closer examination (Table 2), the association between OMB-FEB ($r = 0.286$, $BF_{10} = 2.704$) and SPC-FMC ($r = 0.271$, $BF_{10} = 2.846$) exists, however below threshold for inclusion ($BF_{10} > 3$). Thus, the discussion focuses on understanding the relationship, particularly between TB-FEB (Hallioui et al., 2023; Hami et al., 2020; Jasiulewicz-Kaczmarek et al., 2023; Karuppiah et al., 2021; Saraswat and Agrawal, 2023) and OMB-CBC (Hallioui et al., 2023; Hami et al., 2019; Ibrahim et al., 2019; Jasiulewicz-Kaczmarek et al., 2023; Karki and Porras, 2021; Karuppiah et al., 2021; Ramiya and Suresh, 2021).

3.3. Network analysis of enablers and facilitators

The edge evidence plot of enablers and facilitators (Fig. 7a) shows that only the relationship between OME and TOF ($r = 0.339$, $BF_{10} = 3.167$) and between KSE and SPF ($r = 0.300$, $BF_{10} = 4.882$) comprise moderate evidence ($BF_{10} > 3$). The posterior structure probability (Fig. 7b top) implies certainty of the network structure. The posterior complexity (Fig. 7b bottom) shows the number of present edges according to the proposed criteria, which results in 0.464 sparsity (15/29 non-zero edges). Although most studies stress TE as a prime factor for aiding in the adoption of SM, surprisingly, there is an absence of the relationship with other items reported, indicating zero edges between nodes. This can be attributed to the fact that most authors denote the importance of TE without mentioning the association with other factors. The centrality indices (Fig. 7c) report a similar count of connections as per betweenness, while SPF may act as a mediator. The strength centrality suggests that SPF have the highest absolute weight (0.623), suggesting high influence. However, as per expected influence, the OME (0.842) has the highest positive impact on the network structure, followed by SPF (0.577), while CBF (−0.663) and FMF (−0.454) are negative influential nodes. However, given that the network suggests anecdotal evidence in cases of association with the mentioned negative influential nodes, discussing the impact on the network structure of these two nodes should be performed cautiously.

The network plot (Fig. 7d) suggests the existence of an association between nodes (e.g., OME-FMF, TOF-FMF, FEE-CBF); however, moderate evidence (Table 3) was reported between OME-TOF ($BF_{10} = 3.167$) and KSE-SPF ($BF_{10} = 4.882$). Therefore, the discussion is focused primarily on understanding conditional dependencies of stratified items (i.e., OME and TOF) reported in (Franciosi et al., 2018; Jasiulewicz-Kaczmarek et al., 2020; Ramiya and Suresh, 2021) and items of KSE and SPF reported in (Bredebach, 2022; Franciosi et al., 2022; Suresh and Dharunanand, 2023).

4. Survey results

4.1. Bayes inferential statistics

The results (Table 4) show the existence of a positive correlation of tested variables. The correlation is the highest between digitalization and technology level ($\tau = 0.546$, $BF_{10} = 1453000$). However, although it was expected that with higher levels of technology, the digitalization level tends to rise, there was a case where a company reported technology level 5 while the digitalization level was 1. The companies implementing the ISO 9001 system lack significant differences in the tested variables. The only moderate association was noticed with maintenance (management) waste disposal practices ($BF_{10} = 4.873$). There was no evidence suggesting a difference of Env_Pro per Waste_Disp ($U = 95.0$, $BF_{10} = 0.781$). Similar results were reported when Env_Pro was compared per Renew_Res ($U = 200.0$, $BF_{10} = 0.495$). Lastly, very strong evidence of a correlation between Env_Pro and MSR_Levels ($\tau = 0.326$, $BF_{10} = 52.891$) was reported. This suggests that companies considering environmental protection track the sustainability performances of their maintenance activities.

In the cases of Waste_Disp and Renew_Res, there was no evidence ($BF_{10} < 3$) explaining the difference in levels of technology. There was extreme evidence in favour of the existence of a correlation between Tech_Lvl and Env_Pro ($\tau = 0.527$, $BF_{10} = 490669$) and MSR_Level ($\tau = 0.546$, $BF_{10} = 12454.63$). Similar results were obtained from testing the correlation between Digitalization_Level with both Env_Pro ($\tau = 0.328$, $BF_{10} = 57.534$) and MSR_Level ($\tau = 0.405$, $BF_{10} > 1166.842$). This suggests that MSR_Level tends to increase with the rise of technology and digitalization levels. Lastly, comparing the differences in binary outcomes (i.e., Waste_Disp and Renew_Res), the levels of technology and digitalization show anecdotal evidence ($BF_{10} < 3$).

Prior and posterior testing was performed to understand better the statistical inferences obtained in Bayesian hypothesis testing, including sequential analysis and robustness check of Bayes Factors. The prior-posterior analysis (Median = 0.496 with 95%CI[0.318, 0.672]) of Tech_Lvl and Env_Pro (Fig. 8a-left) suggests extreme data in favour of the alternative by changes in posterior odds ($BF_{10} = 491000$). However, although the prior was not defined, there might be other reasonable choices for selecting prior. That is why additional analysis was performed to ensure the validity of conclusions using a robustness check (Fig. 8a-middle). Now, the Bayes Factor changes to different β prior can be observed. Note that the Bayes Factor gets more significant when the β prior increases. Given the extreme evidence case, where evidence for H_1 is well above $BF > 100$, the results are pretty robust. Thus, changes in prior width would not affect the outcome given the evidence. The sequential analysis (Fig. 8a-right) provides an understanding of the changes in the Bayes Factor (y-axis) and observations (x-axis). This part of the analysis aims to track changes in the Bayes Factor after every sample (observation) point. The results suggest the development of the Bayes Factor, where in cases of digitalization, there is slight variation. However, the evidence is still considered strong with the increase in observations ($BF_{10} > 10$).

Considering the analysis Tech_Lvl and Env_Pro (Fig. 8b-left), the results suggest extreme evidence in favour of the alternative hypothesis

Table 2
The weight matrix (below the main diagonal) and BF_{10} (above the main diagonal).

Variable	TB	OMB	KSB	FEB	SPC	TOC	CBC	FMC
Technological Barriers	–	0.538	0.639	**4.556**	0.667	0.852	0.961	0.961
Organisational and Management Barriers	0.000	–	1.500	2.704	0.587	0.639	**4.882**	1.439
Knowledge and Skills Barriers	0.000	0.170	–	0.754	1.857	0.515	0.667	1.222
Financial and Economic Barriers	0.298	0.286	0.000	–	0.695	0.818	1.632	1.500
Strategic and Planning Challenges	0.000	0.000	−0.189	0.000	–	0.515	0.695	2.846
Technical and Operational Challenges	0.000	0.000	0.000	0.000	0.000	–	0.471	0.695
Cultural and Behavioural Challenges	0.000	0.316	0.000	0.185	0.000	0.000	–	1.381
Financial Management Challenges	0.000	0.113	0.070	0.152	0.271	0.000	0.084	–

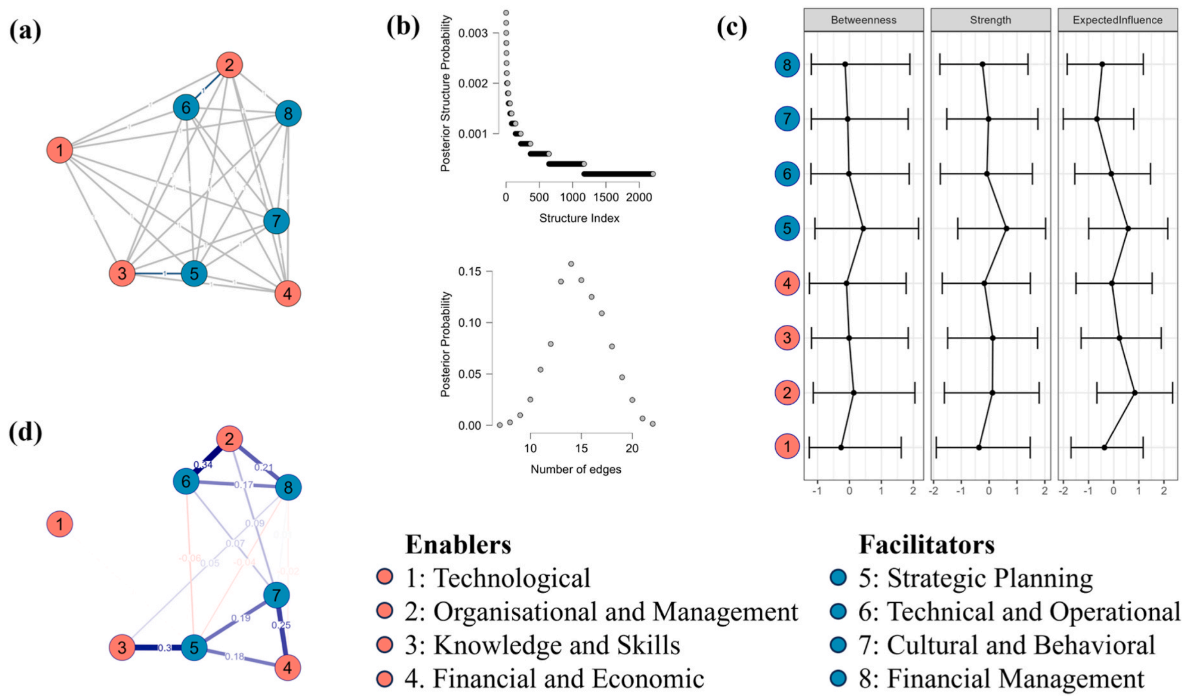

Fig. 7. The BNA-GCGM analysis of enablers and facilitators is reported through: (**a**) Edge evidence plot such that grey edges indicate the absence of evidence and blue edges indicate presence of evidence (e.g., conditional dependence). (**b**) Posterior structure plot (top) – focuses on the specific dependencies (edges) between variables and their probabilities. The *y*-axis represents the probability that a particular network structure is true underlying dependency structure, given the data. The *x*-axis represent different possible graphical structures sampled from the posterior distribution. Each (structure) index represent a unique network structure encountered via Bayesian inference. Posterior complexity plot (bottom) indicates the overall complexity of the model, e.g., number of edges. The *x*-axis represent number of edges in the graph, while *y*-axis represent posterior probability of having a given number of edges. (**c**) Centrality measures of betweenness, strength and expected influence (note that credible intervals are determined by calculating centrality indices for each sample of posterior distribution); and (**d**) BNA network plot where edges indicate strength of partial association between two nodes. The line thickness and saturation represent the strength of the association, while blue and red indicate positive and negative association, respectively.

Table 3
The weight matrix (below the main diagonal) and BF_{10} (above the main diagonal).

Variable	TE	OME	KSE	FEE	SPF	TOF	CBF	FMF
Technological Enablers	–	0.515	0.852	0.754	1.041	0.887	0.515	0.667
Organisational and Management Enablers	0.000	–	0.786	0.852	0.923	**3.167**	1.222	2.030
Knowledge and Skills Enablers	0.000	0.000	–	0.724	**4.882**	0.852	1.000	1.326
Financial and Economic Enablers	0.000	0.000	0.000	–	1.778	0.786	1.941	1.381
Strategic and Planning Facilitators	−0.001	0.000	0.300	0.175	–	1.041	1.941	1.326
Technical and Operational Facilitators	0.000	0.339	0.000	0.000	−0.055	–	1.041	1.564
Cultural and Behavioural Facilitators	0.000	0.088	0.000	0.249	0.188	0.074	–	1.222
Financial Management Facilitators	0.000	0.210	0.052	−0.025	−0.040	0.169	0.005	–

(Median = 0.430 with 95%CI[0.252, 0.608], $BF_{10} = 12500$), with little to no changes in defined user prior (Fig. 8b-middle). Also, the sequential analysis (Fig. 8b-right) shows the development of the Bayes Factor with the rise of sample size. Ultimately, in both cases, it was confirmed that extreme evidence showed a positive correlation between Tech_Lvl and Env_Pro and Tech_Lvl and coded MSR levels.

Although slightly lower, there is still strong evidence in favour of the alternative hypothesis (Fig. 9a-left) that there exists positive correlation between Digitalization_Level and Env_Pro (Median = 0.310 with 95%CI [0.131, 0.488], $BF_{10} = 57.53$). The robustness (Fig. 9a-middle) shows slightly lower results when comparing β priors. Still, the evidence was within the range of very strong evidence ($BF_{10} > 30$). The sequential analysis (Fig. 9a-right) confirms the development of the Bayes Factor. With slight variations in the posterior, the evidence was considered strong with the rise in the number of observations ($BF_{10} > 10$).

Lastly, comparing the competing hypotheses, whether there exists a positive correlation (BF_{10}) or not (BF_{01}), the results suggest extreme evidence (Fig. 9b-left) in favour of the alternative hypothesis (Median = 0.382 with 95%CI[0.204, 0.560], $BF_{10} = 1170$). The robustness (Fig. 9b-middle) shows constant value comparing both maximum and user β priors with evidence mainly in the range of extreme evidence ($BF_{10} = 1000$). The sequential results (Fig. 9b-right) confirms the development of the Bayes Factor; however, there was a sudden drop after the 25th sampling point and, again, a slight rise in BF_{10}. Despite the drop in BF_{10} given the observations, there was still extreme evidence of a positive correlation between Digitalization_Level and MSR_Level ($BF_{10} > 100$).

In sum, it was confirmed that substantial evidence exists favouring the positive relationship between the rise of digitalization (and technology) levels and sustainability aspects, i.e., the rise in MSR levels. Lastly, simple hypotheses testing was extended to multivariate data visualisation using the MCA method. The idea was to provide a general understanding of the interaction and association between investigated items using factor plots. (Note: Although the Bayesian tests statistics are used, frequentist statistics are also reported in Appendix 2.)

Table 4
Summary of Bayes test statistics reported per Kendall's τ-b with Bayes Factor.

Test Pairs		Statistic	Test result	BF_{10}	Lower 95% CI	Upper 95% CI
ISO_9001	Tech_Lvl	MWU	210.500	0.392	−0.771	0.384
ISO_9001	Env_Pro	MWU	225.000	0.346	−0.687	0.444
ISO_9001	Waste_Disp	BFCT	–	4.873	–	–
ISO_9001	Renew_Res	BFCT	–	0.909	–	–
ISO_9001	Digitalization_Level	MWU	245.000	0.319	−0.594	0.539
ISO_9001	MSR_Level	MWU	170.000	0.662	−0.958	0.233
Env_Pro	Waste_Disp	MWU	95.000	0.781	−1.044	0.185
Env_Pro	Renew_Res	MWU	200.000	0.495	−0.855	0.291
Env_Pro	MSR_Level	Kendall	0.326**	52.891	0.129	0.486
Waste_Disp	Renew_Res	BFCT	–	0.449	–	–
Waste_Disp	MSR_Level	MWU	117.000	0.539	−1.053	0.194
Renew_Res	MSR_Level	MWU	231.000	0.378	−0.871	0.281
Tech_Lvl	Env_Pro	Kendall	0.527***	490669	0.318	0.672
Tech_Lvl	Digitalization_Level	Kendall	0.546***	1453000	0.335	0.689
Tech_Lvl	MSR_Level	Kendall	0.456***	12454.63	0.252	0.608
Tech_Lvl	Waste_Disp	MWU	124.500	0.567	−0.870	0.316
Tech_Lvl	Renew_Res	MWU	220.00	0.423	−0.818	0.343
Digitalization_Level	Env_Pro	Kendall	0.328**	57.534	0.131	0.488
Digitalization_Level	MSR_Level	Kendall	0.405***	1166.842	0.204	0.560
Digitalization_Level	Waste_Disp	MWU	194.500	0.332	−0.597	0.573
Digitalization_Level	Renew_Res	MWU	228.000	0.374	−0.734	0.380

NOTE:*$BF_{10} > 10$; **$BF_{10} > 30$; ***$BF_{10} > 100$; MWU = Mann-Whitney *U* test statistic; BFCT = Bayes Factor for Contingency Tables (Gûnel and Dickey, 1974); and CI = Credible Intervals of Bayes Factors.

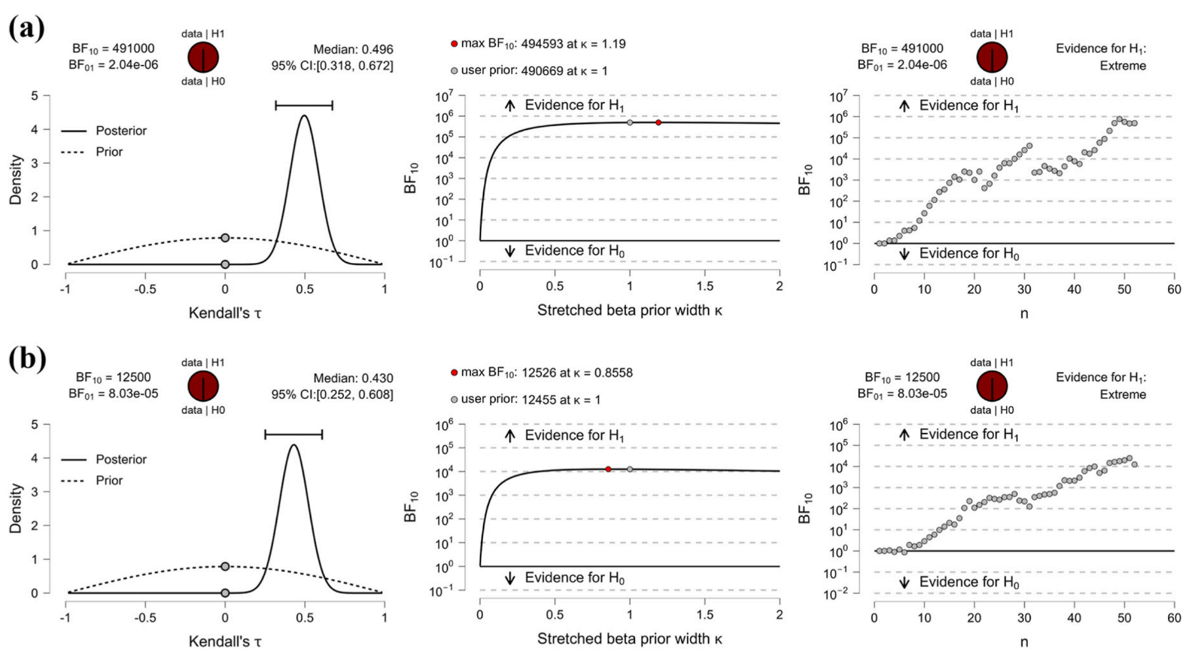

Fig. 8. Bayes Pairwise Plots representing testing between (a) Tech_Lvl and Env_Pro variables and (b) Tech_Lvl and MSR_Level. Both analyses comprise prior and posterior (estimation and testing info), Bayes factor robustness check, and sequential analysis of each sample *n* taken, from left to right, respectively.

4.2. Multiple Correspondence Analysis

The MCA (Multiple Correspondence Analysis) is performed on the survey data using the χ^2 distance metric. The analysis is performed in *Rstudio* (v.2024.04.2764) using *FactoMineR* (v2.11) package. Specifically, the analysis relies on the *Factoshiny* developed by Husson et al. (2017). The environmental protection, digitalization, and technology levels are coded as variables into binary data – "Low" (levels ≤ 3) and "High" (levels >3). This reduced the complexity and noise in the MCA and provided a better understanding of the differences between items. The MSR_Level was not coded into a binary variable but was left as defined.

After coding the variables, the MCA starts by projecting categories in the first two components (C1 and C2). This shows the separation of categories (Fig. 10a). Next, the scree plot (Fig. 10b) shows the amount of inertia (λ) shared within each principal component. The common practice is to perform the analysis using the first two components. There are multiple approaches to determine the amount of information an analyst wants to retain. Like every other principal component method, the idea is to preserve $\lambda > 70\%$ of inertia. However, this is not always the practice in MCA (Orošnjak and Šević, 2023) since the variability of qualitative data is usually quite high, in this case, the analysis using C1-C2 shows $\lambda = 39.07\%$. Nevertheless, five dimensions are used, arriving at $\lambda = 70.77\%$. Still, no additional information was obtained other than what was already observed by the first two components.

The MCA biplot (Fig. 10c) explains the spread between the point cloud of observations and class categories. It is important to check whether there is an equal spread of observations and to avoid potential

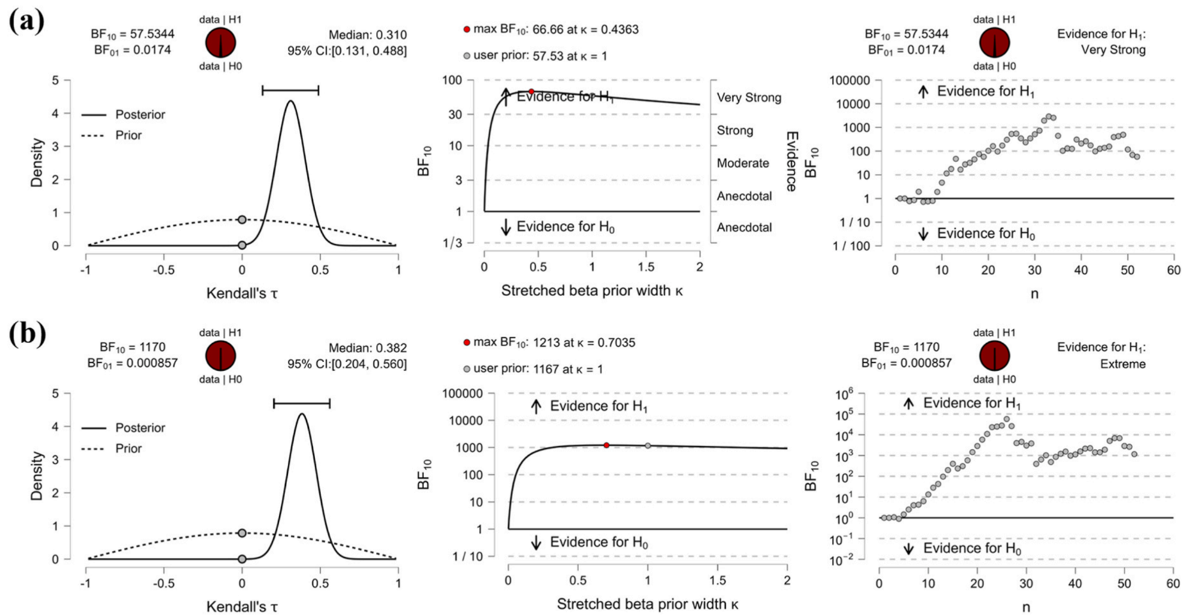

Fig. 9. Bayes Pairwise Plots of (a) Digitalization_Level and Env_Pro and (b) Digitalization_Level and MSR_Level. Both analyses comprise prior and posterior distribution (estimation and testing info), Bayes factor robustness check, and sequential analysis from left to right.

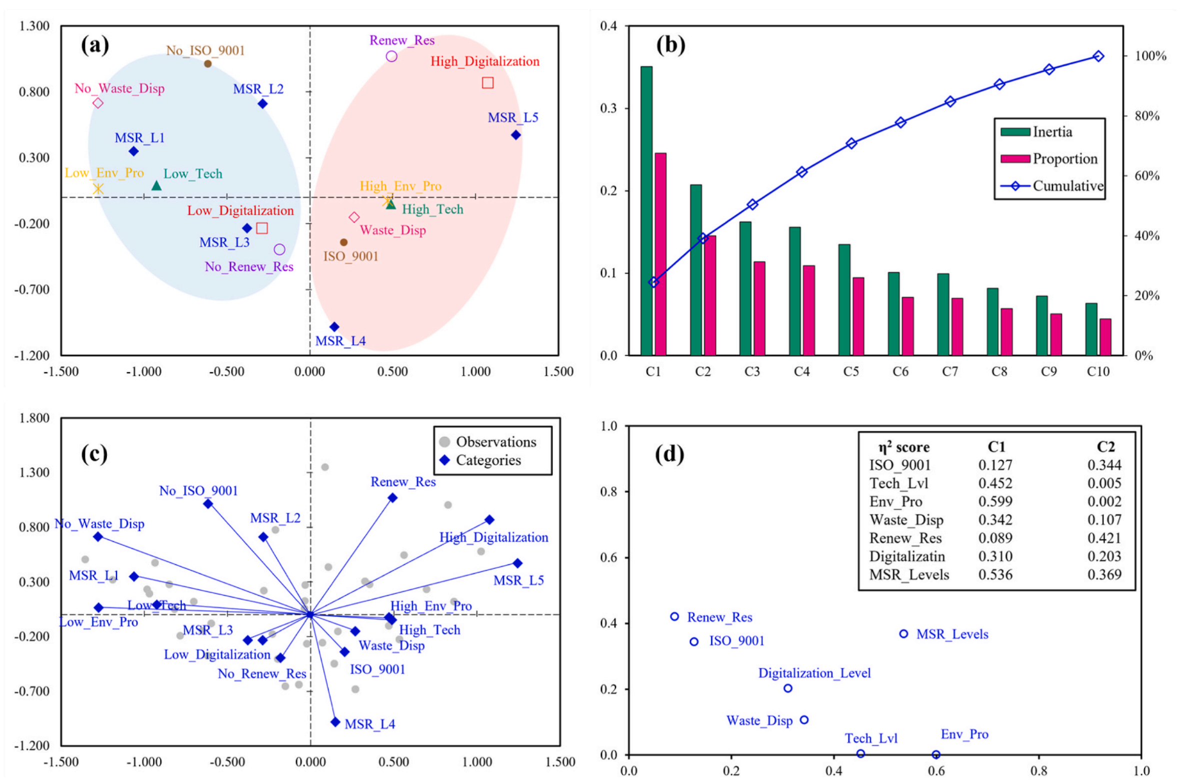

Fig. 10. MCA factor analysis of individuals and items using the first two components (C1-C2). The analysis shows (a) an MCA factor map of categories, (b) a Scree plot of individual and cumulative principal components inertia, (c) an MCA biplot showing observations and categories (items), (d) a correlation ratio of items to principal components.

patterns that exist in observational data (e.g., the Guttman effect (Manté et al., 2022)). Such anomalies are absent in this case, and there is an equal spread of observations. Lastly, an indicator function is introduced that is represented as the correlation ratio η^2 between axis coordinates (components) and each variable (Fig. 10c). The η^2 score usually denotes the percentage of variability the qualitative variable describes, ranging from 0 to 1.

Here, the correlation ratio η^2(C1, Env_Pro) = 0.599 suggests a good separation of points between the categories. If we then observe the categories of "Low_Env_Pro" and "High_Env_Pro" at Fig. 10 we see that low environmental protection is far left, while high environmental protection is on the right side of the C1 axis. In contrast, interpretation by the C2 axis does not offer much to the separation since η^2(C2, Env_Pro) = 0.002. Hence, we can conclude that the value of η^2 suggests how much each axis can be used to interpret the separability of categories. That is why Digitalization_Level(s) and MSR_Level(s) can be used to interpret the association by the first two principal components since the results reasonably describe both components. Namely, correlation ratios η^2 (C1, MSR_Levels) = 0.536 and η^2 (C2, MSR_Levels) = 0.369 somewhat contribute to separating and understanding class categories. The reason estimating η^2 is important is because of components' eigenvalues, which are a representation of means of η^2. This validates MCA dimensions (components) as synthetic (or latent) variables (Husson et al., 2017). In a way, the components are quantitative variables that summarise qualitative variables. This, in turn, suggests that C1 explains the main variables associated with sustainable maintenance aspects—technology, digitalization, environmental protection, and sustainable responsibility—while C2 places more emphasis on explaining organisational-type data—waste management, renewable resources, and quality management practices.

5. Discussion

5.1. Barriers and challenges

The current literature on SM suggests that OMB, followed by TB and KSB, are mostly reported barriers hindering the adoption of SM (Hami et al., 2020; Karki and Porras, 2021). However, the setback is that most prior work relies on theoretical and opinion-based data and lacks effort to support such claims. This study, however, went a step further and analysed the associations and the role of these items. The Bayesian Gaussian Copula Graphical Model was considered appropriate since it can deal with count data. Expected influence was mainly used to understand the impact of each node (item) on the network structure. In contrast, an edge evidence plot describes the significance of conditional (in)dependencies of each particular item and their effect on the network structure, i.e., the adoption of SM.

The barrier/challenge items analysis revealed significant conditional dependencies between organisational and management barriers and cultural and behavioural challenges (BF_{10} = 4.88). This suggests that organisational and management issues and cultural and behavioural challenges are not isolated issues but instead rooted in a broader cultural and behavioural context. For instance, there is a lack of attention to environmental, social and safety aspects (Hami et al., 2020; Ibrahim et al., 2019) and lack of effective measures to reduce environmental impact, including waste minimisation and recycling practices, can be directly related to the top management's commitment to resolving such issues (Ramiya and Suresh, 2021). Similarly, resistance to switching to green practices can be associated with unawareness of maintenance importance and hesitation in strengthening maintenance function by top management (Karuppiah et al., 2021); lack of the right mindset for moving forward (Karki and Porras, 2021); lack of motivation due to poor organisational culture, inadequate leadership, disregarding values and beliefs of employees (Hallioui et al., 2023) leading to poor overall company and social culture (Jasiulewicz-Kaczmarek et al., 2023)This suggests that the lack of supportive organisational culture, motivation, and leadership resists change, ultimately failing to achieve the objective of adopting SM practices.

The network analysis also reveals moderate evidence (BF = 4.56) suggesting conditional dependence between technological and financial barriers. The impact of national labour policies and technological investments (Jasiulewicz-Kaczmarek et al., 2023) (e.g., wage regulations, labour laws, employment taxes) may influence the cost of human capital. This might limit the available budget for investing in advanced technologies and upgrading physical assets (Hallioui et al., 2023) further exacerbating technological barriers. In industries where labour capital is considered a significant cost factor, this may delay or even avoid adopting new technologies, especially if these require upfront investments. Some even argue that sustaining such advanced maintenance practices is often too high – requiring sophisticated technology, skilled personnel and continuous investments to remain effective – creating an additional burden that deters companies from fully committing to the adoption of SM practices despite their long-term benefits (Karuppiah et al., 2021). Broader economic and market conditions (Jasiulewicz-Kaczmarek et al., 2023) can also affect a company's ability to invest in technology, especially with the recent COVID-19 pandemic that produced market instability, which affected companies' priorities in switching from long-term technological upgrades to short-term financial survival. Similarly, the lack of synchronisation in green technologies across different operational processes stems from financial constraints (Karuppiah et al., 2021). Specifically, with a limited budget, even though the company is willing to shift to SM and adopt green technologies, systems do not communicate or integrate effectively. This lack of synchronisation leads to inefficiencies and increased operational costs, further straining financial resources and hindering the adoption of SM practices.

5.2. Enablers and facilitators

The network analysis of enablers and facilitators suggests that OME and SPF positively influence the network structure. In contrast, TE, FMF, and CBF have the most substantial negative influence on the network structure, meaning that the authors suggest these items act more as isolated factors that aid in adopting SM practices. As for the edge evidence analysis, the OME and TOF (BF_{10} = 3.167) and KSE and SPF (BF_{10} = 4.88) suggest moderate evidence of conditional dependencies.

The interaction between OME and TOF highlights the importance of structured decision-making frameworks in enabling the systematic use of energy indicators (or metrics) (Franciosi et al., 2018), which are crucial for monitoring and improving sustainability performance metrics. The role of maintenance on CE (Circular Economy) and as a lever for reuse and remanufacturing, which aligns with quality-related maintenance work impact on sustainability, also reflects the dependent structure of these two components, as suggested by Franciosi et al. (2018). Top management commitment and support are fundamental in driving the change towards adopting SM practices. This support is symbolic; it involves allocating necessary resources, personnel, and time for upgrading maintenance practice as a strategic priority (Jasiulewicz-Kaczmarek et al., 2020). Rhetorically, Ramiya and Suresh (2021) argue that adopting a lean philosophy (e.g., minimising waste and non-value-adding activities in maintenance) provides a foundation that ensures that maintenance is directly aligned with production goals. In sum, adopting SM will be smoother in organisations where top management is committed, demonstrates the ability to provide necessary resources and aligns maintenance with broader sustainability and production objectives.

The relationship between KSE and SPF points to integrating digital technologies in maintenance operations. Namely, Franciosi et al. (2022) remark the use of digital twins in optimising the energy efficiency of physical assets or systems. Thus, virtual representation allows real-time monitoring, simulation and machine performance optimisation, enabling strategic thinking by simulating different operational scenarios. This also allows the identification of inefficiencies, virtual assistance in vulnerability and risk assessment, and the use of Industry 4.0 tools for the formation of sustainability indicators (Bredebach, 2022). Perhaps most importantly, the use of digital twins aids in the training of operators, ultimately reducing unnecessary material resources and time. Consequently, it seems that digital competencies play a pivotal role, especially in providing training and education programs for increasing physical abilities and employee competencies (Suresh and Dharunanand, 2023).

Based on the secondary evidence from retrieved reviews, it can be inferred that the successful adoption of SM practices heavily relies on organisational commitments and digital technologies. For instance, the availability of real-time use of energy metrics for monitoring and tracking sustainability performance equips top management with insights needed to make strategic decisions that drive actionable results – controlling the production process, allocating necessary resources, and aligning maintenance with production and sustainability goals. Simultaneously, digital technologies enhance operational effectiveness by improving maintenance capabilities to respond to disruptions through remote monitoring, diagnostics, and targeted training. While technology and digitalization may play an indirect here, they significantly moderate and amplify the impact of organisational strategies to improve maintenance operations' sustainability performance.

5.3. Survey findings

The results from the Bayesian analysis suggest several important remarks. Strong to extreme evidence ($BF_{10} > 10$) regarding the correlation between technology, digitalization and sustainability indicates a robust relationship between these variables. The findings align with theoretical expectations that as the technology level increases, the digitalization level tends to follow ($BF_{10} > 100$). However, an anomalous case reporting a high level of technology (5) and a low level of digitalization (1) suggests that the relationship might not be purely linear but somewhat influenced by other organisational factors, such as strategic priorities, resource allocation, or even readiness for digital transformation. The analysis of the effect of companies with a Quality Management System (QMS) as ISO 9001 resulted in an unexpected lack of significant effect between categories. Namely, there was only an observation of moderate association with waste disposal practices ($BF_{10} = 4.873$). This may infer that QMS may influence certain activities and environmental practices while implemented, but in this case, its impact on broader technological and digitalization efforts is limited.

The robust evidence considering correlations between environmental protection and both technology ($\tau = 0.527$, $BF_{10} = 490669$) and MSR levels ($\tau = 0.546$, $BF_{10} = 12454.63$) show that companies that emphasise environmental protection practices tend to track and improve the sustainability aspects of their maintenance activities. Strong evidence also supports this by relating digitalization levels to environmental protection ($\tau = 0.328$, $BF_{10} = 57.534$) and proposed MSR levels ($\tau = 0.405$, $BF_{10} = 1166.842$). This demonstrates that organisations advancing in technology and digitalization are more likely to engage in environmentally responsible practices and improve their overall sustainability performance, considering operational and maintenance activities.

The use of Multiple Correspondence Analysis in our study is to offer a multivariate view of the survey data. Namely, after coding environmental protection, digitalization and technology levels into binary categories to simplify and increase interpretability, the MCA provided a clear separation of categories. This reinforced the evidence that higher technology and digitalization levels are strongly associated with maintenance sustainability aspects. Also, even though there was no strong evidence in observed binary items of QMS, waste disposal and the use of renewable resources, the MCA shows that these items tend towards higher levels of technology, digitalization and sustainability. The dual analysis provides strong evidence that digitalization and technology are positively associated with sustainability outcomes. The robustness of findings confirmed through Bayesian analysis, and MCA highlights the role of digital technologies in advancing sustainability efforts within the maintenance practices of manufacturing companies.

6. Conclusions

6.1. Concluding remarks

The study performs the dual analysis. Firstly, an Umbrella Review was used to investigate barriers on one side and enablers on the other, affecting the adoption of sustainable maintenance. From the sample of 20 closely related systematic reviews, several concluding remarks were made. The findings highlight that organisational and management barriers, along cultural and behavioural challenges, are the primary obstacles hindering the adoption of sustainable maintenance. Additionally, financial constraints–labour policies and broader economic conditions–coupled with technological barriers, restrict investments in advanced digital technology and hinder the integration of green policies affecting the progress toward sustainable maintenance practices.

Conversely, organisational and management enablers, particularly structured decision-making frameworks aligned with sustainability objectives, play a crucial role in facilitating the transition. Strategic planning facilitators, such as I4.0 tools for managing sustainability indicators and digital twins for optimising energy efficiency, further reinforce this shift. The industrial analysis presented in the study provide robust evidence supporting the correlation between digitalization, technology and sustainability, with Bayesian analyses indicating strong association ($BF_{10} > 10$). Higher levels of technological advancements were found to be linked with increased digitalization and environmental responsibility. However, the findings also suggest non-linear interactions with organisational factors, implying that the relationship between technology and sustainability is not purely deterministic but rather under the influence of structural and strategic dimensions.

To achieve effective adoption of sustainable maintenance, the study requires a structured decision-making framework that integrates management commitment, digital technology investments, and cross-functional synchronisation, supported by continuous workforce training. The findings contribute both to academic discourse and to practical applications, offering a comprehensive understanding of the role of multiple factors in the adoption of sustainability-driven maintenance practices within industrial settings.

6.2. Limitations

Considering the obtained corpus of systematic reviews, we report several limitations of the study. Namely, the methodological quality and rigour of conducted systematic (and scoping) reviews show that most reviews do not follow an explicit protocol when performing systematic reviews. Secondly, a significant limitation of an umbrella review is the heterogeneity of studies since many reviews do not directly target the proposed research question, resulting in high variability of findings.

From a methodological perspective, the findings are built upon factors coded on items from retrieved studies. Thus, our proposition on categories of individual class categories (e.g., enablers, barriers) significantly differs from traditional ones. Although the conventional body of research assessing barriers and enablers typically follows the same pattern, we decided to offer a fresh perspective by conceptualising factors given their purpose and context within existing frameworks. The findings provide additional insights to practitioners and policymakers for making informative and sustainable decisions.

Although we can say that BNA results of investigated data from retrieved reviews only suggest moderate evidence, this certainly does not downplay our findings and limit our conclusions. On the contrary, this reflects the current state of limited knowledge and understanding of the practical implications of proposed opinions since previously published studies are mostly built on a theoretical and opinion basis. Thus, in support of our arguments, we intend to provide explicit empirical evidence to stress the strength of the evidence for these factors. The fact that most authors latch to the notion of "enabling technologies" for advocating the role of digitalization and technology in adopting sustainable maintenance infers a lack of research and understanding about the roles that these factors play in aiding the implementation of sustainable maintenance practices.

Lastly, given that our sample size is disseminated within manufacturing companies situated in the West Balkan Region, the generalisation of findings is limited for several reasons. Namely, the manufacturing companies in this region may be less developed than those in Western Europe, so perhaps none of the companies indicated that they have fully digitalized (level 5) maintenance practices. Also, the sample size of n = 52 companies may not be considered a representative sample given that it is far beyond the required for the generalisation of findings. Still, the computation of sample size performed via G*Power was fair enough, considering the requirements for performing statistical testing. Also, the robustness check and sequential analysis confirmed that with the changes of parameters and observations, the confidence in findings increases the Bayes factor.

6.3. Implications and future research

Given the progressive nature of SM research and the importance of the topic, we expect that in the future, several survey instruments will emerge to investigate the roles of individual factors in adopting sustainable practices. We expect that our findings will aid understanding and provoke industrial policymakers to shift their attention from existing maintenance practices to sustainable ones. Specifically, the dual role of technology may, on one side, offer significant potential for improving sustainability. At the same time, it may introduce challenges, particularly in the financial and organisational sense. This may require further analysis to understand the conditions under which technology may act more as an enabler rather than a barrier. Lastly, the study identifies a significant gap in the literature regarding the availability of empirical evidence since most of the prior work is theoretical, lacking practical implications. This, in turn, may provide solution space for academics and practitioners to investigate and provide more practical insights and benefits in adopting sustainable maintenance solutions.

CRediT authorship contribution statement

Marko Orošnjak: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nebojša Brkljač:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Kristina Ristić:** Writing – original draft, Resources, Investigation, Data curation, Conceptualization.

Author statement

The large language models ensure the manuscript's grammatical and scientific writing quality. Specifically, Grammarly removes grammar and spelling errors and language corrections, while OpenAI's GPT-4 tool is used in refining sentences. The LLM and AI tools used here are solely used as accelerators for enhancing the writing process, assisting in language and spelling checks and improving writing accuracy. These tools are not used to generate new ideas, insights or sources of intellectual content within the manuscript. All the ideas, comments, discussions, drawings, illustrations, and processing of images (and graphs) originated and are solely the work of the authors of this manuscript.

Data availability statement

The data used in the study is provided in supplementary files.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clpl.2025.100095.

Appendix 1. Questionnaire-based Survey Data

Table A1 provides the survey items. Table A2 (description of technology levels), A3 (description of digitalization levels), and A4 (description of performance measures tracked by the maintenance function) describe particular levels in the companies' assessments.

Table A1
Main survey questions and items

n	Survey item	Q
Q1	Please state your company's primary activity sector.	OQ
Q2	Please describe your company's coded sector category.	OQ
Q3	Please state the number of employees in your company.	OQ
Q4	Have you implemented ISO 9001 and associated procedures for your maintenance processes?	Y/N
Q5	Does your company manage waste (disposal and recycling) within maintenance practices?	Y/N
Q6	Does your company use renewable energy sources as a part of maintenance practices?	Y/N
Q7	How would you describe your company's maintenance technology level?	1–5
Q8	To what extent does your company care for environmental protection in industrial maintenance practice?	1–5
Q9	What is the digitalization level applied within your maintenance function?	1–5
Q10	What performance characteristics and performance are you measuring within your maintenance practice?	List

Table A2
Technology levels

Q7	How would you describe your company's maintenance technology level?
Level 1	Very low (maintenance practices are mostly done manually only).
Level 2	Partially low (representation of technology supports maintenance practices, but manual execution is still dominant).
Level 3	Medium (balanced approach where technology supporting maintenance is more prominent, including some software solutions).
Level 4	Advanced (maintenance practice depends on technology and specialised software, but there is still room for integration).
Level 5	High (extensive use of advanced technologies, predictive analytics and automation, with less manual processes).

Table A3
Digitalization levels

Q9	What is the digitalization level applied within your maintenance function?
Level 1	Initial (Processes are poorly controlled or not controlled at all. Mostly, everything is implemented reactively without adequate organisational and technological tools).
Level 2	Management (Processes are partly planned with the help of digital tools. Decisions and planning are mainly carried out based on the experience of the person in charge of planning maintenance activities).
Level 3	Partially integrated (Certain digital tools for planning and monitoring are planned and implemented in the process, but without integrated applications for exchanging information with the production plant, machine, and personnel).
Level 4	Integrated and interoperable (There are applications for monitoring and information exchange. Digital technologies are used to plan and organise work. Special tools of Industry 4.0 are used (e.g., Data Analytics, Internet of Things, BigData)).
Level 5	Fully digitized (Complete infrastructure enables digital exchange of information, monitoring and condition monitoring. Advanced digital technologies of Industry 4.0 are applied for diagnostics, prognostics and work organisation).

Table A4
Performance metrics

Q10	What performance characteristics and performance are you measuring within your maintenance practice?
ENV	Energy consumed (during activities and maintenance processes).
ENV	Water consumption (during activities and maintenance processes).
ENV	CO2 emission (during activities and maintenance processes).
ENV	Waste generation (during activities and maintenance processes).
ENV	Resource use efficiency (how much efficient use of materials and resources within the maintenance function).
SOC	Employee satisfaction within the maintenance function.
SOC	Health and safety of employees within the maintenance function.
SOC	Training and development of employees within the maintenance function.
SOC	Motivation and satisfaction of employees within the maintenance function.
SOC	The compliance rate with living standards (e.g., equality of pay, working conditions, and competitors in the market).
ECO	Investment in research and development in maintenance (internal and external comparison).
ECO	Economic indicators of savings (during activities and maintenance processes).
ECO	Costs and return on investment (based on internal analysis of the maintenance function).
ECO	Indirect financial impacts (e.g. tracking mean time in operation, meantime in failure, time savings, machine availability).
ECO	Costs and efficiency of use of other resources (within the maintenance function).

Appendix 2. Frequentists test results

Frequentist statistical analysis considers correlation tests (e.g., Spearman's ρ and Kendall's τ-b), but instead of relying on Bayes Factor, the results are verified according to α level (i.e., p-value). In addition, the correlation analysis is performed to measure the association between two variables (Table A5). Also, for the sake of interpretation and easier understanding, we provide both Spearman's ρ and Kendall's τ-b heatmaps in Fig. A1.

For testing the difference between ordinal variables per group (i.e., ISO 9001, Waste management, and Renewable resources), we performed the Mann-Whitney U test (Table A6, Table A7, Table A8) with a confidence interval of 95% ($p < 0.05$) for statistically significant differences. In addition, we report Student's and Welch's t-tests, but considering the underlying variables are ordinal, and some groups have a violation of the normality assumption, the results may not be valid. We report p values, location parameters, standard errors, and 95% confidence intervals in all cases. Lastly, the diagnosticity of p values is performed using VS-MPR (Vovk-Sellke maximum p-Ratio) (Sellke et al., 2001), while strength of the relationship is reported by corresponding test statistic. The analysis suggests that no difference is noticed in testing the ISO 9001 groups ($p > 0.05$). Testing differences between Waste management, only Env_Pro reported significant differences ($U = 95.0$, $p = 0.012$, VS-MPR $= 7.088$). Finally, there was no observable difference between the use of renewable resources in reported variables.

Table A5
Frequentist correlation analysis

Variable	Test statistic	Digitalization_Level	MSR_Level	Env_Pro
MSR_Level	Spearman's ρ	0.476		
	p value	0.001		
	VS-MPR	234.356		
	Kendall's τ-b	0.405		

(*continued on next page*)

Table A5 (*continued*)

Variable	Test statistic	Digitalization_Level	MSR_Level	Env_Pro
	p value	0.001		
	VS-MPR	204.057		
Env_Pro	Spearman's ρ	0.374	0.387	
	p value	0.003	0.002	
	VS-MPR	20.25	26.136	
	Kendall's τ-b	0.328	0.326	
	p value	0.003	0.003	
	VS-MPR	20.647	22.307	
Tech_Lvl	Spearman's ρ	0.624	0.539	0.586
	p value	0.001	0.001	0.001
	VS-MPR	64523.79	1809.288	11531.78
	Kendall's τ-b	0.546	0.456	0.527
	p value	0.001	0.001	0.001
	VS-MPR	15864.91	939.784	5048.389

Note: VS-MPR = Vovk-Sellke Maximum p -Ratio: Based on the p -value, the maximum possible odds in favour of H_1 over H_0.

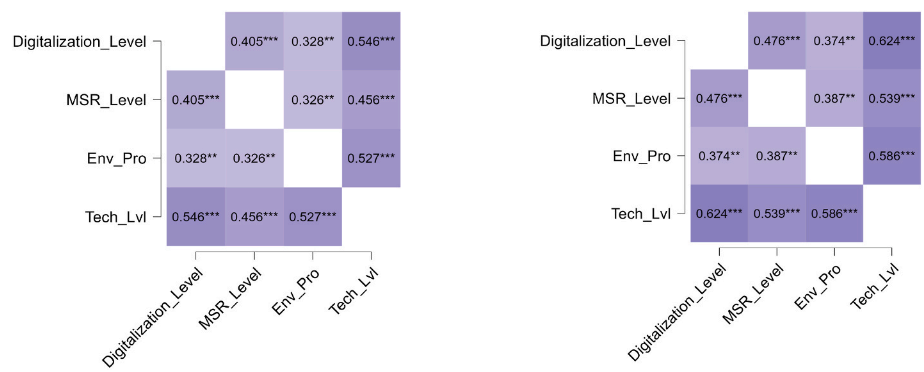

Fig. A1. Heatmap using frequentist approach to the analysis of Kendall's τ-b (left) and Spearman's ρ (right) test statistic. Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ value.

Table A6
Independent Samples *t*-test statistic for ISO 9001 Quality Management System

Variable	Test	Statistic	df	*p*	Loc. param.	SE	$95\%CI_U$	$95\%CI_U$
Tech_Lvl	Student	−1.159	50.000	0.252	−0.410	0.354	−1.121	0.301
	Welch	−1.016	17.007	0.324	−0.410	0.404	−1.262	0.442
	Mann-Whitney	210.500		0.348	0.000		−1.000	0.000
Env_Pro	Student	−0.621	50.000	0.537	−0.179	0.289	−0.760	0.401
	Welch	−0.584	18.676	0.566	−0.179	0.307	−0.824	0.465
	Mann-Whitney	225.000		0.529	0.000		−1.000	0.000
Digit_Level	Student	−0.140	50.000	0.890	−0.051	0.367	−0.789	0.686
	Welch	−0.132	18.745	0.897	−0.051	0.390	−0.868	0.766
	Mann-Whitney	245.000		0.861	0.000		−1.000	1.000
MSR_Level	Student	−1.850	50.000	0.070	−0.769	0.416	−1.605	0.066
	Welch	−1.886	21.321	0.073	−0.769	0.408	−1.617	0.078
	Mann-Whitney	170.000		0.073	−1.000		−2.000	0.000

Note. The Student t-test and Welch *t*-test give the location parameter by mean difference. For the Mann-Whitney test, the location parameter is given by the Hodges-Lehmann estimate. All variables violated the normality assumption in cases where ISO 9000 is "Yes".

Table A7
Independent samples *t*-test for statistical Waste disposal

	Test	Stat	*p*	VS-MPR*	Location par.	SE	$95\%CI_L$	$95\%CI_U$
Tech_Lvl	Student	−1.546	0.129	1.395	−0.620	0.401	−1.426	0.186
	Welch	−1.658	0.122	1.433	−0.620	0.374	−1.431	0.191
	Mann-Whitney	124.500	0.084	1.773	−1.000		−1.000	0.000
Env_Pro	Student	−2.503	0.016	5.657	−0.783	0.313	−1.411	−0.155
	Welch	−2.474	0.030	3.488	−0.783	0.317	−1.476	−0.090
	Mann-Whitney	95.000	0.012	7.088	−1.000		−1.000	0.000
Digit_Level	Student	−0.037	0.971	1.000	−0.016	0.420	−0.860	0.829
	Welch	−0.041	0.968	1.000	−0.016	0.378	−0.832	0.801
	Mann-Whitney	194.500	0.990	1.000	0.000		−1.000	1.000
MSR_Level	Student	−1.904	0.063	2.118	−0.904	0.475	−1.859	0.050
	Welch	−2.289	0.037	2.989	−0.904	0.395	−1.749	−0.060
	Mann-Whitney	117.000	0.060	2.183	−1.000		−2.000	0.000

Note. The Student t-test and Welch *t*-test give the location parameter by mean difference. For the Mann-Whitney test, the location parameter is given by the Hodges-Lehmann estimate. *Vovk-Sellke Maximum p Ratio: Based on a two-sided p-value, the maximum possible odds in favour of H_1 over H_0.

Table A8
Independent samples *t*-test for statistical Renewable resources

	Test	Stati	p	VS-MPR*	Loc. param.	SE	$95\%CI_L$	$95\%CI_U$
Tech_Lvl	Student	−1.175	0.246	1.067	−0.406	0.346	−1.100	0.288
	Welch	−1.354	0.185	1.178	−0.406	0.300	−1.017	0.205
	Mann-Whitney	220.000	0.327	1.006	−19.520		−1.000	0.000
Env_Pro	Student	−1.507	0.138	1.346	−0.417	0.277	−0.973	0.139
	Welch	−1.694	0.101	1.592	−0.417	0.246	−0.921	0.086
	Mann-Whitney	200.000	0.150	1.291	−71.240		−1.000	0.000
Digit_Level	Student	−0.866	0.391	1.000	−0.308	0.356	−1.023	0.407
	Welch	−0.800	0.433	1.000	−0.308	0.385	−1.112	0.495
	Mann-Whitney	228.000	0.423	1.000	−51.130		−1.000	0.000
MSR_Level	Student	−0.775	0.442	1.000	−0.323	0.417	−1.161	0.515
	Welch	−0.733	0.472	1.000	−0.323	0.441	−1.240	0.594
	Mann-Whitney	231.000	0.466	1.000	−51.500		−1.000	1.000

Note. The Student t-test and Welch *t*-test give the location parameter by mean difference. For the Mann-Whitney test, the location parameter is given by the Hodges-Lehmann estimate. * Vovk-Sellke Maximum Ratio: Based on a two-sided p -p-value, the maximum possible odds in favour of H_1 over H_0.

Data availability

Data is provided in supplementary files alongside the manuscript.

References

Acerbi, F., Polenghi, A., Roda, I., Macchi, M., Taisch, M., 2020. Exploring Synergies between Circular Economy and Asset Management, pp. 695–702. https://doi.org/10.1007/978-3-030-57997-5_80.

Adler, R., Ewing, J., Taylor, P., 2011. Copula Gaussian Graphical Models and their application to modeling functional disability data. Ann. Appl. Stat. 5, 969–993. https://doi.org/10.1214/09-STS285.

Ajukumar, V.N., Gandhi, O.P., 2013. Evaluation of green maintenance initiatives in design and development of mechanical systems using an integrated approach. J. Clean. Prod. 51, 34–46. https://doi.org/10.1016/j.jclepro.2013.01.010.

Anandakumar, M.G., Varughese, K.T., 2020. Infrastructural asset management and maintenance of system health in power sector utilities: an overview. Power Res. - A J. CPRI 16, 79. https://doi.org/10.33686/pwj.v16i1.153168.

Aromataris, E., Fernandez, R., Godfrey, C.M., Holly, C., Khalil, H., Tungpunkom, P., 2015. Summarizing systematic reviews: methodological development, conduct and reporting of an umbrella review approach. Int. J. Evid. Base. Healthc. 13, 132–140. https://doi.org/10.1097/XEB.0000000000000055.

Bougioukas, K.I., Liakos, A., Tsapas, A., Ntzani, E., Haidich, A.B., 2018. Preferred reporting items for overviews of systematic reviews including harms checklist: a pilot tool to be used for balanced reporting of benefits and harms. J. Clin. Epidemiol. https://doi.org/10.1016/j.jclinepi.2017.10.002.

Bredebach, C., 2022. What role does maintenance play in achieving sustainability in manufacturing? - a scoping literature review. In: ASME 2022 17th International Manufacturing Science and Engineering Conference. The American Society of Mechanical Engineers, West Lafayette, Indiana, USA. https://doi.org/10.1115/MSEC2022-84064.

Campos, R.S. de, Simon, A.T., 2019. Insertion of sustainability concepts in the maintenance strategies to achieve sustainable manufacturing. Indepen. J. Manag. Prod. 10, 1908–1931. https://doi.org/10.14807/ijmp.v10i6.939.

Do, P., Hoang, A., Iung, B., Vu, H.-C., 2018. Energy efficiency for condition-based maintenance decision-making: application to a manufacturing platform. Proc. Inst. Mech. Eng. O J. Risk Reliab. 232, 379–388. https://doi.org/10.1177/1748006X18762282.

Duque, S.E., El-Thalji, I., n.d. Intelligent maintenance maturity of offshore oil and gas platform: a customized assessment model complies with industry 4.0 vision, in: Liyanage, J., Amadi-Echendu, J., Mathew, J. (Eds.), Lecture Notes in Mechanical Engineering: Engineering Assets and Public Infrastructures in the Age of Digitalization. Springer.

Elia, V., Gnoni, M.G., Tornese, F., 2017. Measuring circular economy strategies through index methods: a critical analysis. J. Clean. Prod. 142, 2741–2751. https://doi.org/10.1016/j.jclepro.2016.10.196.

Foygel, R., Drton, M., 2010. Extended bayesian information criteria for Gaussian graphical models. In: Lafferty, J., Williams, C., Shawe-Taylor, J., Zemel, R., Culotta, A. (Eds.), Advances in Neural Information Processing Systems 23 (NIPS 2010), pp. 1–9.

Franciosi, C., Di Pasquale, V., Iannone, R., Miranda, S., 2020. Multi-stakeholder perspectives on indicators for sustainable maintenance performance in production contexts: an exploratory study. J. Qual. Mainten. Eng. 27, 308–330. https://doi.org/10.1108/JQME-03-2019-0033.

Franciosi, C., Iung, B., Miranda, S., Riemma, S., 2018. Maintenance for sustainability in the industry 4.0 context: a scoping literature review. IFAC-PapersOnLine 51, 903–908. https://doi.org/10.1016/j.ifacol.2018.08.459.

Franciosi, C., Miranda, S., Veneroso, C.R., Riemma, S., 2022. Improving industrial sustainability by the use of digital twin models in maintenance and production activities. In: IFAC-PapersOnLine. https://doi.org/10.1016/j.ifacol.2022.09.215.

Franciosi, C., Tortora, A.M.R., Miranda, S., 2023. A maintenance maturity and sustainability assessment model for manufacturing systems. Manag. Prod. Eng. Rev. https://doi.org/10.24425/mper.2023.145372.

Fruchterman, T.M.J., Reingold, E.M., 1991. Graph drawing by force-directed placement. Software Pract. Ex. 21, 1129–1164. https://doi.org/10.1002/spe.4380211102.

Gûnel, E., Dickey, J., 1974. Bayes factors for independence in contingency Tables. Biometrika 61, 545–557.

Haines, A., Scheelbeek, P., 2020. European Green Deal: a major opportunity for health improvement. Lancet 395, 1327–1329. https://doi.org/10.1016/S0140-6736(20)30109-4.

Hallioui, A., Herrou, B., Katina, P.F., Santos, R.S., Egbue, O., Jasiulewicz-Kaczmarek, M., Soares, J.M., Marques, P.C., 2023. A review of sustainable total productive maintenance (STPM). Sustainability (Switzerland). https://doi.org/10.3390/su151612362.

Hami, N., Ibrahim, Y.M., Yamin, F.M., Shafie, S.M., Abdulameer, S.S., 2019. The moderating role of sustainable maintenance on the relationship between sustainable manufacturing practices and social sustainability: a conceptual framework. Int. J. Eng. Adv. Technol. 8, 222–228. https://doi.org/10.35940/ijeat.E1032.0585C19.

Hami, N., Shafie, S.M., Omar, S., Ibrahim, Y.M., Abdulameer, S.S., Muhamad, M.R., 2020. A review of sustainable maintenance in the manufacturing companies. Int. J. Supply Chain Manag. 9, 935–944.

Hespanhol, L., Vallio, C.S., Costa, L.M., Saragiotto, B.T., 2019. Understanding and interpreting confidence and credible intervals around effect estimates. Braz. J. Phys. Ther. 23, 290–301. https://doi.org/10.1016/j.bjpt.2018.12.006.

Husson, F., Le, S., Pages, J., 2017. Exploratory Multivariate Analysis by Example Using R, second ed. Chapman & Hall/CRC Taylor and Francis Group, Milton Park Abingdon, OX, UK.

Ibrahim, Y.M., Hami, N., Othman, S.N., 2019. Integrating sustainable maintenance into sustainable manufacturing practices and its relationship with sustainability performance: a conceptual framework. Int. J. Energy Econ. Pol. 9, 30–39. https://doi.org/10.32479/ijeep.7709.

IEA, 2023. Global CO2 Emissions by Sector, 2019-2022 [WWW Document]. IEA. https://www.iea.org/data-and-statistics/charts/global-co2-emissions-by-sector-2019-2022, 2.3.25.

Ighravwe, D.E., Oke, S.A., 2019. A multi-criteria decision-making framework for selecting a suitable maintenance strategy for public buildings using sustainability criteria. J. Build. Eng. 24, 100753. https://doi.org/10.1016/j.jobe.2019.100753.

Jasiulewicz-Kaczmarek, M., 2013. Sustainability: Orientation in Maintenance Management—Theoretical Background, pp. 117–134. https://doi.org/10.1007/978-3-642-23553-5_8.

Jasiulewicz-Kaczmarek, M., Antosz, K., Waszkowski, R., Nielsen, I., Čep, R., 2023. "Technology" as the fourth dimension of sustainable maintenance management. IFAC-PapersOnLine 56, 162–167. https://doi.org/10.1016/j.ifacol.2023.10.1563.

Jasiulewicz-Kaczmarek, M., Legutko, S., Kluk, P., 2020. Maintenance 4.0 technologies – new opportunities for sustainability driven maintenance. Manag. Prod. Eng. Rev. 11, 74–87. https://doi.org/10.24425/mper.2020.133730.

Kalantari, E., Kouchaki, S., Miaskowski, C., Kober, K., Barnaghi, P., 2022. Network analysis to identify symptoms clusters and temporal interconnections in oncology patients. Sci. Rep. 12, 17052. https://doi.org/10.1038/s41598-022-21140-4.

Karki, B.R., Porras, J., 2021. Digitalization for sustainable maintenance services: a systematic literature review. Digital Business. https://doi.org/10.1016/j.digbus.2021.100011.

Karuppiah, K., Sankaranarayanan, B., Ali, S.M., 2021. On sustainable predictive maintenance: exploration of key barriers using an integrated approach. Sustain. Prod. Consum. 27, 1537–1553. https://doi.org/10.1016/j.spc.2021.03.023.

Kelter, R., 2020. Bayesian and frequentist testing for differences between two groups with parametric and nonparametric two-sample tests. Wires Comput. Statistic. 13.

Lee, H.-T., Song, J.-H., Min, S.-H., Lee, H.-S., Song, K.Y., Chu, C.N., Ahn, S.-H., 2019. Research trends in sustainable manufacturing: a review and future perspective based on research databases. Int. J. Precision Eng. Manufact.-Green Tech. 6, 809–819. https://doi.org/10.1007/s40684-019-00113-5.

Lin, C.-Y., Chen, P.-R., 2023. Eco-friendly smart design strategy for integrated semiconductor processes. J. Intell. Manuf. https://doi.org/10.1007/s10845-023-02226-w.
Macchi, M., Fumagalli, L., 2013. A maintenance maturity assessment method for the manufacturing industry. J. Qual. Mainten. Eng. 19, 295–315.
Manté, C., Cornu, S., Borschneck, D., Mocuta, C., van den Bogaert, R., 2022. Detecting the Guttman effect with the help of ordinal correspondence analysis in synchrotron X-ray diffraction data analysis. J. Appl. Stat. 49, 291–316. https://doi.org/10.1080/02664763.2020.1810644.
Mehairjan, R.P.Y., van Hattem, M., Djairam, D., Smith, J.J., 2016. Development and implementation of a maturity model for professionalising maintenance management. In: Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015). Springer.
Orosnjak, M., 2021. Maintenance practice performance assessment of hydraulic machinery: West Balkan meta-statistics and energy-based maintenance paradigm. In: 2021 5th International Conference on System Reliability and Safety (ICSRS). IEEE, pp. 108–114. https://doi.org/10.1109/ICSRS53853.2021.9660739.
Orošnjak, M., Brkljač, N., Šević, D., Čavić, M., Oros, D., Penčić, M., 2023. From predictive to energy-based maintenance paradigm: achieving cleaner production through functional-productiveness. J. Clean. Prod. 408, 137177. https://doi.org/10.1016/j.jclepro.2023.137177.
Orošnjak, M., Šević, D., 2023. Benchmarking maintenance practices for allocating features affecting hydraulic system maintenance: a west-balkan perspective. Mathematics 11, 3816. https://doi.org/10.3390/math11183816.
Peters, M.D.J., Godfrey, C.M., Baldini Soares, C., Khalil, H., Parker, D., 2015. The Joanna Briggs Institute Reviewers' Manual 2015, vol. 5005. Methodology for JBI Scoping Reviews. South Australia, Australia.
Pollock, M., Fernandes, R.M., Pieper, D., Tricco, A.C., Gates, M., Gates, A., Hartling, L., 2019. Preferred Reporting Items for Overviews of Reviews (PRIOR): a protocol for development of a reporting guideline for overviews of reviews of healthcare interventions. Syst. Rev. 8, 335. https://doi.org/10.1186/s13643-019-1252-9.
Ramiya, S., Suresh, M., 2021. Factors influencing lean-sustainable maintenance using TISM approach. Int. J. Syst. Assuran. Eng. Manag. 12, 1117–1131. https://doi.org/10.1007/s13198-021-01304-7.
Robinaugh, D.J., Millner, A.J., McNally, R.J., 2016. Identifying highly influential nodes in the complicated grief network. J. Abnorm. Psychol. 125, 747–757. https://doi.org/10.1037/abn0000181.
Roda, C., Voisin, I., Miranda, A., Macchi, S., Iung, M., 2021. Sustainable Maintenance Performances and EN 15341: 2019: an Integration Proposal. Springer.
Saihi, A., Ben-Daya, M., As'ad, R., 2023a. A hierarchical component model for sustainable performance measurement of maintenance practices: a fourth-order PLS-SEM approach. Comput. Ind. Eng. 185, 109699. https://doi.org/10.1016/j.cie.2023.109699.
Saihi, A., Ben-Daya, M., As'ad, R., 2022a. A survey of the underlying success factors of maintenance digital transformation. IFAC-PapersOnLine 55, 2944–2949.
Saihi, A., Ben-Daya, M., As'ad, R., 2022b. An investigation of sustainable maintenance performance indicators: identification, expert validation and portfolio of future research. IEEE Access 10, 124259–124276. https://doi.org/10.1109/ACCESS.2022.3224450.
Saihi, A., Ben-Daya, M., As'ad, R.A., 2023b. Maintenance and sustainability: a systematic review of modeling-based literature. J. Qual. Mainten. Eng. 29, 155–187. https://doi.org/10.1108/JQME-07-2021-0058.
Santos, A.C. de J., Cavalcante, C.A.V., Wu, S., 2023. Maintenance policies and models: a bibliometric and literature review of strategies for reuse and remanufacturing. Reliab. Eng. Syst. Saf. https://doi.org/10.1016/j.ress.2022.108983.
Saraswat, P., Agrawal, R., 2023. Artificial intelligence as key enabler for sustainable maintenance in the manufacturing industry: scope & challenges. Evergreen 10, 2490–2497. https://doi.org/10.5109/7162012.
Sari, E., Ma'aram, A., Shaharoun, A.M., Chofreh, A.G., Goni, F.A., Klemeš, J.J., Marie, I. A., Saraswati, D., 2021. Measuring sustainable cleaner maintenance hierarchical contributions of the car manufacturing industry. J. Clean. Prod. 312. https://doi.org/10.1016/j.jclepro.2021.127717.
Sari, E., Shaharoun, A.M., Ma'aram, A., Yazid, A.M., 2015. Sustainable maintenance performance measures: a pilot survey in Malaysian automotive companies. Procedia CIRP 26, 443–448. https://doi.org/10.1016/j.procir.2014.07.163.
Schuh, G., Lorenz, B., Winter, C.-P., Gudergan, G., 2010. The House of Maintenance - identifying the potential for improvement in internal maintenance organizations by means of a capability maturity model. In: Engineering Asset Lifecycle Management. Springer, London.
Sellke, T., Bayarri, J.M., Berger, J.O., 2001. Calibration of p values for testing precise null hypotheses. Am Stat 55, 62–71.
Sénéchal, O., 2018. Performance indicators nomenclatures for decision making in sustainable conditions based maintenance. IFAC-PapersOnLine 51, 1137–1142. https://doi.org/10.1016/j.ifacol.2018.08.438.
Srinivas, H., 2022. Sustainable Development: Concepts - Cleaner Production [WWW Document]. Sustainability Concepts. https://www.gdrc.org/sustdev/concepts/02-c-prod.html, 9.13.24.
Suresh, M., Dharunanand, R., 2023. Factors influencing sustainable maintenance in manufacturing industries. J. Qual. Mainten. Eng. 29, 94–113. https://doi.org/10.1108/JQME-05-2021-0038.
Ulrich, G., Eberhard, R., 2005. Sustainable maintenance strategies for power plant operators. VGB PowerTech 85, 32–37.
UNIDO, 2024. World Manufacturing Production. Vienna.
United Nations, 2015. Transforming Our World: the 2030 Agenda for Sustainable Development.
van Doorn, J., van den Bergh, D., Bohm, U., Dablander, F., Derks, K., Draws, T., Etz, A., Evans, N.J., Gronau, Q.F., Haaf, J.M., Hinne, M., Kucharsky, Š., Ly, A., Marsman, M., Matzke, D., Gupta, A.R.K.N., Sarafoglou, A., Stefan, A., Voelkel, J.G., Wagenmakers, E.-J., 2021. The JASP guidelines for conducting and reporting a Bayesian analysis. Psychon. Bull. Rev. 28, 813–826.
Vasić, S., Orošnjak, M., Brkljač, N., Vrhovac, V., Ristić, K., 2024. Identification of criteria for enabling the adoption of sustainable maintenance practice: an umbrella review. Sustainability 16, 767. https://doi.org/10.3390/su16020767.
Vrignat, P., Kratz, F., Avila, M., 2022. Sustainable manufacturing, maintenance policies, prognostics and health management: a literature review. Reliab. Eng. Syst. Saf. 218. https://doi.org/10.1016/j.ress.2021.108140.
Xia, T., Xi, L., Du, S., Xiao, L., Pan, E., 2018. Energy-oriented maintenance decision-making for sustainable manufacturing based on energy saving window. J. Manuf. Sci. Eng. 140. https://doi.org/10.1115/1.4038996.
Yildirim, M.B., Nezami, F.G., 2014. Integrated maintenance and production planning with energy consumption and minimal repair. Int. J. Adv. Des. Manuf. Technol. 74, 1419–1430. https://doi.org/10.1007/s00170-014-5834-3.
Zhang, S., Ye, K., Wang, M., 2023. A simple consistent Bayes factor for testing the Kendall rank correlation coefficient. J. Stat. Comput. Simulat. 93, 883–903.
Zhao, J., Gao, C., Tang, T., 2022. A review of sustainable maintenance strategies for single component and multicomponent equipment. Sustainability 14, 2992. https://doi.org/10.3390/su14052992.