A sustainability-oriented KPI framework for digital twin adoption in the sugar industry: ISM–MICMAC approach

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Abstract

Purpose – The sugar industry is always pressured to be suitable and enhance its operational effectiveness. Digital twin (DT) has the potential to transform this industry. However, the lack of industry-specific key performance indicator (KPI) frameworks makes it challenging to implement them. This study provides a hierarchical KPI model for DT adoption in the sugar sector, interconnecting the United Nations' sustainable development goals (SDGs).

Design/methodology/approach – It has two phases: the first is an intense literature review, which identifies 24 relevant KPIs for DT adoption and sets the procedure for expert validation. Second, hierarchical relationships were identified through interpretive structural modeling (ISM) and MICMAC was used to classify KPIs based on driving and reliant power. The developed framework has several dimensions: technology, environmental, strategic, operational, financial and security.

Findings – Operational and environmental KPIs relate to important factors; however, environmental, social and governance (ESG) tracking, stakeholder satisfaction, governance, social and environmental factors, and reduction of defects were also critical outcomes. Key drivers came after technological studies, such as integrating old legacy systems, data integration and return on investment, or digital investment. The KPI hierarchy establishes the structural relationship that ensures DT investments align with sustainability goals, including cutting carbon emissions, maximizing resource usage and reducing water consumption.

Research limitations/implications – Likewise, earlier studies, the existing paper is also not free from limitations. We consulted experts from emerging economies like India to develop ISM modeling and collect data. However, the experts' opinions may change from country to country, impacting results. Also, the proposed research is applicable in the sugar sector.

Originality/value – Developing the DT adoption KPIs in the sugar sector using ISM and MICMAC is a unique contribution of this research. In addition, all KPI frameworks are also interconnected with the United Nations sustainability goals.

Keywords MICMAC analysis, Digital twin (DT), Key performance indicators (KPIs), Industry 4.0, ISM

Paper type Research article

1. Introduction

Considering climate change, the United Nations adopted the 2030 Agenda for Sustainable Development in 2015. This agenda provides details on sustainability for people and the planet, considering the present and the prospects. This agenda has 17 sustainable development goals

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(SDGs), which need to be focused on by all countries. The sugar sector is entirely dependent on sugarcane. Sugarcane is a seasonal crop and makes the industry vulnerable to climate change. As a result, sustainability indicators have become critical for this sector. During sugar manufacturing, huge amounts of energy are consumed in various processes like boiling, crystallization and packaging, which impact climatic conditions. It may hamper the growth of sugarcane and impact the sugar manufacturing (ISO, 2025). Digital twin (DT) can support the sector in manufacturing and sustainability aspects. While integrating DT with the United Nations sustainability goal, complete sector transformation is possible. It means sugar sector has to focus on various SDG like ensuring availability and sustainable management of water (SDG6), providing access to economical, reliable and renewable energy (SDG7), developing strong infrastructure, promote inclusive and sustainable industrialization and foster innovation like digital twin adoption (SDG9), creating infrastructure for endured production patterns and consumption (SDG12) and creating the strategic framework fight climate change and its impacts in the sector (SDG 13).

Moreover, DT is a digital replica of a product, process or portfolio. It can get data using IoT sensors, SCADA systems, programmable logic controller (PLC) and distributed control system (DCS) and other design simulation-based software (Tao *et al*., 2019). With the help of Industry 4.0 technologies, sugar manufacturing can be smarter using real-time data, big data analytics and artificial intelligence (Lu and Xu, 2019). One such application is agriculture 4.0, which brings radical biotechnical innovations (Klerkx and Rose, 2020).

Moreover, DTs are a part of Industry 4.0 technologies. It can support sugar factories in optimizing energy, reducing water consumption, enhancing crystallization quality, reducing downtime using predictive maintenance and ensuring effective utilization of bagasse for cogeneration.

However, DT adoption is limited in agriculture-based businesses. This sector has no ecosystem and governance framework (Borakhade *et al.*, 2025). In addition, issues related to infrastructure readiness (old process with legacy system), higher upgrade costs and CAPEX-based software usage are also hindering progress. Existing human resources lack digital literacy, and existing training models cannot transform their digital abilities. Moving data to the cloud or a hybrid system can cause security and compliance problems.

This sector requires a strong framework for filling the slot between the theoretical advantages and practical implementation for DT adoption (Sepasgozar *et al*., 2024). DT framework can provide a readiness framework to check existing maturing and transformational requirements (Kamble *et al*., 2022).

DT is critical for the sugar sector, so all key performance indicators (KPIs) should be designed carefully. Some aspects should include digital infrastructure, connectivity, speed and cybersecurity. Some internal and external sectoral aspects should also be included. Internal aspects cover efficiency, effectiveness and return on investment, and external aspects include climatic conditions, crop availability and water consumption during irrigation. Significant research gaps exist in literature: people typically look at KPIs independently, without indicating how they relate. For example, sugar processing has its own set of rules that general models do not consider. Also, environmental and ESG measures are rarely seen as the main drivers. To consider these perspectives, the proposed research has the following research objectives (RO):

RO1. To explore the KPIs of adopting DT in the sugar industry.

RO2. To develop a structural hierarchical framework for analyzing relationships among identified KPIs.

This study utilizes ISM and MICMAC analysis to fulfill the gaps in research with the above-stated research objectives. This paper explored 24 KPIs important for adopting digital technology in the sugar business. It mapped their hierarchical linkages to show relationships and results align with the SDGs. Theoretically, the study extends ISM–MICMAC to a new sector by merging multi-domain KPIs into one framework; practically, it gives sugar industry decision-makers a defined, stage-gated plan for DT adoption that combines efficiency with sustainability.

The rest of the paper is set up as follows: Section 2 examines the literature on DT technologies and KPI frameworks. Then, section 3 describes the steps used in the ISM methodology. Moreover, section 4 shows the findings of the ISM hierarchy and KPIs categorization using MICMAC. After that, section 5 discusses the implications, focusing on connections to sustainability. Lastly, section 6 provides limitations and future research directions.

2. Literature review

This section explores research databases, the concept and evolution of DT, and research gaps.

2.1 Exploration of research databases

There were 38,222 records when searching for articles on Digital Twin and KPIs measurement in research databases, including Scopus and Web of Science. Screening had three steps: (1) a review of the title and abstract to get rid of studies that were not about KPIs in manufacturing or process industries; (2) a review of the full text to keep studies that defined or used KPIs in those industries; and (3) quality and relevance checks only to include peer-reviewed journal articles or high-quality industry papers or scientific reports from renowned sources like McKinsey, IBM and ISO. This approach has finalized 77 publications that meet the proposed research requirements.

From the literature, 24 KPIs were found in five groups. Technological KPIs include the integration score, data interoperability, reducing latency, the frequency of model refreshes and hybrid deployment. Operational KPIs include the accuracy of equipment effectiveness, the accuracy of sugar recovery forecasts, the sensor coverage ratio, the accuracy of predictive downtime and the system uptime. Return on digital investment (RoDI), savings on maintenance costs and CapEx per DT node are all financial KPIs. Environmental KPIs include the amount of water used per ton of cane, the carbon emission index and the efficiency of using bagasse. Digital literacy rate, simulation agility, stakeholder satisfaction, access compliance rate and sustainability tracking are all important KPIs for strategy and security.

2.2 Digital twin technologies: concept, evolution and importance for sustainability

The DT idea started in aircraft engineering to create a virtual model that could simulate, monitor and improve the lifecycle of complex assets (Grieves and Vickers, 2017). The development of IoT (Internet-of-Things), cyber-physical systems, cloud computing, Internet speed and big data analytics supports the valuation of DT in various industries. DTs connect the real system with the virtual system. Once a real system provides feedback to a virtual system, various improvements can be made in the virtual system, like process improvement, failure prediction and effective resource utilization. However, all these benefits cannot be obtained due to a lack of digital infrastructure. Any dearth of leadership commitment and failure of change management strategy hinders the adoption of new technology (Klerkx and Rose, 2020; Läpple *et al*., 2015).

However, DTs can transform the sugar sector and integrate all SDGs with energy optimization, reduction of water consumption and waste reduction. Since DT optimized the machine's use, which can help extend equipment life and reduce breakdown. It can provide compounding benefits for man, machine, method, money and the market. Nowadays, every country is interested in national development planning with a sustainability strategy. Every country and industry is finding the best approach for developing a strategy and finding ways for effective DT implementation.

Current research indicates that DTs are becoming a revolutionary instrument in agro-industrial contexts; nevertheless, methodological precision and performance assessment frameworks are inadequately examined. Jones *et al*. (2020) offer a systematic framework to produce DTs and enhance this viewpoint by establishing DTs as the cornerstone of smart manufacturing. Kusiak (2021) stresses the importance of KPIs in measuring efficiency, adaptability and sustainability.

Previous research witnessed businesses' willingness to support environmental protection, realization of environmental responsibilities, supporting environmental protection, driving for environmental responsibility and finding the important factors affecting sustainability (Kumar and Ghodeswar, 2019). As smart manufacturing is becoming a modern trend, it is difficult to avoid its critical dimensions. Technologies like IOT, CPS and DT are supporting the development of DT models. These models play a vital role in predicting the behavior of machines and humans using robust modeling.

There are strong protocols for developing and maintaining the DT model in manufacturing industries. Every DT is a multifaceted model that provides strong empowerment to drive effective processes and meet the business KPIs. Since DT describe the synchronous state of the process, the portfolio's KPIs become critical. Operational KPIs look at things like how well equipment works, how accurate yields are and how many flaws there are (IBM, 2024). RoDI and the financial KPIs examine the economic reasons for digital transformation. Companies increasingly utilize environmental KPIs, such as carbon emissions per product unit and water use per ton of output, to achieve their SDGs and meet corporate sustainability objectives.

This study fills these gaps by creating a framework for digital transformation in the sugar industry, including technological, operational, financial, environmental and strategic/security KPIs based on interdependence. Table 1 shows the summary of KPIs in the sugar industry. Table 2 shows that adding sustainability goals to DT-based KPI frameworks helps the sugar industry use resources better, adopt better technology and reduce carbon emissions.

2.3 Identified literature gaps

This study fills the following gaps in literature:

(1) There are no DT-KPIs interdependency models for agro-industrial settings.

(2) No sector-specific KPI frameworks for the sugar industry that include sustainability criteria are available.

(3) Limited utilization of ISM–MICMAC in modeling digital transformation readiness and outcome paths within process industries.

The research seeks to provide a verified, sustainability-focused KPI model for DT adoption by closing these gaps, based on academic theory and real-world industry practices.

3. Research methodology

This paper uses a quantitative approach to formulate and evaluate a structured model of KPIs for implementing DT technology in the sugar sector using interpretive structural modeling (ISM). This technique examines variables/attributes underpinned by a literature assessment and expert consultations to form a hierarchical structure (Agarwal *et al*., 2007). The research flowchart is given in Figure 1. ISM was chosen because it shows how KPIs are related in a hierarchy, points out the most important aspects that affect many other indicators, and gives a step-by-step approach for putting it into action. Other approaches, like decision-making trial and evaluation laboratory (DEMATEL) and analytic network process (ANP), were not used because they are used to bifurcate variable categories (cause and effect) and computing weights, respectively (Mangla *et al*., 2018).

Table 1. Summary KPIs in sugar industries

KPI theme	Notation	Statements	Reference
Technological	KPI1	DT Integration Score: the percentage of old OT systems (SCADA/PLC) that are linked to the DT platform	Stewart (2025)
Technological	KPI2	Data Interoperability Index: the percentage of data transfers that follow semantic ontology rules	ISO 23247 (2025)
Technological	KPI3	DT Latency Reduction: The average time it takes for data to sync from operations technology (OT) to DT in milliseconds	McKinsey (2024)
Technological	KPI4	Hybrid Model Deployment: Number of active DT modules in sugar operations	Huang *et al.* (2023)
Technological	KPI5	Model Refresh Frequency: how many times, the DT model gets updated in real time each hour	Liang *et al.* (2023)
Operational	KPI6	Overall Equipment Efficiency Prediction Accuracy: the ratio of DT-predicted and actual Effectiveness of All Equipment	Wang *et al.* (2021)
Operational	KPI7	Sugar Recovery Forecast Accuracy: The percentage of sugar recovery predictions that match lab results	Stewart (2025)
Operational	KPI8	Sensor Coverage Ratio: the average number of IoT sensors for each step in a process, like boiling or grinding	Stewart (2025)
Operational	KPI9	Predictive Downtime Accuracy: the percentage of correct DT maintenance alerts that come before a failure	IBM (2024)
Operational	KPI10	DT Uptime: The percentage of time the DT system is available during production hours	Augustine (2020)
Financial	KPI11	RoDI = return on investment (ROI) on digital twin deployment after one harvest season. These are initial returns and multi-season follow-up depends on learning curves and capital intensity in mills	Yang *et al.* (2026)
Financial	KPI12	Percentage of maintenance costs saved: the difference between what DT-based projections say and what has happened in the past	Aivaliotis *et al.* (2019)
Financial	KPI13	CapEx per DT Node: the amount of money needed to set up a sensor, computer, and network unit	McKinsey (2024)
Environmental	KPI14	Water Use per Ton Cane: DT keeps track of how many litres of water are utilised per tonne of cane	Stewart (2025)
Environmental	KPI15	Carbon Emission Index: DT keeps track of and lowers the Carbon Emission Index, which is the amount of CO_2 released per ton of sugar (kg)	Arsecularatne *et al.* (2024)
Environmental	KPI16	Bagasse Utilization Efficiency: the percentage of bagasse that is reused, tracked by DT	Stewart (2025)
Strategic	KPI17	Digital Literacy Rate: the percentage of DT-trained workers that use dashboards at least once a week	Omrany *et al.* (2025)
Strategic	KPI18	DT Simulation Agility Index: The number of hours it takes to simulate changes in a process or supply chain	McKinsey (2024)
Strategic	KPI19	Strategic Positioning Index: Measures the organization’s readiness to leverage DT for future competitive advantage and alignment with industry trends	Bunjaridh *et al.* (2025)
Security	KPI20	Stakeholder Satisfaction Score: % of those that rate DT usefulness at least 8 out of 10	Tripathi *et al.* (2024)
Security	KPI21	Access Compliance Rate: the percentage of DT services that have role-based access control and audit logs	ISO 23247 (2025)

(*continued*)

Table 1. Continued

KPI theme	Notation	Statements	Reference
Environmental	KPI22	Sustainability Tracking Rate: the percentage of important ESG KPIs that DT keeps an eye on	Zhao *et al*. (2021)
Operational	KPI23	Flexibility Index for Processes: Time to change process settings for seasonal changes	McKinsey (2024)
Operational	KPI24	Defect Rate Reduction: The percentage of non-conforming output that goes down because of DT alerts	Sresakoolchai and Kaewunruen (2023)

Source(s): Authors' own compilation

Table 2. SDG linkages relevance in sugar industries

SDG code	SDG statement	Focus area	Relevance to sugar industry
SDG 6	Clean water and sanitation	Sustainable water use	Use less processed water, reuse condensate and cut down on waste discharge
SDG 7	Economical renewable energy	Energy	Effective utilization of bagasse for energy conversation and consume fewer fossil fuels
SDG 9	Industry, innovation and infrastructure	Innovation	Use smart process control, IoT sensors and DT-based optimization systems to make mills more effective
SDG 12	Responsible consumption and production	Effectiveness	Make processes better, use less raw materials and get the most out of the byproducts
SDG 13	Climate action	Carbon reduction	Reduce the amount of carbon released for every ton of sugar produced

Source(s): Authors' own compilation

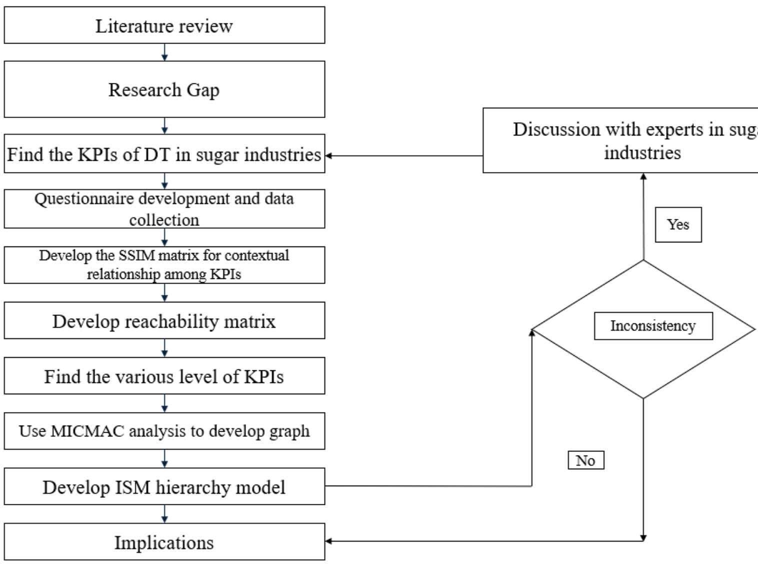

Figure 1. Research design overview. Source: Authors' own compilation

3.1 ISM technique

This study uses the ISM, a multi-criteria decision-making (MCDM) approach and MICMAC methods to offer a realistic and context-rich approach to DT KPIs and integrates it with SDGs. Various other MCDM techniques include total interpretive structural modelling (TISM), DEMATEL, best-worst method (BWM), analytical hierarchy process (AHP), graph theory, structural equation modeling (SEM) and ANP (Jakhar and Barua, 2014; Mangla *et al.*, 2018; Mathivathanan *et al.*, 2021; Shibin *et al.*, 2017). After careful evaluation, ISM was selected because it provides a hierarchical structure of variables that can present mutual interrelationships (Mathiyazhagan *et al.*, 2013). MICMAC analysis is done based on driving and dependence power (Agi and Nishant, 2017; Rana *et al.*, 2020).

ISM is used in a variety of application areas in distinct industrial settings, for instance, analyzing on-site industrialized construction (Liu *et al.*, 2025); Lean 4.0 assessment in manufacturing (Qureshi *et al.*, 2025); and analysis of smart warehouse (Singh and Singh, 2025). Also, Kamble *et al.* (2020) analyzed the enablers for blockchain adoption in the agrifood supply chain using ISM and concluded traceability as a significant enabler. Moreover, Latifi *et al.* (2021) assessed the drivers impacting conservation agriculture, performed MICMAC analysis, identified organizational culture, and reported policy making and monitoring as independent drivers. In addition, a research study by Agrawal and Vinodh (2019) applied ISM to assess a sustainable additive manufacturing system and concluded that manufacturing flexibility, new product development time and technological availability are pivotal factors. Also, Roy *et al.* (2025) used the ISM approach to analyze resource-efficient circular supply chain practices and assessed that favorable policies, stakeholder collaboration, coordination and synergetic relationships are triggering aspects.

The steps involved in ISM are as follows:

Step 1: Development of Structural Self-Interaction Matrix (SSIM)

The SSIM records expert opinions on how KPIs relate to each other. Experts used the following symbols to figure out the directional relationship for each pair of KPIs (i, j):

(1) V: KPI i influences KPI j.

(2) A: KPI j influences KPI i.

(3) X: KPI i and KPI j influence each other.

(4) O: There is no direct link.

The consensus SSIM was made through workshops that were led by experts, making sure that every expert agreed on what it meant.

Step 2: Constructing Reachability Matrices

The SSIM was transformed into the initial reachability matrix (IRM) by applying binary values (1 or 0) in accordance with ISM transformation criteria. The final reachability matrix (FRM) was created by adding transitive linkages, which allowed for identifying indirect dependencies using logical reasoning.

Step 3: Level Partitioning

Level partitioning was done using reachability, intersection and antecedent set. Levels were assigned to those KPIs with the same reachability and intersection sets. In the next iteration, the KPIs which are assigned levels were removed from the subsequent iterations, and the same steps were performed until all KPIs were assigned levels.

Step 4: ISM Digraph Construction

This step includes the development of a hierarchical structure, also called an ISM digraph, which shows directional links and puts KPIs in their driving dependency relationship. Table 3 also shows the methodological steps of ISM–MICMAC.

3.2 Expert selection process

A panel of 12 experts was put together. It included five industry practitioners (senior engineers and plant managers from sugar mills in India and Thailand who had worked with automation), four technology providers (experts in DT solutions, IoT and industrial analytics) and three academicians (researchers in industrial engineering, sustainable manufacturing and information systems). The panel members had an average of 15.4 years of professional experience, adding much information to the study. The number of experts is found satisfactory compared to other studies that applied a similar approach, ISM, to analyze variables. For example, Iqbal (2025) took data from 12 experts for analyzing driving variables for building information modeling; Chuaphun and Samanchuen (2024) gathered data from seven experts and examined success factors for virtual learning, and Asif *et al*. (2024) collected data from 10 experts to analyze enablers of diary supply chain management.

Experts gave each KPI a score of 1–5 for how relevant, measurable and applicable it was to the industry. Experts participated voluntarily and gave their consent before doing so. To protect business privacy, all data were anonymized, and private information was not published. The sample questionnaire is provided in Appendix. After three rounds of iterations, when the expert consensus was obtained in terms of pairwise comparison among KPI's, then SSIM was developed. The presented study computed Kendall's W of concordance using SPSS, and its value comes out to be 0.956, which reveals that process mapping is reliable, consistent and free from any biasness.

4. Results

Based on sectoral criticality and SDGs, 24 KPIs of DT were analyzed using ISM and MICMAC, and a hierarchical structure was developed. This structure has two powers called driving and dependent, which are also connected to sustainability and SDGs. The structure provides the KPIs to measure various aspects of DT adoption in the sugar sector, along with sustainability. It will help to drive successful DT implementation in the sugar mill. Independent performance measurements can be used as triggering factors; linkage measures

Table 3. Methodological steps of ISM–MICMAC

Step	Description	Input	Output
Literature review	Systematic identification of potential KPIs from literature review	38,222 initial records; 77 final publications	24 preliminary KPIs
Expert validation	Scoring and the discussion by an expert panel in two rounds	12 experts (industry and academia)	24 validated KPIs
SSIM development	Using expert opinions to look at the relationship among KPIs	24 validated KPIs	Structural Self-Interaction Matrix (SSIM) matrix
Reachability matrix	Transformation of SSIM into initial and final reachability matrices	SSIM	Final Reachability Matrix (FRM)
ISM modelling	Hierarchical placement of KPIs by driving vs dependence power	FRM	ISM Digraph (KPIs hierarchy)
MICMAC analysis	Categorization of KPIs into independent, linkage, dependent, autonomous	ISM results	MICMAC quadrant (strategic classification)

Source(s): Authors' own compilation

need to be stable, so they do not cause problems, and dependent measures show their reliance on driving KPIs. This framework helps the sugar sector prioritize investment areas, identify critical performance signals to monitor and anticipate the outcomes of DT implementation over time.

4.1 ISM-derived hierarchical structure

The ISM-derived hierarchy of 24 DT (Table 4) KPIs in the sugar industry was aligned with the United Nations SDGs. The most aligned is with SDG 9 (industry, innovation and infrastructure), specifically Target 9.4 on resource efficiency and Target 9.5 on innovation. Environmental KPIs are connected to SDG 6 (Clean Water, Target 6.4), SDG 12 (Responsible Production, Targets 12.2, 12.5, 12.6) and SDG 13 (Climate Action, Target 13.2) through things like how much water is used, how much bagasse is used and how much carbon is released. Financial KPIs, such as ROI and maintenance savings, align with SDG 8 (Economic Growth, Target 8.2). SDG 4 (Education, Target 4.4) and SDG 16 (Institutions, Targets 16.6, 16.10) are related to people and

Table 4. Summary of ISM-derived hierarchical structure

ISM level	KPI code	Related SDGs	Reasoning
Level I	KPI18	SDG 9.4	Faster simulation makes businesses run more smoothly, which is in line with Target 9.4
	KPI19	Indirect: SDG 9, SDG 17	Strategic positioning is a sign of adopting novel concepts (SDG 9) and collaborating (SDG 17)
	KPI21	SDG 16.6, 16.10	Makes institutions more accountable and gives people more access to information
	KPI22	SDG 12.6, 13.2	Fits with sustainable practices of the adoption of (12.6) and climate measures (13.2)
Level II	KPI13	SDG 9.4	The investment of money into DT nodes contributes to making industrial infrastructure cleaner and more efficient
	KPI20	Indirect: SDG 16	Build trust in digital systems, indirectly contributing to strong institutions
Level III	KPI8	SDG 9.5	Supports innovation and strengthens the technology infrastructure
	KPI11	SDG 8.2, 9.4	Improves productivity (8.2) and industrial efficiency (9.4)
Level IV	KPI6	SDG 9.4	Makes better use of industry resources
	KPI12	SDG 8.2	Cost savings enable productivity improvement
	KPI14	SDG 6.4, 12.2	Matches Target 6.4 (using water efficiently) and Target 12.2 (using resources in a way that is good for the environment)
	KPI15	SDG 13.2	Supports businesses embrace climate measures in their daily operations
	KPI24	SDG 12.5	Links to Target 12.5 (cutting down on waste)
Level V	KPI3	SDG 9.4	Allow industrial digital infrastructure to work more efficiently
	KPI16	SDG 12.2, 7.2	Supports the use of renewable energy (7.2) and sustainable resource utilization (12.2)
	KPI23	SDG 9.4	Flexibility makes industry more efficient
Level VI	KPI4	SDG 9.5	Make research and development and innovation stronger
	KPI9	SDG 9.4	Accuracy in maintenance makes businesses run more effectively
	KPI10	SDG 9.1, 8.2	Supports productivity (8.2) and ensures that infrastructure is strong (9.1)
	KPI17	SDG 4.4, 8.2	Links to improving abilities (4.4) and getting more work done (8.2)
Level VII	KPI5	SDG 9.5	Continuous updates demonstrate how innovative is a company
	KPI7	SDG 9.5, 12.2	Encourages innovation and makes more efficient use of resources
Level VIII	KPI2	SDG 9.1, 17.18	Standardized data exchange helps infrastructure (9.1) and expanding up data capacity (17.18)
Level IX	KPI1	SDG 9.1, 9.4	Directly upgrades industrial infrastructure, making it more efficient

Source(s): Authors' own compilation

security. Stakeholder satisfaction indirectly bolsters SDG 9 (innovation) and SDG 17 (Partnerships). In general, using DT in sugar production improves industrial efficiency (SDG 9), environmental sustainability (SDGs 6, 12, and 13), productivity (SDG 8), labor skills (SDG 4) and institutional trust (SDG 16). In the ISM digraph, continuous arrows show direct links, and indirect links (using the transitivity principle) are shown using dashed arrows in Figure 2.

4.2 MICMAC analysis results

Figure 3 describes the framework of all KPIs in different classifications. The result drives KPIs in various groups like autonomous, dependent, independent and linkages. This outcome was based on driving and depended on the power of the analysis. This classification helps with setting strategic priorities. The FRM was used to determine each KPI’s driving power by row sum and the dependence power by column sum. Figure 3 shows a Cartesian coordinate system used to depict the found values. The plot was then divided into four quadrants – independent, linkage, dependent and autonomous – based on driving and reliance power.

(1) Independent factors: high influence and minimal reliance

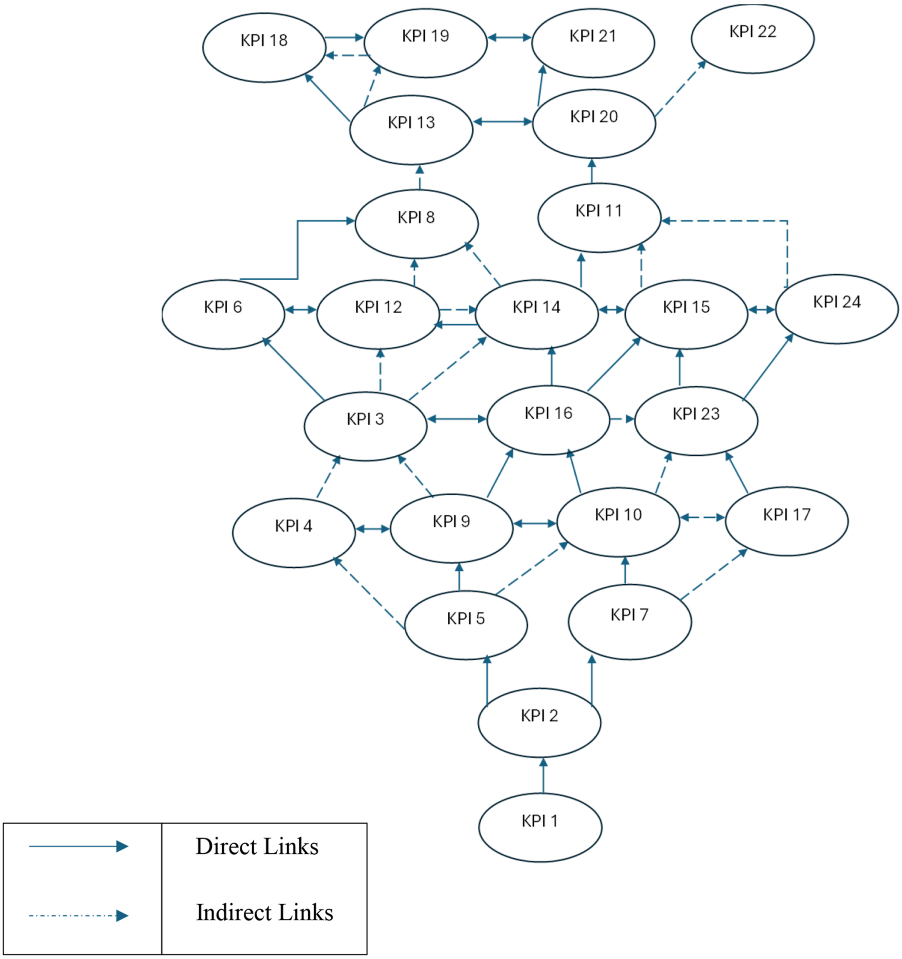

Figure 2. ISM digraph for KPIs. Source: Authors’ own compilation

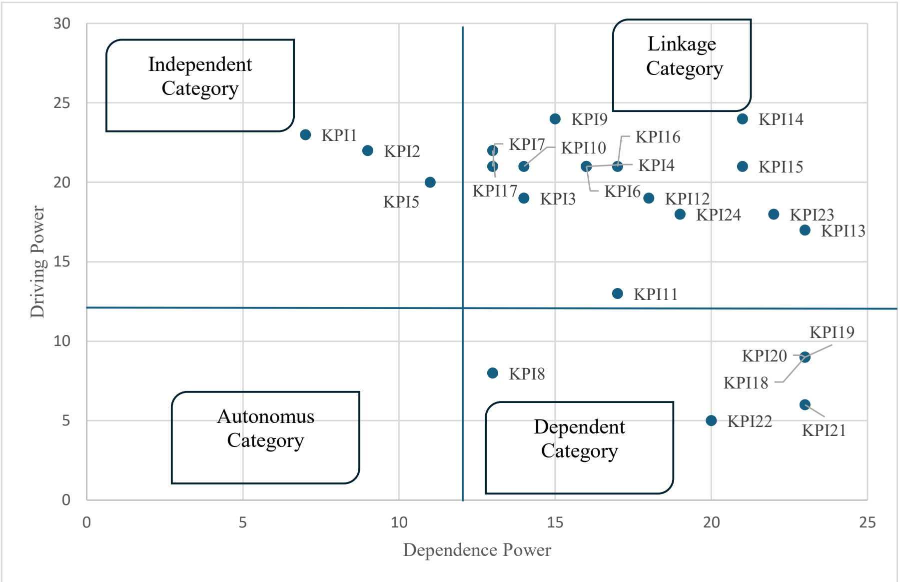

Figure 3. Result of MICMAC analysis. Source: Authors' own compilation

(2) Linkage factors: both strong influence and strong reliance

(3) Dependent factors: minimal influence but great need

(4) Independent factors: little influence and little reliance

As per Table 5, the MICMAC study shows that the system is driven by independent KPIs, such as DT integration (KPI1), Data Interoperability (KPI2) and Model Refresh Frequency (KPI5). These are incredibly vital and are called triggering KPIs and driving others. Linkage KPIs are significantly dependent on each other and greatly impact each other. They are vital for the system's stability and should be observed closely when being put into place. Linkage KPIs, such as Latency Reduction (KPI3), Hybrid Model Deployment (KPI4), and Equipment Effectiveness (KPI6), are the most important since they affect and are affected by many other KPIs. Also, Sensor Coverage Ratio (KPI8), DT Simulation Agility Index (KPI18), Stakeholder Satisfaction (KPI19), Stakeholder Satisfaction Score (KPI 20), Access Compliance (KPI21), Sustainability Tracking Rate (KPI22) are all dependent KPIs. It means that they depend on other KPIs to work. Autonomous KPIs do not have much driving or dependent power. In the presented study, no KPI falls under the autonomous category.

5. Discussion

The DT Integration Score shows how successful production systems work with DT technologies. Many Supervisory Control and Data Acquisition (SCADA) and Programmable Logic Controller (PLC) systems in the sugar sector are old, which makes integration a technical and strategic problem (Stewart, 2025). Data interoperability enables moving environmental and operational data by integrating various processes, which is important for ESG reporting. RoDI checks to see if DT projects make money, which is very important in marketplaces where costs are important.

Table 5. Summary of MICMAC analysis results

Category	KPI code	Relationship with SDGs
Independent KPIs	KPI1	Updating old technology Integrating OT makes infrastructure (SDG 9.1) and resource use (SDG 9.4) more efficient
	KPI2	Standardized data interchange helps the sector stay strong (SDG 9.1) and builds data capacity (SDG 17.18)
	KPI5	Frequent updates show that a company has a lot of research and development and innovation (SDG 9.5)
Linkage KPIs	KPI3	Faster synchronization makes manufacturing facilities work better
	KPI4	Integrating AI with physics models boosts the ability to come up with new ideas
	KPI6	Accuracy aligns with resource-efficient infrastructure (SDG 9.4)
	KPI7	Forecasting supports innovation and sustainable production
	KPI9	Trustworthy alerts reduce downtime, improving industrial efficiency
	KPI10	Continuous uptime supports resilient infrastructure (SDG 9.1) and productivity (SDG 8.2)
	KPI11	Profitability reflects productivity gains (SDG 8.2) and industrial modernization (SDG 9.4)
	KPI12	Reduced costs strengthen productivity growth
	KPI13	Capital costs represent industrial investments for efficiency improvements
	KPI14	Matches water-use efficiency (SDG 6.4) and sustainable consumption (SDG 12.2)
	KPI15	Carbon intensity reduction directly supports climate action (SDG 13.2)
	KPI16	Bagasse reuse reduces fossil fuel reliance (SDG 12.2) and supports renewable energy (SDG 7.2)
	KPI17	Skills development (4.4) supports productivity growth (8.2)
	KPI23	Flexibility enhances industrial resilience and efficiency
	KPI24	Reducing defects lowers waste, supporting sustainable production (SDG 12.5)
Dependent KPIs	KPI18	Simulation agility enhances process efficiency and planning
	KPI19	Reflects innovation adoption (SDG 9) and partnerships (SDG 17)
	KPI20	Builds stakeholder trust, indirectly contributing to strong institutions (SDG 16)
	KPI21	Ensures accountability (SDG 16.6) and access to information (SDG 16.10)
	KPI22	Real-time ESG tracking supports sustainable practices (SDG 12.6) and climate integration (SDG 13.2)
	KPI8	Wider IoT sensor coverage supports industrial innovation capacity

Source(s): Authors' own compilation

DT in sugar manufacturing should be the driver of innovation in the industry, with the readiness of digital infrastructure, which is in line with the ISM result. DT can also enable better visibility into the supply chain network and enhance productivity. In sugar manufacturing, various machines are used. Integrated systems of these machines, along with their actuators and sensors, can relate to high-speed local Internet (industrial 5G) for data exchange and processing. It will enhance the process capability based on data analytics and drive sustainable equipment, components and materials. So, all KPIs can evolve along with manufacturing and sustainability-related aspects (Tao *et al.*, 2019). DT implementation supports all selected sectoral areas like sugar manufacturing for sustainable energy, water, disaster risk reduction and technology development of micro-, small and medium-sized enterprises (MSMEs). These initiatives underscore the importance of integrated approaches and stakeholder participation in planning and decision-making, necessitating robust KPIs to track progress and ensure sustainable outcomes.

After preparing the ISM model, the MICMAC diagram of the KPIs is prepared based on their driving power and dependence. FRM calculates driving power and dependence (Dubey *et al.*, 2017). Management should know that linking DT and sustainability KPIs translates into appropriate strategies and collaboration with stakeholders and ecosystem partners. The role of sustainability is enabled by continuous improvement through DT technologies. Improving operational performance and sustainability will also help the sector become economically viable and stable. Results clearly indicate that KPI 4 and KPI 5 can be hindered if the model is unsuitable and cannot monitor various KPIs. ISM layers define the structural hierarchy among the anticipated KPIs.

5.1 Implications for managers

This paper provides several implications for the sugar sector for DT adoption with relevant KPIs developed through an ISM-based framework. The DT model for the sugar sector is subjected to various key challenges hindering its adoption. The ISM-based framework provides a countermeasure to such a challenge. The models serve as a communication mechanism to help interpret the behaviors of machines or systems and to predict their future state based on real-time data, historical data, experience and knowledge, as well as on data from models. Therefore, models and data can be considered as the core elements of a DT. This research provides a framework to define the KPIs at various stages to monitor sustainability and DT adoption effectiveness. DT has not been tested enough in the sugar sectors as a pilot and lacks validation of this technology, which can put the solutions built around it at risk. Therefore, organizations must invest in digital infrastructure, system integration and an ecosystem.

The sugar industry should arrange training programs to improve the employees' digital skills and enhance their ability to use the DT properly in their day-to-day functioning. The employees should be well-trained to equip themselves with ongoing advancement in DT to deal with the increasing complexity of this technology. It will also help overcome their reluctance to use more advanced technology like DT for better work efficiency. A better understanding of the functioning of DT will also help determine how it can be effectively integrated with the existing legacy systems to ensure seamless functioning of the unified system. It can happen only when sugar industries can better prepare and equip their employees with the advancements of this technology through ongoing training programs and integrate sustainability in the entire ecosystem. Sugar mills should also consider this technology's legal and ethical issues and regulatory compliance for better adoption. It is signified by the high driving and high dependence power acting as key mediating variables between the absolute driving and dependence variables. Industries should understand the legal issues arising from data sharing and cybersecurity. Table 6 shows the summary of sustainability implications in content of DT adoption in sugar industries.

5.2 Policy and regulatory implications

SDG report 2025 clearly describes that 56% of global domestic wastewater generated (332 billion cubic) was safely treated, largely unchanged from 2020. However, data on industrial wastewater remain scarce, with only 22 countries reporting. Comprehensive global reporting on total wastewater is not expected until 2027. To achieve this goal, policymakers can incorporate KPI-based sustainability reporting. This framework can include incentivizing Industry 4.0 adoption through SDG-aligned tax benefits and subsidies that can encourage

Table 6. Summary of sustainability implications

Stage	Focus area
Foundation	Create digital infrastructure (integration, interoperability) that can collect data on sustainability metrics
Enablement	Use prediction and optimization models to change how operational resources are used
Execution	Make sure that people and governance are ready to track sustainability
Results	Get measurable savings in waste and environmental impact

investment in technological innovations and green initiatives. Clear guidelines on sustainability, data privacy, cybersecurity and intellectual property rights will drive the adoption of DT in the sugar sector.

6. Conclusion, limitations and future research directions

This study also strongly recommends KPIs related to DT adoption and sustainability. During detailed analysis, a framework has been developed to assess the various dimensions like readiness, strategy, technology, security and return on investment. Finally, DT-driven KPI tracking systems help to find the gaps, provide recommendations, support achieving sustainability and integrate SDGs into the business framework for achieving the 2030 Agenda for Sustainable Development. This research provides the ISM and MICMAC validated framework for DT adoption KPIs. These KPIs are integrated with the United Nations Sustainable Development Framework. This study finds the literature gap and provides strong recommendations to drive sustainability in sugar industries. Also, in the scholarly literature, there is limited incorporation of sustainability and ESG metrics into digital transformation preparedness frameworks. However, the ISM hierarchy showed a nine-level development from basic enablers like the DT Integration Score, the data interoperability index, and the RoDI to high-dependence outcomes like the sustainability tracking rate the flexibility index and the defect rate reduction.

Moreover, from a sustainability point of view, the framework showed that improvements in environmental performance (like using less water and cutting carbon emissions) are lagging indicators of how mature DT adoption is. It is only possible after technological integration, operational reliability and workforce readiness have all stabilized. This information is also useful for ensuring that DT adoption plans align with the United Nations SDGs, especially SDGs 6, 7, 9, 12 and 13.

Moreover, the research advances theoretical frameworks by applying ISM–MICMAC to a novel industrial sector and integrating sustainability measurements into the KPI network. It helps the sugar industry by giving decision-makers a stage-gated, SDG-aligned roadmap that lets them set investment priorities, keep track of progress in adoption and evaluate long-term operational and environmental performance.

6.1 Limitations and future research directions

Likewise, earlier research studies, the presented research is not free from limitations. For developing ISM modeling and collecting data, we consulted experts from the emerging economy, India. However, the opinion of experts can vary from country to country, which can cause a change in results. Also, the proposed research is applicable in the sugar industry. Similar studies in other process industries like pulp and paper, cement and textiles can be conducted, and results can be compared. It can help in endorsing a universal paradigm for DT adoption. Also, ISM helps to develop a structural hierarchical framework among identified KPIs by collecting data at instant of time, i.e. cross-sectional data were used. Therefore, future longitudinal studies spanning several harvest cycles can be conducted by considering dynamic factors like market conditions, technological innovations and regulatory changes. Moreover, behavioral perspectives, including employee engagement, leadership commitments and change management, were not considered, which gives scope to budding researchers to work in this direction. Also, most small-scale industries lack funds and are unaware of advanced tools to measure environmental KPIs, as measurement of KPIs may become difficult for most mills.

Moreover, in future studies, the technological feasibility of each KPI can be explored and investigated. Also, empirical studies can be conducted, and findings can be compared. Future research may also use system dynamics using ISM–MICMAC to model feedback loops, delays and adoption scenarios.

6.2 Closing remarks

The sugar business is getting much attention; it needs to improve its efficiency, lower its environmental impact and stay competitive in a global dynamic market. DT technology presents a transformative opportunity; yet its effective application necessitates a comprehensive grasp of the interrelated performance measures that facilitate adoption and yield outcomes.

This study provides a proven hierarchical model that combines technological, operational, financial, environmental and strategic/security KPIs. This model is useful for decision-makers in business and adds to the knowledge on digital transformation. The stage-gated roadmap based on the ISM–MICMAC structure gives clear directions for ensuring that DT investments align with operational goals and commitments to sustainability. The study supports the idea that sustainability in manufacturing is not a separate goal, but rather the result of a well-planned digital transformation process. This process combines technological readiness, operational stability, maturity and workforce capability to create measurable social and environmental benefits.

Appendix

Sample questionnaire

The sample questionnaire was bifurcated into two parts, Part-1 contained questions related to demographics and Part-II had the questions related to main part of the study.

Part-1

Name of the Respondent: ……………………………………………………………

Age: ……………………………………………………………………………

Qualification: ………………………………………………………………………

Designation:…………………………………………………………………………

Years of Experience:……………………………………………………………………

Industry type:…………………………………………………………………………

Organization’s Turnover:………………………………………………………………

Years of Establishment of organization.…………………………………………………

Part-B: Use symbol V, A, X and O to fill this matrix

Table A1. SSIM format for KPIs

KPIs	KPI24	KPI23	KPI22	KPI21	KPI20	KPI19	KPI18	KPI17	KPI16	KPI15	KPI14	KPI13	KPI12	KPI11	KPI10	KPI9	KPI8	KPI7	KPI6	KPI5	KPI4	KPI3	KPI2
KPI1																							
KPI2																							
KPI3																							
KPI4																							
KPI5																							
KPI6																							
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KPI22																							
KPI23																							

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