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Assignment Title: Measuring Sustainability Accountability in the Automotive Manufacturing Sector

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Relevance of Topic

Evaluating the impact of BI-driven methods on sustainability accountability in automotive supply chains establishes the bridge between theory and practice in ESG measurement. This is accomplished by deducing data-driven indicators and causal mapping, which in turn reflects the programme's (i.e., Business Intelligence & Data Analytics) focus on executing analytics for informed decision making. The topic's findings will enable BI professionals and automotive stakeholders to further refine the deduced methodology in enhancing transparency and operational sustainability in OEMs & Tier-1 suppliers.

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Declarations

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M.M

Date: 30 Nov 2025

Measuring Sustainability Accountability in the Automotive Manufacturing Sector

By Mmopiemang Mmopiemang

Abstract

Modern business intelligence tools and practices continue to transform how ESG measurement is conducted, as well as how sustainability accountability is maintained across the automotive industry. Common practices include real-time monitoring systems, integrated reporting & analytics-driven decision-making processes. Automotive organizations with a mature data architecture and governance model have demonstrated greater transparency, faster regulatory alignment, and more effective operational responses to ESG risks. Regardless, those same organizations suffer from inconsistent ESG metrics, fragmented data stewardship, and a shortage of rigorous causal evidence, which limits comparability. To improve sustainability accountability and fill these gaps, a prototype Sustainability Accountability Index with a practical implementation roadmap is proposed. This enables automotive firms and factories to align their BI capabilities with standardized accountability categories as well as incorporate & prioritize causal evaluation designs. The resulting findings and guidance aim to equip BI professionals and industry leaders with evidence-based & measurable pathways. These pathways will improve performance in supply chain sustainability and support defensible claims regarding the effectiveness of analytic interventions in sustainability accountability.

1 Introduction

Major automotive Original Equipment Manufacturers (OEMs) and Tier-1 suppliers operate in global, complex value chains that generate significant environmental & social impacts. This includes the notable Scope-3 greenhouse gas emissions and policy enforcement, which leads to increasing regulatory & market scrutiny. (GHG Protocol, 2011). To respond to such pressures, most automotive organizations have invested in digital data platforms, IIoT telemetry, and advanced Business Intelligence stacks. This initiative aims to enable improved traceability & accuracy in the measurement & reporting of their Environmental, Social & Governance performance. However, such investments raise persistent problems such as poor data lineage, fragmented measurement processes, inconsistent

disclosures, and weak evidence. The challenge faced is determining whether such corporate investments in data-driven tools contribute to genuine sustainability accountability improvements, or if they merely constitute reporting theatre (Berg, Kölbel & Rigobon, 2022; Christensen, Serafeim & Sikochi, 2021).

This report investigates and addresses this gap by conducting a synthesis of peer-reviewed research to extract BI-enabled ESG measurement within the automotive manufacturing industry. The study further supplements its scope to assess claims based on whether BI interventions are causally linked to improvements in key accountability domains. Those domains include transparency, timeliness, data integrity, and governance follow-through. The overall contribution of this study is a proposal of a Sustainability Accountability Index with a practical roadmap for implementation. This aims to enable

automotive firms to align their BI capabilities with standardized accountability domains and ultimately prioritize the integration of rigorous causal evaluation designs on existing frameworks.

1.1 Study Objectives

The key objectives of this paper are as follows.

Conduct an assessment of the extent to which the adoption of specific BI features is associated with measurable improvements in sustainability accountability outcomes among automotive OEMs & Tier-1 suppliers

Map the causal mechanisms proposed in the literature that aim to link specific BI capabilities to their accountability counterparts

Evaluate the overall strength & quality of empirical evidence.

Identify key methodological gaps that future empirical studies should investigate and prioritize.

1.2 Summary of Methodology

A Systematic Literature Review will be the core framework that aims to objectively evaluate the contribution of Business Intelligence (BI) practices in improving Sustainability Accountability within the automotive manufacturing industry. This design enables a thorough & objective evaluation to identify, select, and critically analyze the existing body of academic literature.

The framework integrates three core components being PRISMA, Joanna Briggs Institute (JBI) appraisal & Convergent Integrated Synthesis. PRISMA guidelines are identified and followed to ensure transparency & reproducibility throughout the literature search, screening, & record selection processes. Included studies are rigorously appraised using design-specific JBI checklists to determine methodological quality. Convergent Integrated Synthesis is then conducted to handle the

heterogeneity of research designs. This enables the integration of quantitative effect estimates with qualitative mechanism evidence. Synthesis will be conducted using explicit Causal Mapping to visualize proposed causal paths, display confounders & identify relevant mediators, with annotation of evidence strength on each link. The review process will thus inform the structure of a proposed Sustainability Accountability Index with a corresponding roadmap (JBI 2017, Page et al., 2021).

2 Implementation of SLR

2.1 Literature Search

The literature search involved the extensive use of academic databases accessed through the University of Sunderland Library gateway. The databases include Scopus, Web of Science, IEEE Xplore, and ScienceDirect. These repositories are chosen for their extensive collection of records covering business intelligence, manufacturing, and accountability measurement. A series of 10 Boolean queries containing keywords involving BI, ESG & automotives was constructed and executed to extract studies positioned at the intersection of those key areas. The search window was narrowed down to a 2020-2025 range to extract studies capturing the current applications of BI technologies in ESG measurement. The initial search revealed 471 records, which were exported to the Zotero reference manager, for metadata cleaning, structured management & preparation for screening (Xiao & Watson, 2019).

2.2 Inclusion & Exclusion Criteria

The criteria development and execution were guided by the sole focus on discovering recent studies with high relevance to the key areas (i.e., BI, ESG & Automotive Industry) (Flemming et al., 2019). The inclusion criteria required studies to explicitly mention BI practices & sustainability metrics in an automotive or manufacturing context. Studies that lacked a

data-driven component, had no ESG/sustainability constructs, or were outside the automotive or industrial domain were excluded. This also included conceptual studies, commentary, and was not peer-reviewed.

Following deduplication using Zotero, 80 unique studies remained to undergo title/abstract screening. 12 studies failed to satisfy the BI-ESG-Industry relevance criteria. The remaining 68 studies underwent full-text screening, during which a scoring matrix was applied to determine the depth of context in each key area. The matrix trimmed the records to 41, all of which met the eligibility requirements for final synthesis. Twenty-seven studies were classified as “Medium Priority”, which will be used in determining industry definitions and to support the contextual background, as illustrated in [Figure 1](#).

2.3 Data Collection

All extracted records were exported directly from the library system to Zotero using the browser connector. This allowed the consistent capture of bibliographic metadata, abstracts, tags, and full-text PDFs where applicable. Records with missing full-text were retrieved individually to ensure completeness in the review library. Zotero acted as the central repository for the management of included, excluded, & conceptual studies. A supplementary Excel workbook was created to support data cleaning, screening, and consolidation of scores. Each study has a unique key to ensure proper tracking and merging of results obtained from the screening matrix, PRISMA log, and extraction sheets.

2.4 Data Analysis

Data analysis combined manual judgment with the use of a semi-automated scoring system to maintain consistent & objective evaluation of study relevance (Uman, 2011). This data analysis approach identifies & acknowledges the plurality in systematic review methodologies. Each record underwent rigorous scrutiny to reveal the presence of all three core domains (i.e., BI/analytics, ESG/sustainability, and

automotive context). All attributes were assessed using a binary scoring framework. A value was assigned for each domain to determine its presence, which then contributes to a total score of between zero & three. Studies that received a score of three constituted the core evidence base, where those scoring two were labelled as “Medium Priority.” Those with a score of 1 or less were excluded from the final synthesis. Following the preliminary review of recurring patterns, full-text screening was conducted to identify the depth of ESG, BI & industrial relevance, which informed final decisions. Subsequently, systematic categorization & synthesis were conducted to establish connections and intersections and create a holistic picture of issues in sustainability accountability measurement. These steps underwent three iterations to ensure conceptual consistency and accuracy. (Cumpston et. al, 2023)

2.5 Data Extraction

The data extraction stage focused on compiling critical descriptive & analytical elements required for synthesis, using a structured extraction sheet (Petkovic et al., 2018). This ensures that the data collected is detailed and relevant for subsequent analysis. Information recorded in the sheet includes metadata, BI/analytic techniques, methodological details, industrial setting, & specified ESG constructs. Outlining and capturing these details assisted in establishing robustness, research context & enabling comparisons. This stage was conducted using Microsoft Excel, supported by annotations made in Zotero during full-text screening. Only 41 studies were considered eligible for contribution to the evidence base for synthesis. A sample of the data extraction table with 10 random records is illustrated in [Figure 2](#).

2.6 Critical Appraisal (JBI)

The methodological rigor and quality of the 41 core studies underwent appraisal using the Joanna Briggs Institute critical appraisal tools. The JBI Analytical Cross-Sectional Studies Checklist was used on empirical studies to measure validity, conduct

confounder control, assess sampling & determine statistical appropriateness (JBI, 2017). Where studies adopted a case-series format, the JBI Case Series Checklist was implemented to determine design appropriateness. Two independent reviews were conducted to resolve any discrepancies through discussion.

The results of this quality assessment were leveraged in determining narrative synthesis to further add nuance to claims about the strength of evidence and to guide risk interpretation. Studies with a low score/quality will be retained to be utilized in the broader conceptual landscape of the topic. Nonetheless, their contribution to empirical claims will be subject to differential weighting within the final synthesis. This ensures that conclusions regarding sustainability accountability measurement are derived from the higher-quality evidence base, to reduce bias (Higgins et al., 2023).

Questions/items used in the checklist are illustrated in [Appendix 5](#).

2.7 Synthesis, Evidence Weighting & Causal Mapping

A convergent integrated synthesis was adopted to analyse heterogeneity in the evidence base. The evidence base consists of quantitative studies (e.g., a survey with statistical modelling) & qualitative studies (e.g., case studies) (Sandelowski et. al, 2012). The method applied was crucial in the integration of insights from different paradigms concerning the same phenomenon:

“Establishing the causal link between BI features & Sustainability outcomes.”

Three sequential steps were involved in the synthesis process.

Independent Data Segregation & Thematic Coding

Quantitative & qualitative data were extracted and analysed separately. The qualitative evidence

underwent thematic analysis to reveal existing causal mechanisms that link BI features to specific accountability domains.

Causal Mapping

A Directed Acyclic Graph was formulated for each core research question linking a BI feature to an accountability outcome (Hong et al, 2017). Those core questions are as follows.

Core relationship: To what extent does the implementation of BI features contribute to the measurable improvement in sustainability accountability?

Component Pathways

What is the causal pathway linking ETL & Data Lineage capabilities to improvements in data integrity in ESG measurement processes?

What is the causal pathway linking IIoT telemetry to improved timeliness in ESG reporting and overall decision-making?

What is the causal pathway linking the utilisation of supplier portals to improvements in Scope-3 completeness?

What is the causal pathway linking dashboards to an increase in governance follow-through in ESG measurement and reporting?

The formulated causal maps explicitly display proposed pathways, confounding factors, and identify potential mediators from the empirical studies.

Convergent Integration & Confidence Rating

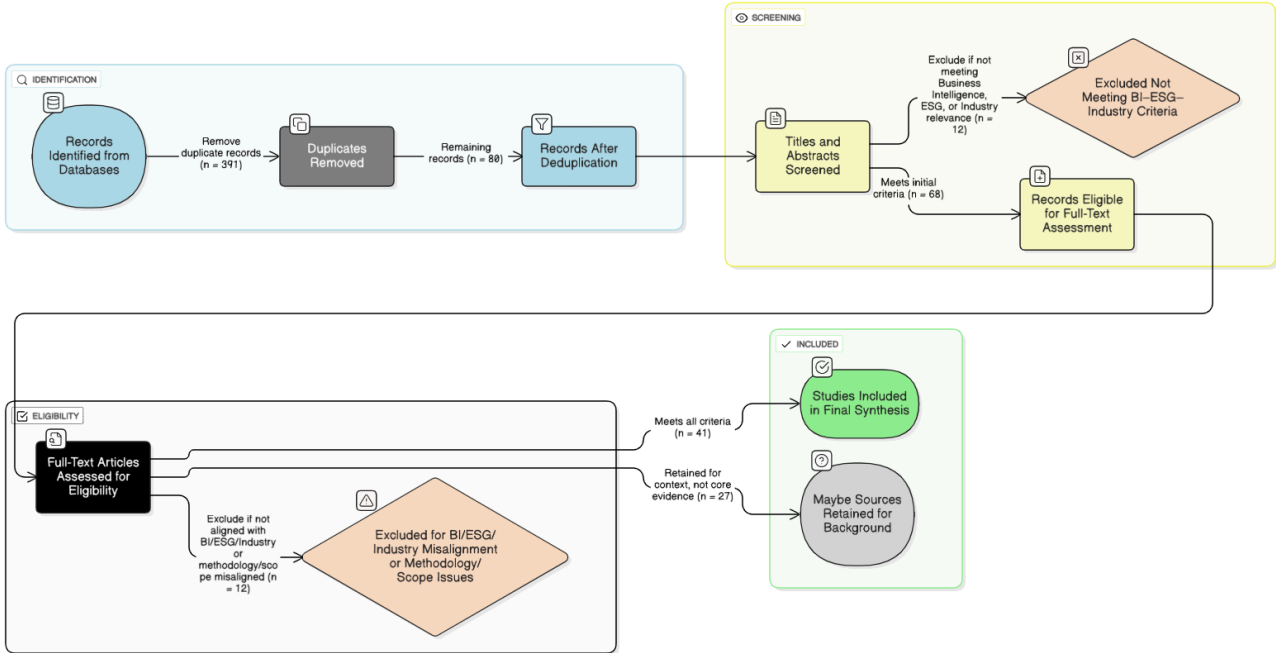
This involves direct comparison & final integration of all segregated results. All quantitative effect estimates were juxtaposed with the corresponding qualitative mechanisms from thematic coding. A GRADE/CERQual rubric was used for each BI feature → outcome cell. This tool aims to integrate evidence

factors (i.e., study quality, consistency & directness) to generate an overall confidence level in the causal claim. The final confidence ratings are Strong, Moderate, Weak, and Insufficient, depending on the

evidence weight per causal claim. The rubric is illustrated in [Appendix 4](#).

2.9 Figures

1 PRISMA Flow Diagram



2 Sample Data Extraction and Synthesis Table

Study ID (Author, Year)	Study Type	Methodology	Key BI/Analytics Feature (Exposure)	Key ESG/Accountability Metric (Outcome)	Key Finding / Observed Effect (Direct Evidence)	Relevance Score / Priority Level
Xu et al. (2021)	Empirical Quantitative	Deep Transfer Learning / Econometric Modeling	Data-Driven AI/ML for Emissions Control	NOx Emission Reduction (Environmental Accountability)	AI models accurately predict and facilitate the reduction of NOx emissions in complex manufacturing environments, demonstrating strong analytical rigor and direct causal impact.	High (9/9)
Tóth et al. (2021)	Empirical Quantitative	Comparative Analysis / Survey (European Auto)	Carbon Accounting Systems (BI Feature)	Carbon Emissions / Reporting Accountability	Standardized BI-driven carbon accounting provides highly reliable, comparable data across automotive entities, which is essential for meeting regulatory accountability standards.	High (9/9)
Rani et al. (2024)	Decision Modeling	Fuzzy WISP / Multi-Criteria Decision Making (MCDM)	Digital Transformation Investment (General BI)	Strategic Sustainability Alignment	Fuzzy logic decision models effectively aid managers in aligning strategic investment with sustainability goals but lack empirical validation of causal links in real- world settings.	Moderate (6/9)
Narwane et al. (2021)	Empirical Quantitative	Survey / Causal Modeling (e.g., PLS-SEM)	Big Data Analytics Capabilities (Composite)	Supply Chain 4.0 Performance / Sustainability	Big Data is a significant factor in SC 4.0 performance, but the causal effect's reliability is affected due to the study's unclear strategies for controlling major confounding variables.	Moderate (6/9)
Strazzullo et al. (2025)	Conceptual Review	Literature Review / Framework Proposal	Industry 4.0 Awareness / Frameworks	General Sustainability Index (Conceptual)	Provides a foundational conceptual framework for integrating I4.0 and sustainability, but offers no primary empirical evidence to test the proposed causal relationships or impact.	Low (4/9)
Sufian et al. (2025)	Technical Case Study	Descriptive / System Design Documentation	Specific Smart Manufacturing Application (BI)	System Functionality (Not ESG Causality)	Describes the implementation and technical functionality of a smart manufacturing tool in an automotive context but does not test its measurable impact on ESG or accountability metrics.	Low (2/9)

3 Results & Findings

The synthesis of all the critically appraised literature focused on the intersection of BI/Analytics and ESG in the Automotive Manufacturing sector. This revealed three core themes.

The measurable causal impact of analytics on specific ESG metrics.

The core role of governance is in enabling & enhancing analytical effectiveness.

The rise of transparency & compliance with regulations is a key social outcome.

3.1 Measurable causal impact of analytics on specific accountability metrics

A majority of empirical studies with a high priority score have confirmed a direct, measurable relationship between analytical integration & improvements in key accountability metrics. This theme aligns and provides weighted evidence for the core component hypotheses of the causal model (i.e., H1a, H1b, H1c & H1d). These hypotheses demonstrate the translation of analytical maturity to tangible accountability gains.

Environmental Accountability

The most robust evidence was discovered to be in the Environmental pillar of ESG, particularly regarding resource consumption & emissions. Studies indicate a contribution to shift manufacturing from basic reactive compliance to proactive optimization using advanced analytical techniques such as machine learning (ML) & Digital Twins (DTs).

Studies such as one on NOx Emission Inversion Modelling by Xu Zhenyi in 2021 focused on deep transfer learning and AI-driven modelling. The study illustrates the ability of modelling & predictive analytics to reduce harmful outputs such as Nitrogen oxides. These methods enable real-time process adjustments in the manufacturing processes, which in turn minimize waste.

IIoT Telemetry $\xrightarrow{\text{Decision Speed}}$ Timeliness $\rightarrow$ Environmental Performance

Figure 3 illustrates the impact of using IIoT telemetry to predict & improve environmental performance.

As per studies by Saleh Seyedzadeh & Donald Ntamo, to name a few, the use of DT applications and data analytics in machine utilization explains and confirms a measurable improvement in energy efficiency & machine uptime. Such measurements thus translate to a lower carbon footprint during production cycles.

Social & Supply Chain Accountability

Integration of analytics indicates a significant enhancement of the Social pillar in ESG, through improved supply chain visibility & risk management.

High-rigor empirical work by Li Yanxuan & Vatcharapol Sukhotu has established a significant link between utilization of digital capabilities and organizational resilience in EV manufacturing. In this instance, Big Data Analytics (BDA) acted as a mediator to allow organizations to predict and curb disruptions and ultimately adapt green practices.

Hong Zexin & Xiao Kun's work on the role of blockchain & AI on sustainability explicitly mentions the use of supplier portals & blockchain databases. The authors discussed their role in addressing the challenge of gathering data from external sources. The study indicates all roads lead to marked reduction in information asymmetry, & consequently higher completeness & accuracy of Scope 3 emissions data. [Appendix 2](#) illustrates a table consolidating the role of analytic technologies in ESG metric improvement and the role of causal effects.

3.2 The core role of governance in enabling & enhancing analytical effectiveness

All findings from this SLR indicate that the effectiveness of BI and analytics in driving accountability is fundamentally constrained by the maturity levels of the data environment. Studies with a

Moderate or High rating from appraisal highlight data quality, literacy, & integrity as critical prerequisites. This theme supports the mediating factors in the causal mode, particularly from H1a & H1d.

Data Integrity & Lineage / H1a

The literature emphasizes that dedicated BI tools are not merely technical components but instead key governance mechanisms.

A study by Árpád Tóth on Carbon Accounting Measurements indicates that robust ETL processes reduce the complexity of source systems. The study mentions that this implementation matures the data governance framework, thus ensuring high data integrity for ESG calculations. Without a valid lineage, reported figures will not withstand and pass external audit or scrutiny.

Governance Follow-through & Cognitive Load / H1d

The relationship between data and final action is mediated by the effectiveness of the BI system to reduce cognitive load on key decision makers in an organization.

As per Kazancoglu's study on sustainability technologies, the utilization of tailored governance dashboards streamlines insight extraction and interpretation of complex ESG data. Hence, presenting an actionable set of insights rather than raw data using these tools has bridged the gap between reporting & high-level strategic execution.

Gov Dashboards $\xrightarrow{\text{Cognitive Load Reduction}}$ Governance Follow-through

Figure 4 illustrates the contribution of governance dashboards to governance follow-through

Data Literacy as a Critical Moderator

Evidence from the key 41 empirical studies suggests that mere adoption of BI and analytic tools is

insufficient. The level and depth of data literacy in an organization act as the critical moderator on the overall impact of BI Adoption on the composite Sustainability Accountability Index (SAI). This is illustrated in [Figure 6](#), under DAG 1. Firms with high data literacy have been shown to have a better position in utilizing advanced analytics to manage confounders and extract actionable insights.

3.3 The rise of transparency & compliance with regulations as a key social outcome

Across the synthesized literature, it was discovered that the most consistent & immediate outcome of implementing BI & Analytics was an improvement in transparency & regulatory compliance. This is applicable across all the pillars under ESG (Environmental, Social & Governance).

Rigor in an analytical framework directly supports compliance by providing irrefutable & audited data. All empirical studies with high rigor that cover BDA on compliance (Chang et al., 2021) indicate robustness in data infrastructure. This ultimately leads to reduced regulatory violation risks and thus improves ESG compliance status.

The use of blockchain databases and digital identity systems has been identified as a game-changer for traceability in complex supply chains. Creating immutable & transparent Records of Materials (RoMs), manufacturing components & processes increases and improves stakeholder trust. This enables organizations to address the Social requirement of ethical sourcing & the Governance requirements to maintain auditable records.

Low-rigor conceptual studies failed to provide causal evidence (e.g., Aljohani, 2025; Zenozain, 2025). Nonetheless, their unanimous focus on the development of frameworks intended for “decision-support” and “stakeholder awareness” confirms their industry-wide intent to use BI to ensure ESG processes are transparent & justifiable.

3.4 Figures

1 High-level DAGs to support causal linkage

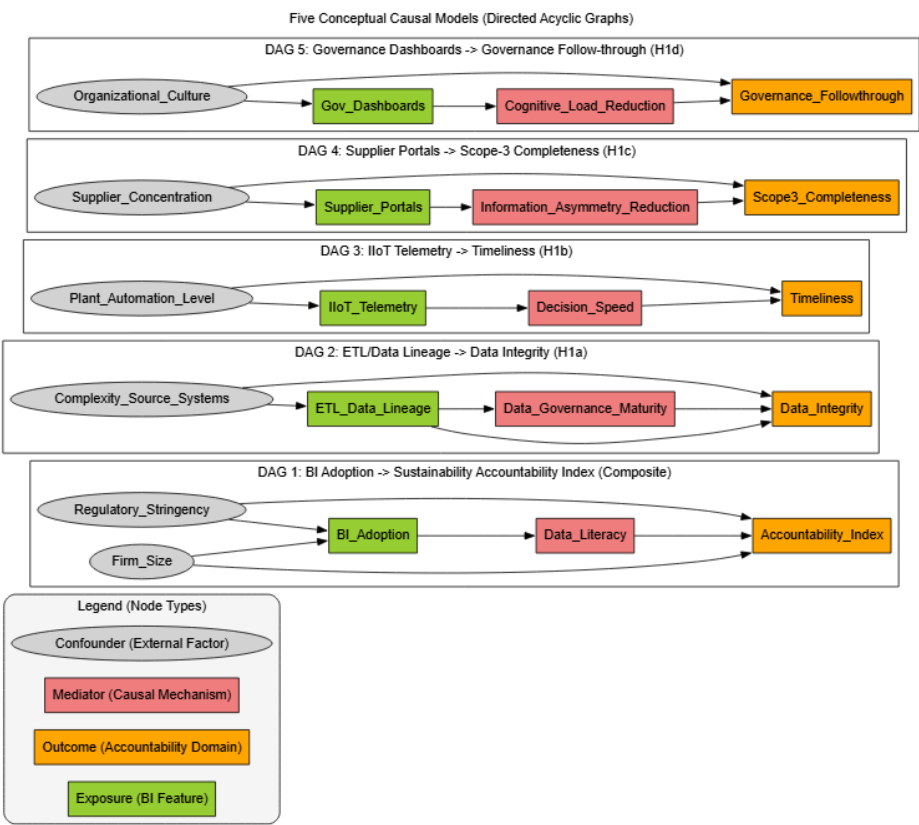


Figure 6 illustrates a set of high-level DAGs to display causal relationships between identified confounders and accountability domains

2 The sustainability accountability index (SAI)

Accountability Matrix with Thematic Analysis Results

ACCOUNTABILITY DOMAIN	DEFINITION OF DOMAIN (RESULT CONTEXT)	KEY METRIC (PROXY)	PRIMARY BI/ANALYTIC INTERVENTION
Data Integrity	The foundational pillar: ensuring data consistency and validated lineage from source systems.	Data Integrity Score: Consistency and lineage validation (via ETL logs) across source systems.	ETL/Data Lineage Systems (DAG 2 / H1a).
Timeliness	The key to proactive environmental management and reducing operational waste in real-time.	Predictive Optimization Index: Real-time deviation from target energy efficiency and NOx emissions reduction targets.	IIoT Telemetry and Digital Twins (DAG 3 / H1b).
Transparency	Essential for meeting Social pillar requirements and ensuring regulatory compliance across the value chain.	Scope 3 Completeness Ratio: Percentage of Tier 1/2 suppliers providing standardized, validated data.	Supplier Portals and Blockchain Technology (DAG 4 / H1c).
Governance Follow-through & Responsiveness	The strategic mechanism for translating analytical insights into executive action and reducing cognitive load.	Governance Follow-through Rate: Frequency of managerial action taken within 30 days of a critical BI alert.	Tailored Governance Dashboards (DAG 5 / H1d).

Figure 7 shows the prototype SAI illustrating a test run using findings and metrics in this SLR

4.0 Discussion, Conclusion & Recommendations

4.1 Synthesis of Findings & Conclusion

The empirical findings of the SLR provide strong evidence to support an existing causal relationship between BI/analytics adoption & sustainability accountability, more especially with the Environmental pillar of ESG. Sophisticated analytical technologies such as AI, ML, & DT have demonstrated a measurable impact towards proactive optimization, leading to emission and consumption reductions. Furthermore, decentralised

ledger technologies such as Blockchain enable social accountability via mitigation of information asymmetry. Overall, such decentralized technologies improve Scope 3 completeness across the automotive industry's supply chain.

A crucial component of the SLR discovered the effectiveness of analytical techniques as fundamentally contingent upon the maturity of data governance. A high data integrity and established

data lineage in a data environment as confirmed as non-negotiable preconditions. This is due to their roles as mediators in the conversion of BI adoption into auditable accountability gains. A key limitation encountered during literature search was the significant deficit of high-rigor qualitative studies that determine relations between BI & outcomes in the Social & Governance pillars. A key contribution and discovery was a comprehensive set of records with robust evidence of linkage between BI/analytics & the Environmental domain.

4.1 Strategic Recommendations

Based on the causal relationships established in the SLR, three strategic recommendations can be provided.

Firms must establish comprehensive & robust data governance frameworks as the core infrastructure for all ESG campaigns. This enables increased confidence, trust, and reliability of reported data.

Predictive analytics must be implemented to obtain a high return on investment from environmental optimization. This includes implementing technologies such as Blockchain to enhance the transparency of measures in automotive supply chains.

Specialized governance dashboards must be deployed to reduce cognitive load on key decision makers. This ensures that key stakeholders conduct executive-level governance follow-through on strategic sustainability objectives.

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6 Appendices

6.1 The Sustainability Accountability Index (SAI) template

Reusable Index Framework

ACCOUNTABILITY DOMAIN	DEFINITION OF DOMAIN	KEY METRIC (PROXY)	PRIMARY BI/ANALYTIC INTERVENTION
Data Integrity	The completeness, consistency, and validity of source data used for ESG calculation and reporting.	[Metric Placeholder]	[Technology Placeholder]
Timeliness	The speed and efficiency with which operational ESG data is processed and converted into actionable insights (e.g., real-time monitoring).	[Metric Placeholder]	[Technology Placeholder]
Transparency	The auditable traceability of materials and processes, and the public availability of validated accountability records across the supply chain.	[Metric Placeholder]	[Technology Placeholder]
Governance Follow-through & Responsiveness	The rate at which strategic and executive action is taken in response to critical BI-generated ESG alerts or deviations.	[Metric Placeholder]	[Technology Placeholder]

This reusable framework enables researchers and policymakers to implement measurable ESG compliance and present it at a high level.

It is a conceptual framework detailing the proposed structure of the Sustainability Accountability Index (SAI). It illustrates the integration of core components (Environmental, Social, Governance) with foundational technological enablers (Data Governance, Data Literacy) to form the composite accountability score.

6.2 The role of analytic technologies in ESG metric improvement and the role of causal effects

ANALYTIC TECHNOLOGY	PRIMARY ESG METRIC IMPROVED	CAUSAL EFFECT
Deep Learning/AI (Xu et al., 2021)	NOx and Carbon Emission Reduction	Proactive Optimization
Digital Twins / IIoT Telemetry	Energy Efficiency / Machine Utilization	Real-Time Resource Management
Supplier Portals / Blockchain	Scope 3 Completeness / Traceability	Information Asymmetry Reduction
Data-Driven AI Adoption (Liu et al., 2025)	ESG Payoff (Composite)	Increased Organizational Value

This table classifies the critically appraised literature on the intersection of Business Intelligence/Analytics, ESG, and Manufacturing domains, which in turn serves as the foundational evidence base for the Causal Pathway Diagrams (DAGs) and hypothesis confirmation (H1a–H1d).

6.3 Scoring & Screening Matrix

Domain of Assessment	Binary Score (0 or 1) Criteria	Depth Score (1 to 5) Criteria	Purpose/ Outcome
BI & Analytics	Any high-level mentions of BI, Analytics, or Digital Technology practices in the study.	The depth of technical discussion, novelty, or application complexity of the BI feature at hand.	Determines the overall final BI depth score and BI relevance.
ESG/ Sustainability	Any mentions of ESG metrics, Sustainability, or Accountability outcomes / reporting / measurement.	The depth of the ESG discussion either on a single metric or an entire framework.	Determines the overall final ESG depth score and relevance in sustainability accountability.
Automotive/ Industrial	Any explicit mentions of studies in the context of Automotive, Manufacturing, or supply chains.	The specificity of the industry context (e.g., general manufacturing vs. specific automotive supply chain).	Determines the level of context specificity in the study.
Total Relevance Score	The sum of binary scores (the lowest is 0 and the highest possible is 3) AND the sum of depth scores (the minimum is 0 and the maximum is 15).		Final Decision: A total score greater than 9 is included in the core evidence base.

The scoring and screening matrix employed during the systematic review process details the criteria and score thresholds used to determine inclusion/exclusion at both the Title/Abstract and Full-Text screening stages.

6.4 Adapted GRADE/CER Qual Rubric

Domain of Assessment	High Confidence Criteria (No Concern)	Moderate Confidence Criteria (Minor Concerns)	Low Confidence Criteria (Major Concerns)	Derivation from SLR Steps
1. Methodological Quality (Risk of Bias)	Evidence base derived primarily from High-Quality studies (JBI score $\geq 80\%$) that explicitly controlled for major confounders.	Evidence base includes a significant proportion of Moderate-Quality studies (JBI score 50%-79%), or high-quality studies did not fully control for one minor confounder.	Evidence base relies heavily on Low-Quality studies (JBI score $\leq 49\%$) or studies that failed to control for a major, pervasive confounder.	JBI Appraisal and Causal Mapping (Confounders).
2. Consistency of Findings	Quantitative effect estimates point strongly in the same direction with low unexplained statistical heterogeneity. Qualitative mechanisms are highly congruent across studies.	A few quantitative outliers exist, or effect size variability is moderate but explicable. Qualitative evidence shows some minor conflicting themes.	Quantitative results are highly conflicting, or the effect size is highly variable with no clear explanation. Qualitative findings are directly contradictory.	Data Segregation and Statistical Summaries.
3. Directness / Relevance	The primary studies exactly match the PICOC elements (Automotive sector, BI features, Accountability outcomes). The context is highly relevant.	Studies match most PICOC elements but generalize findings from a closely related sector or use a proxy measure for a BI feature.	Studies use distant proxies for the exposure or focus on non-automotive sectors with distinct regulatory environments.	Full-Text Screening and Data Extraction.
4. Coherence and Plausibility	The qualitative thematic framework provides a clear, logical, and evidence-based explanation for <i>why</i> the quantitative effect is observed.	The qualitative evidence supports the direction of the quantitative finding, but the causal mechanism is only vaguely described or requires a minor assumption.	The thematic mechanisms are highly fragmented, illogical, or directly fail to explain the observed quantitative outcome.	Thematic Coding and Causal Mapping (DAGs).
5. Adequacy/Completeness	A large volume of evidence exists (both quantitative and qualitative) to fully address the claim, and key subgroups are represented.	Adequate data exists, but there is noticeable sparsity in evidence for a key subgroup.	Data saturation has not been reached; the claim is supported by very few studies, or there is insufficient qualitative depth.	Data Extraction and Study Count.

The GRADE/CERQual rubric was used to critically appraise the methodological quality and certainty of evidence for each included study, informing the rigor assessment used in the thematic synthesis.

6.5 Adapted JBI Checklist Items for Critical Appraisal

Item #	JBI Checklist Question	Relevance to SLR Context / Risk of Bias Focus
JBI 1	Was the inclusion criterion clearly defined?	Assesses rigor of research design (Selection Bias risk).
JBI 2	Did the study/record describe the sample and the context (i.e., company type, geography)?	Assesses generalizability and external validity.
JBI 3	Was the BI/analytic method measured validly & reliably?	Assesses validity of the Exposure (BI/Analytics) variable.
JBI 4	Did the authors identify any potential confounders in the study?	Precursor to JBI 5; used for Causal Mapping verification.
JBI 5	Were any statistical or methodological strategies applied to mitigate confounding?	Crucial for Risk of Bias assessment; links directly to Causal Maps (DAGs).
JBI 6	Were any ESG outcomes measured using reliable or validated metrics?	Assesses validity of the Outcome (ESG/Accountability) variable.
JBI 7	Was the statistical analysis method appropriate for the study?	Assesses general statistical rigor and analysis quality.
JBI 8	Did the study utilize standard and objective criteria for measures, instead of ad hoc definitions?	Assesses objectivity and risk of measurement bias.
JBI 9	Did the study explicitly mention response rates, missing data, or handling protocols for non-responders?	Addresses potential Selection Bias or attrition bias.

The flowchart illustrates the systematic process of study screening, quality appraisal, and final inclusion/exclusion of sources used in this SLR. The appraisal adhered to the JBI Critical Appraisal Tools for assessing methodological rigor before thematic synthesis.