

Governance of Real Time Sustainability KPIS in Manufacturing – Bi, IIoT and AI Enhanced Lean Six Sigma

Nicoleta-Mihaela CASANEANU (DASCALU)*

“Gheorghe Asachi” Technical University of Iasi, Romania

**Corresponding author, nicoleta-mihaela.dascalu@student.tuiasi.ro*

Marius PISLARU¹

“Gheorghe Asachi” Technical University of Iasi, Romania

marius.pislaru@academic.tuiasi.ro

Elena-Lidia ALEXA

“Gheorghe Asachi” Technical University of Iasi, Romania

elena-lidia.alexu@academic.tuiasi.ro

Geanina GIOSAN

“Gheorghe Asachi” Technical University of Iasi, Romania

geanina-ionela.salceanu@student.tuiasi.ro

Abstract. Sustainability goals have been set by companies in recent years. The difficulty with these goals, however, remains the fact that they do not often translate into the actions of the workers in production. The monitoring of company sustainability often comes from utility bills, which are only available on a monthly basis. Thus, the workers in the factory will often only see the sustainability data from their utility bills once the actual production for that month is already in the past. This article addresses the gap between these two concepts with the presentation of a set of indicators of the production of manufactured products that focus on the production of greenhouse gases, energy, water, quality issues, and the efficiency of the machinery used in production. The indicators themselves were based upon principles of the Greenhouse Gas Protocol, ISO 50001, ISO 14001, AI technologies, Lean Six Sigma, and industrial data platforms. The focus of the article and the sustainability goal framework is upon the integration of these elements into the one framework for assessing the production of manufactured products in a factory. The article begins by explaining the concept of the framework and testing the framework upon a single production line in the factory of an automotive manufacturer. Finally, the article concludes by suggesting that the framework can assist in the diagnosis of the reasons behind the problems in the production of manufactured products, improve the monitoring of the sustainability indicators of production of manufactured products.

Keywords: sustainable manufacturing, real-time sustainability KPIs, Industrial Internet of Things, business intelligence dashboards, Lean Six Sigma governance, AI-assisted statistical process control, energy and emissions performance.

Introduction

Environmental, social, and governance (ESG) aspects have become increasingly important to manufacturers over the past decade. Many of these manufacturers are faced with stricter requirements for their sustainability reports, such as the Corporate Sustainability Reporting Directive (CSRD) established by the EU (Kotsantonis & Serafeim, 2019; Gibson Brandon et al., 2021). Additionally, many of these factories, especially energy-intensive ones, have faced increases in energy prices and the expansion of carbon pricing schemes, bringing focus to the need to become sustainable (Shah et al., 2023; Sarfraz et al., 2023). However, many of these factories only evaluate

their sustainability performance ex post facto, failing to track the performance of each individual machine or product in the factory (Xu & Duan, 2019). In response to this deficiency, there is a need for the establishment of real-time indicators that align with sustainability goals and for the use of ISO 50001 as a management tool rather than just a reporting tool for sustainability (Menghi et al., 2019; International Organization for Standardization, 2018).

The presented paper provides a framework that combines elements of business intelligence, industrial internet of things (IIoT) data, Lean Six Sigma principles and artificial intelligence (AI) within the context of manufacturers to report on their sustainability goals, as indicated in the Greenhouse Gas Protocol, ISO 50001 and ISO 14001 environmental standards (World Resources Institute & World Business Council for Sustainable Development, 2015; International Organization for Standardization, 2018), and within the context of control and automation systems within a factory (Bertsimas & Kallus, 2020; Xu & Duan, 2019). The paper outlines the minimum viable set of indicators to be incorporated within factories, investigates two potential hypotheses regarding these indicators, and provides the structure for one of these indicators. It hypothesizes that such indicators will allow manufacturing facilities to manage the sustainability performance of their products, and that a separate data management system will be required to contain the data from the indicators to be utilized for external reporting and to mitigate risks related to sustainability audits (Kotsantonis & Serafeim, 2019; Menghi et al., 2019). Finally, the paper presents a framework for ensuring that the indicator system is implemented in full within the factory before going online with the indicators and framework for the management of the factory (Kotsantonis & Serafeim, 2019; Menghi et al., 2019). The design science research methodology will be incorporated to implement the developed system and indicators into a pilot factory line for the purposes of research and development (Xu & Duan, 2019).

The paper contributions include the definition of the minimum viable indicator set, the framework for the structure and implementation of these indicators within factories, the use of Lean Six Sigma methodologies within the sustainability management of the factory, and the development of an evaluation framework for the sustainability performance management of the factory (Menghi et al., 2019; Bunse et al., 2011; Xu & Duan, 2019; Zhang et al., 2017; Montgomery, 2019; Bertsimas & Kallus, 2020; Kotsantonis & Serafeim, 2019).

Literature review

Sustainability measurement in manufacturing has evolved from corporate-wide indicators of sustainability towards indicators at the operational level of the manufacturing line. Several sustainability metrics, such as energy intensity, carbon dioxide equivalent (CO₂e) intensity for scopes 1 and 2, water intensity, scrap rate and first-pass yield, are now included in industrial manufacturing standards. Studies have shown that energy- and carbon-normalized indicators are effective in sustainability management (Bunse et al., 2011). The advent of the Industrial Internet of Things (IIoT) enables manufacturing lines to capture sustainability indicators in real time. Within IIoT platforms, data can be captured in two layers: a stream layer to collect low-latency events and a batch layer to enable long-term analysis of data. Within these layers, edge technologies can be used to collect data at low cost, while the cloud layer allows long-term, efficient processing of data (Lee et al., 2015; Wang et al., 2022). The Open Platform Communications Unified Architecture (OPC UA) and Message Queuing Telemetry Transport (MQTT) communication protocols enable data to be captured from smart devices on the shop floor and within the manufacturing line. Furthermore, the use of time-series databases, schema registries and business intelligence semantic models allows for the consistent recording and utilization of sustainability data in manufacturing (Xu & Duan, 2019).

Lean Six Sigma (LSS) is a widely used process-improvement methodology that can be applied within manufacturing environments to control production processes. Concepts such as Critical to Quality (CTQ) and Suppliers–Inputs–Process–Outputs–Customers (SIPOC) help practitioners identify critical sustainability indicators. Furthermore, the Define–Measure–Analyze–Improve–Control (DMAIC) cycle allows teams to control their sustainability indicators, while the Define–Measure–Analyze–Design–Verify (DMADV) framework can be used to design and stabilize new manufacturing processes that embed sustainability indicators (Montgomery, 2019). In addition, the fragmented nature of information technology and operational technology in manufacturing allows companies to apply LSS not only to their production processes, but also to their data-management processes (Wang et al., 2022). Business-excellence frameworks such as the European Foundation for Quality Management (EFQM) model can also be used to implement sustainability management at the line level through indicators that link corporate sustainability goals with operational indicators (Kotsantonis & Serafeim, 2019).

Artificial intelligence (AI) adds another dimension to sustainability management in manufacturing. AI can be used to monitor manufacturing lines and identify deviations from targeted production outcomes. For example, unsupervised anomaly-detection models and short-term forecasting models allow manufacturers to identify deviations that may lead to defective items or excess energy use (Bertsimas & Kallus, 2020). Prescriptive analytics can then be used to identify changes in production processes that alleviate these problems. AI can be deployed in manufacturing with low latency to support proactive changes to production and to complement rules-based systems such as statistical process control, rather than replacing them altogether. In this way, AI for manufacturing can help processes become more cost-efficient by utilizing energy more effectively in the production of high-quality units (Zhang et al., 2017).

Although many technologies and approaches to sustainability measurement have been proposed for manufacturing environments, the integration of these technologies to implement real-time sustainability indicators on the shop floor remains under-represented. Many published reports and articles on sustainability indicators in manufacturing focus on company-level indicators rather than on line- or shop-floor-level indicators (Bunse et al., 2011). Similarly, although various reports discuss Industry 4.0 and the capabilities of IIoT in manufacturing, few address the governance of sustainability indicators that should be embedded in data-management and manufacturing processes (Lee et al., 2015; Wang et al., 2022; Xu & Duan, 2019). These gaps indicate the need for a framework that connects standards, technologies and governance of sustainability indicators in manufacturing in order to control production processes on the shop floor.

Table 1. Standards alignment for real-time sustainability KPIs

Area	Primary standards / sources	What it ensures
KPI scope and boundaries	GHG Protocol; ISO 14001:2015	Clear scope definition and auditable environmental objectives.
Energy KPI specification and management	ISO 50001:2018	Consistent EnPIs, target setting, and improvement cycles.
Data and system integration	ISA-95:2010; OPC UA; MQTT	Interoperable, low-latency integration across systems.
Data modeling and dashboards	BI semantic models	Single-source KPI logic and consistent reporting.
Measurement governance	LSS DMAIC/DMADV; MSA; SPC	Credible measurements and robust process alerts.
AI augmentation roles	Anomaly detection; forecasting; prescriptive analytics	Explainable, prioritized support for early intervention.

Source: own research.

The existing literature and standards provide many of the necessary ingredients for creating a robust set of KPIs to manage sustainability in manufacturing. However, there is currently no single, integrated model that combines these ingredients into one effective workflow. The next section of this paper introduces the minimum viable KPI set proposed in this study. This minimum viable KPI set is designed to meet the need for lean, theoretically grounded environmental KPIs that remain manageable for managers and manufacturing line operators.

Proposed minimum viable KPI (MVKPI) set

This paper proposes a minimum viable key performance indicator (MVKPI) set that manufacturing companies can use to manage the sustainability of their operations in real time. The MVKPI set includes indicators that can be readily understood and acted upon by manufacturing line teams, while also reflecting the environmental and efficiency drivers identified in the literature. The indicators are aligned with the principles of the Greenhouse Gas Protocol, the ISO 50001 energy management standard and Lean Six Sigma, which together guide the use of these indicators for efficiency improvement (World Resources Institute & World Business Council for Sustainable Development, 2015; International Organization for Standardization, 2018; Montgomery, 2019). The proposed MVKPI set is intended for daily use by manufacturing line teams to manage key environmental and sustainability drivers in the facility, including energy use, emissions, water consumption, quality losses, production downtime and the overall effectiveness of manufacturing equipment.

Table 2 presents the proposed MVKPI set for real-time management in manufacturing. Each KPI is defined with a formula, units, time window, primary data source, data-quality checks and a designated decision owner responsible for producing or monitoring the KPI. While these indicators cover the essential environmental and sustainability management components of a manufacturing facility, companies can tailor the list to their specific operations and product portfolios.

Table 2. Minimum viable KPIs for real-time sustainability

KPI	Time window	Primary source	Quality checks	Owner
Energy Intensity per Good Unit	5–15 min; hourly/daily	Energy meters; MES	Spikes, alignment, bills	Production; Energy
CO ₂ eIntensity (Scope 1+2)	15–60 min; daily	Carrier meters; EF; MES	EF updates, reconciliation	ESG; Production
Water Intensity	15–60 min; daily	Flow meters; MES	Backflow, zeroing, totals	Utilities; Production
Scrap Rate	Real-time; shift-level	MES quality; counters	Rework split, duplicates	Quality; Line Supervisor
Rework Rate	Real-time; shift-level	MES rework; routing	Scrap split, routing	Quality; Prod. Eng.
Downtime Energy Loss	5–15 min; daily	State tags; meters	Mapping, baseline, warm-up	Maintenance; Line Supervisor
Renewable Energy Share	Daily; monthly audit	Inverters; contracts	Double counting, accuracy	Energy; ESG
OEE-Green	Shift-level; daily	OEE inputs; EI/GU	Guards, mix, targets	Operations; Energy

Source: own research.

The indicators in Table 2 illustrate how operational KPIs can be managed effectively through IIoT-based data acquisition and the management principles of Lean Six Sigma

manufacturing. In addition, each indicator has been developed with reference to recognized standards (e.g. Greenhouse Gas Protocol, ISO 50001, ISA-95), enabling manufacturing organizations to trust the real-time management of their sustainability initiatives.

Methodology

This research adopted a design science methodology to develop a framework for sustainability management. The framework incorporates a minimum viable KPI (MVKPI) set, a stream–batch data architecture with a governed semantic layer, a dashboard hierarchy with trust signals and AI-assisted SPC and is guided by Lean Six Sigma principles. The framework is intended to be piloted on a line in an automotive plant before being replicated elsewhere in energy-intensive industries. The research is design-oriented and empirical in the implementation of the artefact on an automotive production line. However, validation of the long-term impact of the framework on performance is deferred to future studies that focus on performance metrics of the implemented system on multiple production lines and in several plants.

Scope and design

The methodology focuses on the establishment of line- and plant- level indicators for the performance of sustainability practices within production processes. These include indicators for energy intensity, CO₂ e intensity, water intensity, scrap and rework, downtime energy loss, renewable energy share and overall equipment effectiveness (OEE Green). These indicators are the subject of the development of four main artefacts: the MVKPI semantic model, the stream–batch data backbone, the dashboard hierarchy and the AI services that support automated SPC analysis. Indicator requirements are informed by existing guidelines for sustainability reporting, such as the GHG Protocol, and by standards for environmental management systems, such as ISO 14001, and energy management systems, such as ISO 50001. Furthermore, insights from manufacturing professionals in the industry were incorporated into the design of the system. However, the data collected for this project includes only data from an automotive production line and does not investigate historical performance data for the line itself, focusing solely on the design and feasibility of the sustainability reporting framework at the pilot line. These four artefacts and their sequencing are summarized in Figure 1, which outlines the methodological stages of the MVKPI-based real-time sustainability framework.

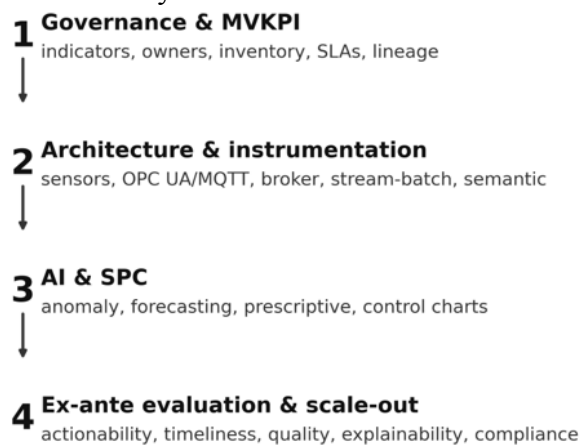


Figure 1. Methodological stages for the MVKPI-based real-time sustainability framework.

Source : own research.

1. Governance-first set up

Prior to the implementation of the sustainability reporting system, the governance framework for the system must be established. The MVKPI system is defined with a formula for each MVKPI, a unit that each MVKPI represents, the time window during which the indicator is calculated, the boundary that defines the scope of the indicator and a decision maker who is responsible for ensuring that the indicator provides reliable sustainability information. Data sources that provide information for each indicator are documented as inventory items that connect sensors and meters to the production database. Service level agreements (SLAs) are established between those who use the information provided by the system and those who operate the system, in terms of the reliability, freshness and availability of the data provided per indicator. Furthermore, the system includes features to track the data lineage of the indicators, who has access to which data and information provided by the system, and who has created and changed the system's indicators and dashboards.

2. Architecture and instrumentation

The data architecture for the system is based on a broker-based stream –batch pattern, with a connection to the production processes through sensors and meters implemented on the production line. These meters and sensors connect through controllers to the production system via protocols such as OPC UA and MQTT. The data provided by these meters and sensors is processed at the edge (if necessary) before being sent to the system's data backbone. Data ingestion is organized into topics that represent the information provided by the meters and sensors, with corresponding schemas defined for that data. A stream processor analyzes the data within the system and writes it to a time-series database, and the data is then sent to a data lake for longer-term storage. A semantic model defines the key elements of the production system and the sustainability indicators associated with them. This semantic model forms the backbone of the system and allows sustainability indicators and dashboards to be computed from the data sent by individual meters and sensors on the production line.

3. AI augmentation and SPC

The implementation of AI and SPC in the system is performed only after the data within the system meets the standards for data quality and measurement system analysis. The AI system includes the following functionalities: anomaly-detection algorithms that identify anomalies in sustainability indicators; short-term forecasting models that predict values for sustainability indicators; prescriptive models that provide recommendations for set-points for the production system based on the predicted values of those sustainability indicators; and automated SPC checks that ensure that sustainability indicators do not go beyond control limits and do not exhibit patterns that may indicate problems within the system. Furthermore, AI provides explainability features for the sustainability indicators and for the predictions of the system's AI models. SPC and AI models are developed, tested and maintained in the system through a model registry that tracks the version of each model. While AI performs these functions, SPC continues to play a role in enforcing sustainability constraints on the system as an additional layer of automated checks.

4. Ex-ante evaluation design

Prior to the system being deployed on additional production lines, it is evaluated using five performance metrics. These metrics allow an assessment of the extent to which the system meets

its own objectives and the objectives of the stakeholders who require sustainability indicators and dashboards. The five metrics include the actionability of sustainability indicators, the timeliness with which sustainability indicators are provided to those who need them, the quality of the underlying data, the explainability of sustainability indicators to stakeholders and the compliance readiness of the system. Each of these metrics includes a set of indicators that are monitored by the system during the pilot period on the production line. The data collected on these indicators is used to decide whether the system can be replicated on other production lines and in other facilities. Additionally, the use of a table such as Table 3 allows stakeholders to evaluate the sustainability system within a dashboard view of the production line, providing a simple means of tracking the success of the system.

Table 3. Example indicators for ex-ante evaluation dimensions

Dimension	Example indicator	Typical target (pilot)
Actionability	Share of alerts leading to executed actions	> 60% of MVKPI alerts acted on
Timeliness	P95 latency sensor → alert	< 2 minutes (operational view)
Data quality	% of critical sensors meeting MSA and SLA	> 95% inspection over pilot period
Explainability	Share of alerts with accessible diagnostics	> 80% with clear root-cause view
Compliance readiness	Coverage of KPI lineage and versioning	Full lineage and versions for all MVKPIs

Source: own research.

These example indicators make the evaluation criteria concrete and allow pilot teams to track progress in a simple, dashboard-friendly way.

Results and discussions

The following section outlines how the proposed framework behaves when implemented on a pilot level. Additionally, the implications of the framework will be discussed, as well as the framework's strengths and limitations. The frameworks are distinct from the previously developed frameworks due to the frameworks combining a minimum viable KPI set, the framework's architecture to comply with existing industry standards, and a series of governance artifacts into one unified workflow.

The framework is implemented according to the following stages of implementation: governance and scoping of the system, the instrumentation and data foundation layer of the system, the development of the MVKPI and dashboard layer of the system, the implementation of the AI and statistical process control layer of the system, and the evaluation of the pilot level implementation of the framework. Each of these stages is crucial to the development of the framework and demonstrates a way for the system to minimize issues during later stages of implementation and development. The stages of development can also be implemented in the order mentioned because it is necessary to develop the governance structures of the framework prior to the instrumentalization of the system. Another important aspect of the implementation is the order in which the framework can be implemented. The framework can be developed beginning with the static indicators of the framework and moving toward the real-time dashboards of the framework, followed by the analytics-enabled industrial control system of the framework. Each of these stages of implementation provides a step in the development of the framework that can be used to assess the success of the implementation of each stage of the framework prior to moving to the next stage of development of the framework.

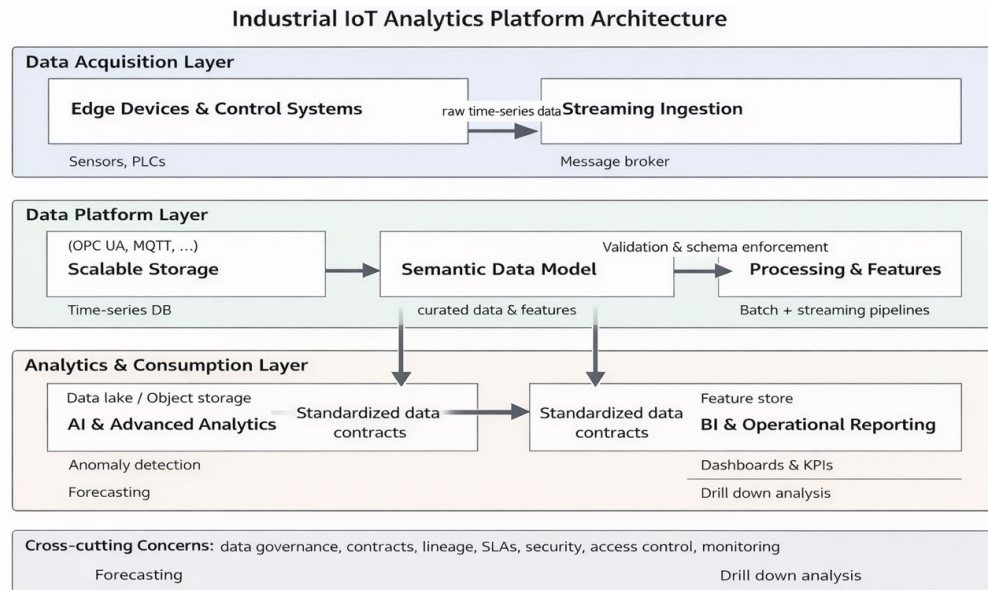


Figure 2. Layered Architecture of an Industrial IoT Analytics Platform

Source : own research.

The Figure 2 illustration depicts the architecture of the framework as it is implemented on a pilot basis. The instruments and meters connected to the framework provide data to the data broker, where it is preprocessed before being transmitted to the time-series and data lake storage systems of the framework. From the time-series and data lake storage systems, data can be transmitted to the semantic model and business intelligence layer of the framework that feeds strategic, tactical, and operational dashboards of the framework. These dashboards display data quality indicators alongside the reported sustainability and operational data to provide trust in the reported data to the stakeholders of the dashboard. The implementation of these dashboards is made possible through a small set of industry standards to report sustainability indicators to stakeholders in a compact and easily viewable format. Figure 2 shows the implementation of the data pipeline from the edge instruments to the different layers of the framework and finally to the various dashboards. Despite some of the challenges associated with implementing the framework in an industrial setting, the MVKPI-based dashboards can provide improved visibility to the stakeholders concerning sustainability indicators. For example, the dashboards provide information on indicators such as energy, CO₂ e, water, quality losses, downtime losses, the renewable percentage, and overall equipment effectiveness (OEE). The observation of the positive effects of this implementation demonstrates the benefits of the framework and architecture. However, the long-term performance of the framework has not been observed yet. Nevertheless, further performance evaluation studies are needed for a more concrete understanding of the benefits of implementing this framework.

Table 4. Observed benefits and trade-offs of the MVKPI-based system

Aspect	Observed benefits	Trade-offs and requirements
Visibility and timeliness	Real-time view on core sustainability indicators at line and shift level	Requires reliable instrumentation and robust connectivity
Decision support	Structured diagnosis via governed MVKPIs, SPC and analytics	Needs clear roles, escalation paths and change control
Audit readiness	Lineage, versioned definitions and data-quality badges	Demands ongoing data-contract and documentation discipline
Operator engagement	Transparent tiles with simple trust signals and drill-through	Requires training and integration in daily routines

Source: own research.

The observations regarding the implementation of the MVKPI-based framework are summarized in the Table 4 document. The benefits and drawbacks of the framework in terms of each aspect have been summarized in Table 4. The benefits include real-time visibility into sustainability indicators, structured diagnostics, better auditability of the sustainability data, and improved operator engagement. The drawbacks of the framework include the need for robust instrumentation, clearly defined governance structures of the framework, and potential challenges in integrating the frameworks with the remaining infrastructure within the manufacturing facility.

The sustainability framework has been implemented in the initial stages of the plant and, from the perspectives of the stakeholders involved in the management of that sustainability data, there are a few hypotheses that have been supported by the framework's implementation. Specifically, there are higher levels of trust in the actionable sustainability data and in the governance of that data. Additionally, there are higher levels of trust in the sustainability data itself as a result of the implementation of data contracts. Stakeholders also have some visibility into the sustainability data itself, including its quality and lineage. Despite these positives, there are limitations to the sustainability framework, and the sustainability framework is still in its early stages of management. Furthermore, while there have been some benefits to the sustainability framework, there have also been some limitations. The implementation of the sustainability framework has resulted in some costs to the organization as a result of the instrumentation, storage of the sustainability data, AI management features, and management by the various sustainability management departments of the plants.

Another limitation to the current management of the sustainability framework is that it has only been implemented for Scope 1 and 2 sustainability data, but not Scope 3 sustainability data. Finally, despite the increased management of the sustainability framework and its trust in the data, there are no cost savings reported for the organization as a result of the framework's management. However, the management of the sustainability framework has supported the hypothesis that the management of a limited number of sustainability indicators for each plant within the organization will help the organization achieve its sustainability goals.

Conclusion

The paper proposes a governance-first blueprint for managing sustainability in manufacturing that combines a minimum viable set of KPIs with an IIoT-based stream-batch architecture, a governed BI semantic layer and AI-assisted SPC that can assist in making both operational and business excellence decisions. While the proposal includes a pilot-level implementation of the proposed system, it does not include any randomized experiments or long term, multi-site case studies to indicate the performance of the system or the cost-savings it can achieve for manufacturing

organisations. Nevertheless, the blueprint can be reused by manufacturing companies that wish to implement an IIoT-based system for managing their sustainability and operational efficiency; such implementations would begin with establishing governance of sustainability and a minimum viable KPI set, implementing an ISA 95 aware system with a semantic model, and then implementing AI-assisted SPC only after establishing data quality within the system. Furthermore, the blueprint allows for the integration of sustainability indicators and AI-assisted SPC into Lean Six Sigma methodologies and other business excellence models that are already in use within the manufacturing firms with which it will be implemented.

Future work that could be performed with this blueprint would involve implementing the system within multiple manufacturing lines or plants to determine the impact that its implementation can have upon energy and CO₂ e intensity per positive unit of some manufacturing output; extending the system to be able to incorporate Scope 3 emissions and indicators through the integration of data from suppliers and logistics processes; or using the semantic and architectural models established within the blueprint to develop a transfer learning model or automated system for carbon accounting for the plants and processes within the manufacturing organisation. Each of these future directions for the blueprint provides a means of testing the blueprint on scenario-based ex-ante studies, in addition to the current pilot study and future long-term studies that will be able to evaluate the impact that such a system will have on real manufacturing organisations over time.

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During drafting, the authors used AI-assisted tools such as ChatGPT-4 for grammar and language clarity. These tools were not used to generate research ideas, methods, data, analyses or conclusions.

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