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Intelligent Value Stream Mapping with Embedded Predictive Analytics

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KEYWORDS

Intelligent Value Stream Mapping; Predictive analytics; Lean manufacturing; Digital twin; Industry 4.0.

ABSTRACT

This review examines Intelligent Value Stream Mapping (VSM) with embedded predictive analytics as an advanced lean manufacturing approach for overcoming the static, retrospective, and manually dependent limitations of conventional VSM. It focuses on how real-time data, machine learning, digital twins, and Industry 4.0 technologies can transform VSM into a dynamic decision-support system for proactive waste reduction and process optimization. The study synthesizes literature on traditional VSM, predictive analytics, data-driven manufacturing architectures, digital value stream twins, process mining, edge/cloud analytics, and lean tool integration. It evaluates data acquisition from sensors, IoT/RFID devices, ERP, MES, and shop-floor systems, together with preprocessing, feature engineering, predictive modelling, simulation, dashboard visualization, and decision-support mechanisms. The review shows that Intelligent VSM strengthens bottleneck prediction, inventory and lead-time management, continuous kaizen, demand-driven scheduling, and integration with Kanban, Andon, Poka-Yoke, Heijunka, and other lean tools. Evidence from the literature shows measurable gains, including 28% reduction in expected delivery time, 67.84% lead-time reduction, 20% productivity improvement, 25% OEE improvement, production balance improvement of 29.07%, and ANN prediction performance with MSE below 0.001 in selected applications. However, adoption remains constrained by poor data quality, heterogeneous system integration, black-box model behaviour, scalability limits, latency constraints, weak alignment with lean simplicity, and lack of standardized implementation frameworks. Future research should prioritize AI-driven optimization, digital twin ecosystems, edge-enabled real-time analytics, interpretable human-centered dashboards, and scalable standardized methodologies.

1. Introduction

1.1 Background and Context

Value Stream Mapping (VSM) is a foundational lean tool used to visualize material and information flows across production systems, enabling the identification of waste, bottlenecks, and inefficiencies (Karmaoui et al., 2023; (Khakpour et al., 2024; Ferreira et al., 2022). Originating from the Toyota Production System, VSM provides a two-dimensional representation of both value-added and non-value-added activities along a product's journey from supplier to customer (Karmaoui et al., 2023; Salwin et al., 2023). Traditional VSM relies on manual data collection and periodic observation, producing static snapshots of system states (Khakpour et al., 2024; Frick & Metternich, 2022). Modern manufacturing environments generate continuous operational data through sensors, IoT devices, and enterprise systems (Ferreira et al., 2022; Nwamekwe et al., 2025). These data streams create opportunities to transform VSM from a static visualization tool into a dynamic, intelligent system (Salvadorinho & Teixeira, 2021; Nwamekwe et al., 2025e). By embedding predictive analytics and Industry

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4.0 technologies into VSM, organizations gain the ability to anticipate process variations, detect emerging inefficiencies, and support proactive decision-making (Rossi et al., 2022; Butt, 2020).

1.2 Problem Statement

Conventional VSM lacks the capacity to capture real-time system behaviour or predict future states, as it depends on historical averages and manual inputs (Khakpour et al., 2024; Frick & Metternich, 2022; Serrato, 2021). This static nature limits its responsiveness in dynamic environments with high variability (Chen et al., 2022; Lugert et al., 2018). Researchers have noted that VSM fails to present workshop problems in real time and struggles to represent complex manufacturing systems realistically (Chen et al., 2022; Yılmaz et al., 2022). Predictive analytics and machine learning offer strong capabilities for modelling complex patterns and forecasting system behaviour (Saad et al., 2021; Tripathi et al., 2022). These techniques are frequently applied independently of lean frameworks, creating a disconnect between data-driven insights and operational improvement tools (Sordan et al., 2021; Nwamekwe et al., 2025d). Integrating predictive analytics directly into VSM addresses this gap by enabling continuous monitoring, real-time scheduling, and intelligent waste detection within a unified lean framework (Salvadorinho & Teixeira, 2021; Nwamekwe et al., 2026; Saad et al., 2021).

1.3 Objective of the Review

This review synthesizes existing approaches for integrating predictive analytics into value stream mapping. It examines data architectures, modelling frameworks, and application strategies reported across manufacturing domains (Khakpour et al., 2024; Ferreira et al., 2022; Frick & Metternich, 2022). It also identifies challenges related to data integration, model interpretability, and real-time implementation that remain barriers to widespread adoption (Nwamekwe et al., 2025c; Lugert et al., 2018; Bega et al., 2023).

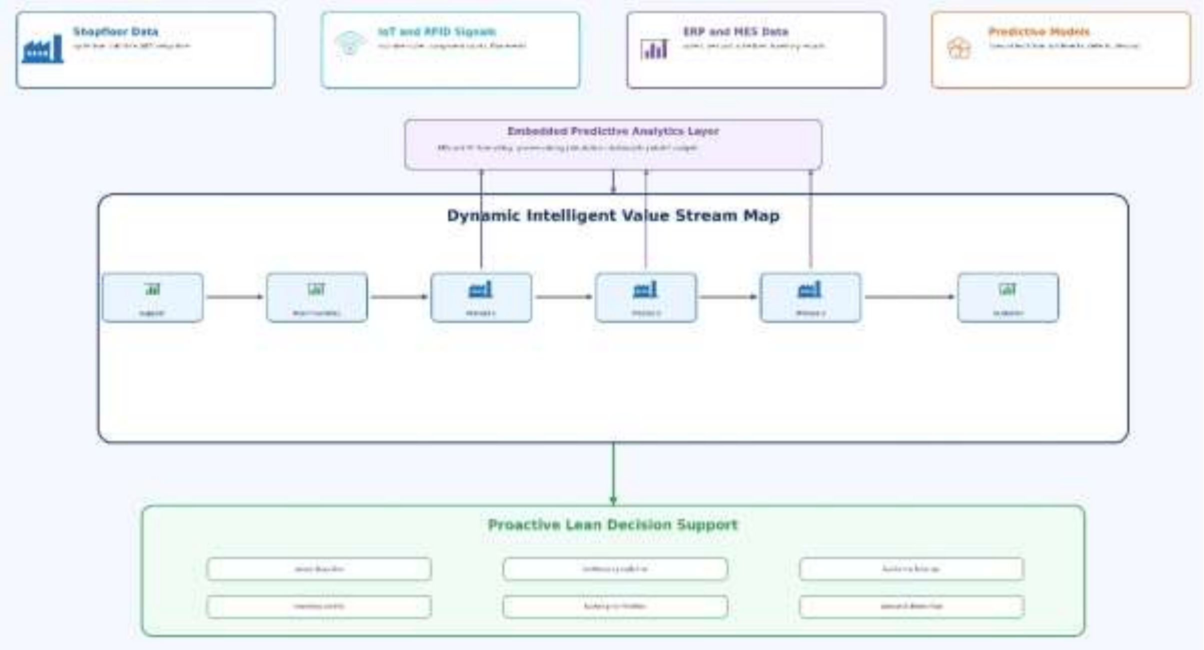

Figure 1: Conceptual Framework for Intelligent Value Stream Mapping with Embedded Predictive Analytics

Figure 1 presents the conceptual architecture of Intelligent Value Stream Mapping (VSM), illustrating how shop-floor data, IoT/RFID signals, ERP/MES systems, and predictive models converge within an embedded analytics layer. The framework transforms conventional VSM into a dynamic decision-support system that continuously monitors processes, predicts future states, identifies waste, and supports proactive lean interventions for improved operational efficiency.

2. Conceptual Foundations of Intelligent Value Stream Mapping

2.1 Traditional Value Stream Mapping

Value Stream Mapping (VSM) originated from the Toyota Production System and serves as a primary lean tool for visualizing material and information flows across production processes (Karmaoui et al., 2023; Khakpour et al., 2024). It represents all actions required to deliver a product to the customer, covering both value-added and non-value-added activities (Ferreira et al., 2022; Salwin et al., 2023). Standard VSM elements include process steps, cycle times, takt time, inventory levels, and information flows (Frick & Metternich, 2022; Nwamekwe et al., 2025a). Practitioners draw two maps: a current state map depicting existing conditions and a future state map outlining targeted improvements (Salvadorinho & Teixeira, 2021; Rossi et al., 2022). VSM supports waste identification across categories such as overproduction, waiting, transportation, excess inventory, and defects (Butt, 2020; Serrato, 2021). Its visual simplicity makes it accessible to cross-functional teams and widely adopted across manufacturing, logistics, and service sectors (Chen et al., 2022; Lugert et al., 2018). The tool remains a starting point for lean deployment in most organizations (Ferreira et al., 2022).

2.2 Limitations of Static VSM

Traditional VSM captures a single snapshot of the production system at one moment in time, relying on deterministic parameters and manual data collection (Yılmaz et al., 2022; Saad et al., 2021; Tripathi et al., 2022). It assumes stable operating conditions and uses averaged values for cycle times, setup times, and demand rates (Sordan et al., 2021; Bega et al., 2023). This static nature prevents VSM from reflecting temporal variability, stochastic process behaviour, or fluctuating demand patterns (Nwamekwe et al., 2025b; Saad et al., 2021). Researchers have noted that VSM fails to present workshop problems in real time and struggles to represent the complexity and dynamic behaviour of production processes (Kumar et al., 2023; Zoubek et al., 2021). An empirical survey of 170 lean experts found that 92 percent requested further development of VSM through digitalization to compensate for its weaknesses, with inflexibility identified as the most serious challenge (Khakpour et al., 2024). Static VSM also lacks the ability to predict inventory levels or evaluate what-if scenarios for different future states (Wu et al., 2025; Zoubek et al., 2021). These shortcomings limit its effectiveness in environments characterized by high product variety, customization demands, and supply chain uncertainty (Chidiebube et al., 2025a; Tripathi et al., 2022).

2.3 Predictive Analytics in Manufacturing

Predictive analytics applies statistical and machine learning models to forecast future outcomes based on historical and real-time data (Azizah, 2025; Karmaoui et al., 2023). In manufacturing, these techniques enable early detection of process deviations, equipment failures, and quality defects before they occur (Igbokwe et al., 2025; Shan et al., 2023). Tripathi et al. (2022) demonstrated the use of artificial neural networks (ANN) coupled with VSM to predict production times in an earthmoving equipment manufacturing unit, achieving high accuracy with mean squared error values below 0.001. Machine learning models, including neural networks and regression techniques, support proactive scheduling, demand forecasting, and resource allocation decisions (Onyeka et al., 2024; Karmaoui et al., 2023). Process mining approaches extract real-time behavioural patterns from event logs, enabling dynamic monitoring and deviation tracing (Tripathi et al., 2022). The integration of predictive models with IoT sensor data and enterprise systems creates a foundation for data-driven decision-making across the production value chain (Chen et al., 2022; Igbokwe et al., 2025b).

2.4 Integration of VSM and Predictive Analytics

Intelligent VSM integrates predictive models and Industry 4.0 technologies directly into the value stream framework to create a dynamic, continuously updated system (Chen et al., 2022; Richter et al., 2023). This integration enables real-time monitoring of process performance through IoT-enabled sensors and dashboards (Chen et al., 2022; Liu & Yang, 2020). Richter et al. (2023) introduced Dynamic Value Stream Mapping (DVSM) as a smart IT platform that sustains lean tools through real-time scheduling and dispatching modules, optimizing flow along the value stream and minimizing manufacturing lead time. Ferreira et al. (2022) extended VSM to the Industry 4.0 context using agent-based simulation, incorporating supply chain and internal uncertainty sources such as demand variability, machine maintenance, and cycle time fluctuations. The Lean Process Mining method proposed by Tripathi et al. (2022) implements prediction-recommendation-prevention strategies within the value stream, enabling online observation of process behaviour and avoidance of defective products during production. Saini and Thomas, (2023) combined VSM with system dynamics modelling to create a Dynamic Value Stream Map that allows simulation-based experimentation with process improvements over short, medium, and long-time horizons. These integrated approaches transform VSM from a periodic diagnostic exercise into a continuous, adaptive management system.

2.5 Performance Metrics for Intelligent VSM

Performance measurement in intelligent VSM extends beyond traditional lean metrics to incorporate predictive accuracy and dynamic responsiveness indicators. Lead time variability is a primary metric, with Saad et al. (2021) demonstrating through dynamic and fuzzy VSM that incorporating uncertainty in supplier and customer shipping times reduced expected delivery time by 28%. Throughput prediction accuracy is measured through model validation, as shown by Azizah (2025), who reported ANN prediction models with testing MSE of 0.01 and MAE of 0.0002 for production time forecasting. Inventory level forecasting becomes feasible when simulation complements static VSM, enabling practitioners to observe how inventory varies across different scenarios (Wu et al., 2025; Serrato, 2021). Waste reduction metrics in intelligent VSM include value-added percentage, process cycle efficiency, and non-value-added time reduction (Peças et al., 2021; Ilangakoon et al., 2021). The Intelligent VSM model proposed by Chen et al. (2022) tracks system performance through an Integrated Efficiency Monitoring System (IEMS) with dashboard visualization at regular intervals. Overall Equipment Effectiveness (OEE) serves as a composite metric capturing availability, performance, and quality dimensions within the digitalized value stream (Igbokwe et al., 2024; Chen et al., 2022).

Figure 2: Evolution from Static Value Stream Mapping to Intelligent Predictive Value Stream Models

Figure 2 illustrates the progression of VSM from traditional static mapping to intelligent predictive models. The evolution advances through digital and dynamic VSM stages toward a predictive framework capable of real-time monitoring and forecasting. The expanded performance logic demonstrates the transition from conventional lean metrics to predictive, dynamic, and operational metrics that support continuous process optimization and data-driven decision-making.

3. Data Architectures and Modelling Frameworks

3.1 Data Acquisition and Integration

Intelligent VSM requires the integration of data from multiple heterogeneous sources across the production environment. Shopfloor sensors, enterprise resource planning (ERP) systems, and manufacturing execution systems (MES) form the primary data infrastructure (Karmaoui et al., 2023; Khakpour et al., 2024; Ferreira et al., 2022). Ferreira et al. (2022) demonstrated how data acquisition systems collect and translate signals from the shop floor, with MES serving as the essential link between the shop floor layer and the enterprise layer. IoT devices and RFID technologies enable automated data capture of component counts, machine states, and process parameters in real time (Salwin et al., 2023; Frick & Metternich, 2022). Nwamekwe et al. (2026a) extended VSM 4.0 to include detailed specifications of data points, communication protocols, and data processing information, addressing shortcomings in technical data flow documentation. The integration challenge lies in connecting diverse communication protocols such as OPC-UA, ProfiNet, and MQTT across heterogeneous IT environments (Ferreira et al., 2022; Salvadorinho & Teixeira, 2021). Salvadorinho and Teixeira (2021) identified that heterogeneous IT landscapes and complex value streams create significant barriers to establishing the digital shadow of a value stream, requiring systematic approaches to data capture, processing, and integration.

3.2 Data Preprocessing and Feature Engineering

Raw manufacturing data from sensors and enterprise systems contain noise, missing values, and inconsistencies that require systematic preprocessing before predictive models operate effectively. Rossi et al. (2022) described how event logs extracted from manufacturing information systems need filtering, transformation, and structuring to enable process mining and dynamic waste identification. Time-series feature extraction is critical for capturing temporal patterns in cycle times, machine states, and throughput rates (Butt, 2020; Serrato, 2021). Serrato (2021) demonstrated the importance of handling uncertainty and imprecision in VSM parameters by integrating fuzzy logic to represent vague efficiency and effectiveness variables. Normalization of process variables ensures comparability across different workstations and production lines (Chen et al.,2022; Lugert et al., 2018). Chen et al. (2022) collected production time data across 31 working days for training and testing an ANN model, illustrating the data volume and structure needed for reliable prediction. Feature engineering also involves extracting derived metrics such as OEE components, takt time deviations, and inventory accumulation rates from raw sensor streams (Yılmaz et al., 2022; Khakpour et al., 2024).

3.3 Predictive Modelling Techniques

Several modelling approaches support predictive analytics within intelligent VSM frameworks. Regression models address continuous variable forecasting, such as production time and lead time estimation Chen et al., 2022; Saad et al., 2021). Chen et al. (2022) applied artificial neural networks coupled with VSM to predict production times, achieving MSE values below 0.001 for training data. Classification models support event prediction tasks, including defect detection and process state identification (Rossi et al., 2022; Tripathi et al., 2022). Tripathi et al. (2022) employed lightweight convolutional neural networks (MobileNetV2) for wood quality classification and deep residual networks (ResNet) for thickness detection within a VSM-driven production improvement framework. Time-series models address temporal forecasting of demand patterns, inventory levels, and throughput variations (Serrato, 2021; Sordan et al., 2021). Saad et al. (2021) developed a hybrid ANN model based on analytic network process data to predict optimal sequences of VSM tools for lean implementation. System dynamics models complement statistical approaches by simulating feedback loops and nonlinear interactions within the value stream (Serrato, 2021; Bega et al., 2023).

3.4 Real-Time Data Streaming and Analytics

Streaming architectures enable continuous data processing and support real-time updates of value stream models. Nwamekwe et al. (2020) distinguished between stream analytics, where incoming sensor data is analysed immediately using computationally sparse algorithms operating on limited data windows, and batch analytics for larger historical datasets. The Lean Process Mining approach proposed by Rossi et al. (2022) processes event logs dynamically to trace process deviations in real time and identify waste sources as they emerge. Khakpour et al. (2024) implemented an Integrated Efficiency Monitoring System (IEMS) that continuously monitors IoT-enabled manufacturing setups and visualizes performance on dashboards at regular intervals. Streaming platforms such as Apache Kafka and MQTT protocols facilitate efficient data transmission between physical assets and digital models (Kumar et al., 2023; Nwamekwe and Igbokwe, 2024). Salvadorinho and Teixeira (2021) proposed a design model for the digital shadow of a value stream that systematically captures, processes, and integrates production data to enhance traditional VSM with continuous data provision.

3.5 Integration with Digital Twins

Digital twins provide virtual representations of value streams that enable simulation and optimization based on real-time data. Zoubek et al. (2021) proposed a digital twin-based VSM framework for brick manufacturing that continuously visualizes, monitors, and improves flow, value creation, and waste elimination. Yılmaz et al. (2022) introduced the Digital Value Stream Twin (DVST) concept, arguing that digitalization leads to increasing data availability that supports targeted data preparation for VSM. The digital twin approach connects physical production systems with their virtual counterparts through bidirectional data exchange (Khakpour et al., 2024; Wu et al., 2025). Khakpour et al. (2024) described digital twins as high-fidelity representations of operational dynamics enabled by near real-time synchronization between cyberspace and physical space. Chidiebube et al. (2025b) extended VSM to the Industry 4.0 context using agent-based simulation within a digital twin framework, incorporating supply chain uncertainty sources such as demand variability and machine maintenance schedules. Azizah (2025) developed a Dynamic VSM as a smart IT platform that sustains lean tools through real-time scheduling and dispatching modules integrated with digital twin capabilities.

3.6 Visualization and Decision Support

Intelligent VSM includes dynamic visualization tools that display both current and predicted system states to support operational decision-making. Khakpour et al. (2024) designed dashboard-based visualization within their Intelligent VSM model, displaying system performance metrics at specified regular intervals through the IEMS. Sordan et al. (2021) proposed an improved VSM procedure incorporating simulation and multiple-attribute decision-making methods, enabling practitioners to evaluate and prioritize multiple future-state scenarios based on performance criteria such as inventory levels, lead times, and service levels. Bega et al. (2023) combined VSM with system dynamics modelling to create interactive simulation interfaces that allow managers to experiment with process improvements across short, medium, and long-time horizons. Ezeanyim et al. (2025) enhanced VSM 4.0 with additional properties for data point specification and processing information, providing domain and software engineers a unified methodology for collaborative decision-making. Tripathi et al. (2022) embedded visual detection models within the production process and established FlexSim simulation models to compare production line performance before and after improvement, increasing the production balance rate by 29.07%. These visualization approaches transform VSM from a static paper-based tool into an interactive decision support system.

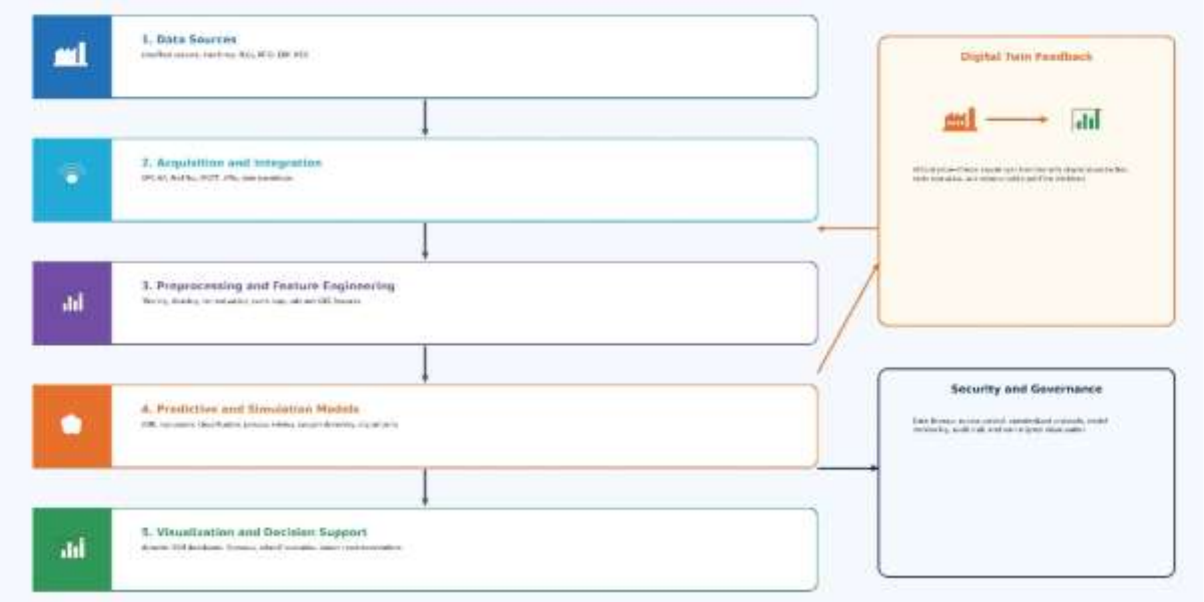

Figure 3: Data-Driven Architecture for Intelligent Value Stream Mapping with Real-Time Analytics

Figure 3 depicts the data architecture supporting Intelligent VSM. Manufacturing data flows from sensors, ERP, MES, and IoT systems through acquisition, preprocessing, feature engineering, predictive modelling, and visualization layers. Digital twin feedback and governance mechanisms provide continuous optimization and control. The architecture enables real-time analytics, predictive decision-making, and seamless integration of Industry 4.0 technologies within lean manufacturing environments.

4. Applications in Lean Manufacturing Systems

4.1 Bottleneck Prediction and Flow Optimization

Predictive models embedded within intelligent value stream mapping (VSM) offer a proactive approach to identifying bottlenecks before they disrupt production flow. Traditional VSM provides only a static snapshot of the production system, which limits its ability to anticipate how inventory levels or throughput will change under varying conditions (Siddique, 2024; Alsaadi, 2024). By integrating Industry 4.0 technologies such as IoT sensors and big data analytics, intelligent VSM enables real-time monitoring of manufacturing processes, allowing deviations to be traced dynamically (Clancy et al., 2022; Alabi, 2024). This real-time capability supports the prediction of constraints at specific workstations, enabling timely corrective action. For instance, IoT-enabled future-state VSM systems continuously monitor operations through integrated efficiency dashboards, identifying bottleneck operations and predicting future system states (Hamzeh et al., 2021). Simulation tools complement this by introducing a dynamic dimension to VSM, allowing practitioners to assess how different scenarios affect flow parameters such as lead time and work-in-process inventory (Salvadorinho & Teixeira, 2021). Such predictive capacity transforms bottleneck management from a reactive exercise into a planned intervention, maintaining continuous flow across the value stream (Clancy et al., 2022; Kumar et al., 2023).

4.2 Inventory and Lead Time Management

Intelligent VSM forecasts inventory levels and lead times with greater accuracy than conventional mapping approaches, directly supporting waste reduction. Traditional VSM has long been recognized for its ability to visualize material and information flows and identify non-value-added activities that inflate inventory and extend lead times (Caldera et al., 2019; Zgodavová et al., 2020). When augmented with predictive analytics, VSM moves beyond static depiction to forecast future inventory positions and delivery cycles. Studies have demonstrated substantial improvements: one electronics manufacturing application reported a 67.84% reduction in production lead times through lean principles combined with VSM (Ullah et al., 2024), while a valve manufacturing case achieved a 20% productivity improvement by targeting lead-time-consuming phases identified through VSM and kaizen (Emeka et al., 2025). The availability of real-time data provided by digitalization and Industry 4.0 technologies proves useful for analysing current inventory problems through value stream mapping (Rao & Nallusamy, 2018). Cloud manufacturing and IoT further enhance VSM by enabling real-time collection of data across the value chain, improving the accuracy of inventory and lead time forecasts (Nallusamy & Saravanan, 2018). These capabilities allow production planners to anticipate material requirements and adjust schedules proactively, reducing both excess inventory and stockout risks.

4.3 Process Improvement and Continuous Kaizen

Data-driven insights from intelligent VSM provide a structured foundation for continuous improvement initiatives, enabling targeted kaizen interventions based on predicted outcomes rather than retrospective analysis. Kaizen, as a core lean philosophy, relies on identifying waste and implementing incremental improvements (Ilangakoon et al., 2021; Chidiebube et al., 2025). When VSM is combined with predictive analytics and IoT, the identification of improvement opportunities becomes more precise and evidence-based. For example, an intelligent VSM system implemented in an electronics component industry used IoT-enabled monitoring to continuously track process performance, with kaizen activities tasked to eliminate shortfalls identified through the dashboard at regular intervals (Hamzeh et al., 2021). Process mining approaches integrated with VSM further support continuous improvement by employing prediction-recommendation-prevention strategies that avoid defective product occurrence during production, rather than relying on detect-and-repair methods that disrupt flow (Clancy et al., 2022). Artificial neural networks have also been applied to predict optimal sequences of VSM tools for lean implementation, reducing bias and improving the accuracy of improvement decisions (Tripathi et al., 2022). The combination of AI and lean principles has shown measurable results; one study reported a 25% improvement in overall equipment effectiveness by combining value stream mapping, five-why analysis, and kaizen practices with machine learning (Nwamekwe and Nwabunwanne, 2025). These approaches ensure that kaizen activities are directed at the areas with the highest predicted impact.

4.4 Demand-Driven Production Systems

Predictive analytics aligns production schedules with demand patterns, reducing overproduction and stockouts. Overproduction is one of the most significant wastes in lean manufacturing, and traditional pull-based systems address it through demand-driven scheduling (Okpala et al., 2024a; Onyeka & Emeka, 2025). Intelligent VSM enhances this capability by incorporating demand forecasting into the value stream analysis. Industry 4.0 technologies such as AI and big data analytics optimize supply chains and production schedules, further reducing waste and enhancing efficiency (Siddique, 2024; Rao & Nallusamy, 2018). Real-time data from IoT devices and cloud computing platforms enable manufacturers to sense demand signals and adjust production rates accordingly (Nallusamy & Saravanan, 2018; Saad et al., 2023). The integration of predictive analytics with lean manufacturing supports the transition from sense-and-respond to predict-and-act decision-making paradigms (Romo et al., 2024). This shift is particularly important in volatile markets where demand unpredictability requires agile responses. Studies confirm that the combination of Industry 4.0 technologies with lean manufacturing has a positive impact on sustainability performance, including reduced overproduction and improved resource utilization (Rao & Nallusamy, 2018; Ezeanyim et al., 2025a). By embedding demand forecasting within the value stream, manufacturers achieve tighter alignment between production output and customer requirements.

4.5 Integration with Lean Tools

Intelligent VSM enhances established lean tools by providing data-driven, real-time capabilities that amplify their effectiveness. For Kanban systems, cloud computing combined with machine learning has been proposed to create "Cloud Kanban," enhancing pull-based production control with real-time data and predictive capabilities (Saad et al., 2023; Nallusamy & Saravanan, 2018). IoT technologies such as RFID enable digital traceability and provide real-time information that strengthens Kanban-driven material flow management (Saad et al., 2023). For Andon systems, the concept of smart Jidoka based on cyber-physical systems enables real-time quality alerts and autonomous decision-making on the shop floor (Okpala et al., 2024; Alabi, 2024). Industry 4.0 technologies digitize and improve traditional lean tools, creating enhanced versions such as Kanban 4.0, Poka-Yoke 4.0, and VSM 4.0 that are connected, intelligent, and easier to implement (Soltani et al., 2019; Wang et al., 2019). For Heijunka (production leveling), simulation and big data analytics support more accurate leveling decisions by predicting demand variability and process fluctuations (Nallusamy & Saravanan, 2018; Salvadorinho & Teixeira, 2021). The dynamic VSM framework integrates lean tools with Industry 4.0 technologies to digitalize lean manufacturing, producing appropriate reactions and directives to match virtual and actual value stream performance (Emeka et al., 2025a; Hamzeh et al., 2021). This integration ensures that lean tools operate with greater precision and responsiveness in modern manufacturing environments.

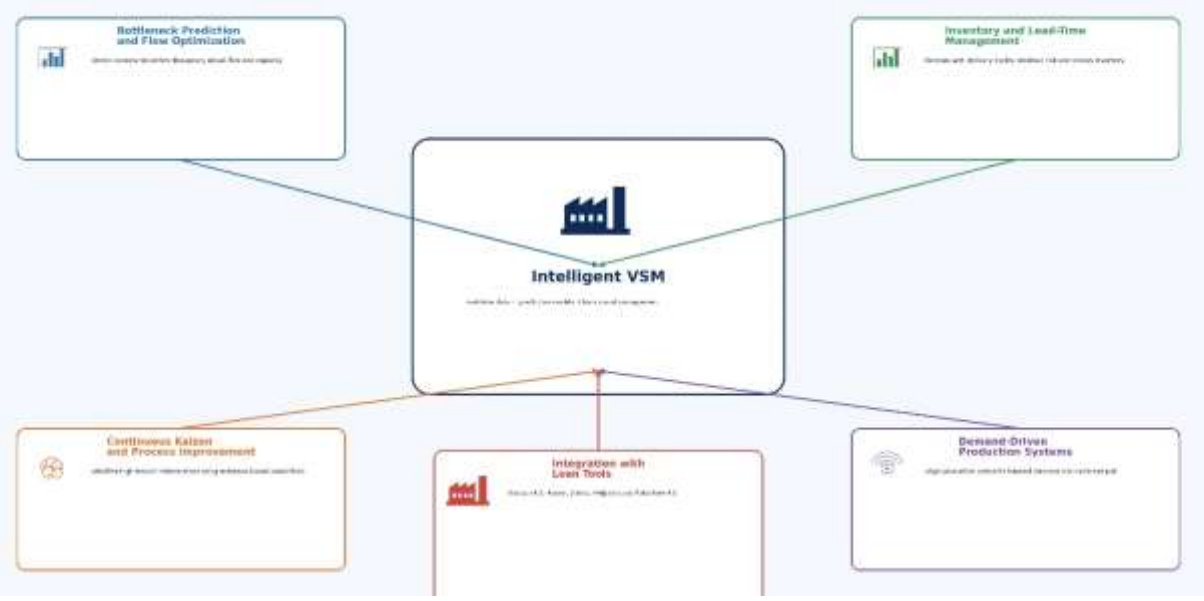

Figure 4: Application Domains of Intelligent Value Stream Mapping in Lean Manufacturing

Figure 4 highlights the principal application areas of Intelligent VSM. At its core, the framework supports bottleneck prediction, inventory and lead-time management, continuous process improvement, integration with lean tools, and demand-driven production systems. These applications collectively enhance manufacturing responsiveness, reduce waste, improve flow efficiency, and enable proactive management of operational performance across the value stream.

5. Key Challenges and Research Gaps

5.1 Data Quality and Integration Issues

A persistent challenge in intelligent value stream mapping lies in the quality and consistency of data drawn from multiple sources. Manufacturing environments generate data through sensors, enterprise resource planning systems, and manual inputs, each with different formats, frequencies, and reliability levels (Huang et al., 2019; Khakpour et al., 2024). Traditional VSM relies on data collected directly from the manufacturing floor, often through manual observation and interviews with department managers (Chen et al., 2022; Vitalis et al., 2024). When predictive analytics models are layered onto VSM, the accuracy of their outputs depends entirely on the quality of input data (Tashkinov, 2025; Okpala et al., 2025). Inconsistent or incomplete data leads to flawed predictions and misguided improvement actions. Industry 4.0 technologies such as IoT and RFID improve data collection by enabling automated, real-time capture of process parameters (Huang et al., 2019; Fischer et al., 2022). Yet integrating these heterogeneous data streams into a unified analytical framework remains difficult, particularly for small and medium enterprises that lack the infrastructure and technical expertise to manage complex data pipelines (Alsaadi, 2024; Peças et al., 2021). The absence of standardized data formats across different manufacturing systems compounds this problem, making interoperability between legacy equipment and modern digital tools a significant barrier (Saad et al., 2023; Igbokwe et al., 2025a).

5.2 Model Interpretability

Complex predictive models, including artificial neural networks and deep learning architectures, often function as "black boxes" that produce outputs without transparent reasoning (Kumar et al., 2023; Berge et al., 2023). This opacity creates a trust deficit among manufacturing practitioners and lean managers who need to understand why a specific intervention is recommended before acting on it (Tashkinov, 2025; Okeagu et al., 2024). In lean manufacturing, decisions about waste elimination and process improvement have traditionally been driven by direct observation and team-based problem solving, where the logic behind each action is visible and shared (Khakpour et al., 2024; Okpala et al., 2024). When an ANN model predicts the optimal sequence of VSM tools, for instance, the internal computations remain hidden from the user, even though the output is validated against empirical cases (Kumar et al., 2023). Research on clinical decision support systems has shown that transparent processing pipelines, where data transformations are traceable step by step, improve adoption and trust compared to opaque models (Berge et al., 2023). Manufacturing applications face the same challenge. Practitioners need interpretable models that align with the lean principle of visual management, where information is accessible and understandable at a glance (Peças et al., 2021; Liu & Yang, 2020). Without interpretability, even accurate predictive models' risk being sidelined in favour of familiar manual methods.

5.3 Scalability of Data Processing Systems

Handling large volumes of real-time data from multiple workstations, sensors, and supply chain nodes demands scalable computing architectures (Gómez–Pulido et al., 2020; Song & Nang, 2024). As manufacturing systems grow in complexity, the number of data points generated per second increases substantially, straining conventional processing infrastructure (Huang et al., 2019; Igbokwe et al., 2024a). Multi-agent systems built on cost-effective embedded hardware, such as Arduino and Raspberry Pi platforms, have been proposed for dynamic VSM in small and medium enterprises (Huang et al., 2019). These systems work well at a limited scale but face performance bottlenecks when deployed across larger production networks with dozens of machines and hundreds of sensors. Cloud computing offers a path to scalability by offloading data storage and computation to remote servers, but this introduces latency and dependency on network connectivity (Peças et al., 2021; Ilangakoon et al., 2021). Edge computing architectures address some of these concerns by processing data closer to the source, reducing the volume of data transmitted to central servers (Song & Nang, 2024; Gómez–Pulido et al., 2020). The trade-off between local processing capacity and centralized analytical depth remains an open design question for intelligent VSM systems. Scalable architectures must balance computational load distribution with the need for holistic, plant-wide visibility into value stream performance (Fischer et al., 2022; Tashkinov, 2025).

5.4 Real-Time Implementation Constraints

Effective predictive analytics within VSM requires low-latency data processing to support timely decision-making on the shop floor (Khakpour et al., 2024; Huang et al., 2019). Traditional VSM provides only a static snapshot of the production system at a single point in time, which limits its usefulness for responding to dynamic changes in material flow, machine status, or demand (Liu & Yang, 2020; Chen et al., 2022). Transitioning to dynamic or real-time VSM introduces strict timing requirements. Data from IoT sensors must be collected, transmitted, processed, and presented to decision-makers within time frames short enough to allow corrective action before waste accumulates (Fischer et al., 2022; Peças et al., 2021). Studies on dynamic VSM using cyber-physical systems have demonstrated near-real-time monitoring, but achieving true real-time performance across an entire value stream remains technically demanding (Huang et al., 2019; Shan et al., 2023). Communication delays between distributed sensors and central processing units introduce lag that degrades the timeliness of predictions (Gómez–Pulido et al., 2020). The processing time for complex machine learning models adds further delay, particularly when models require retraining with new data (Tashkinov, 2025; Okpala et al., 2025a). For intelligent VSM to support operational decisions at the pace of production, the entire data pipeline from sensor to dashboard must operate within the takt time of the manufacturing process, a constraint that current implementations struggle to meet consistently.

5.5 Alignment with Lean Principles

Predictive analytics systems must align with the core lean objectives of simplicity, waste reduction, and respect for people (Khakpour et al., 2024; Okpala et al., 2024). Lean manufacturing emphasizes visual management, standardized work, and operator empowerment, all of which depend on tools being accessible and easy to use (Santhiapillai & Ratnayake, 2020; Vilaça et al., 2025). Adding layers of predictive analytics and digital infrastructure risks introducing complexity that contradicts these principles (Saad et al., 2023; Alsaadi, 2024). If operators and frontline managers find the system difficult to understand or interact with, the technology becomes a source of waste rather than a tool for eliminating it (Tashkinov, 2025). Research has noted that the integration of Industry 4.0 technologies with lean manufacturing requires careful consideration of process improvement as part of the overall adoption plan (Ilangakoon et al., 2021; Salvadorinho & Teixeira, 2021). The technology should serve lean goals, not the other way around. Systems that generate excessive data, require specialized technical skills to operate, or produce recommendations disconnected from shop floor realities undermine the lean philosophy of continuous improvement driven by the people closest to the work (Peças et al., 2021; Kumar et al., 2023). Achieving alignment means designing intelligent VSM tools that are intuitive, transparent, and directly connected to measurable waste reduction outcomes.

5.6 Lack of Standardized Frameworks

No unified methodology exists for implementing intelligent VSM with embedded predictive analytics (Khakpour et al., 2024; Liu & Yang, 2020). Existing approaches vary widely in their choice of technologies, analytical methods, and integration strategies. Some researchers combine VSM with simulation and multi-criteria decision-making tools (Liu & Yang, 2020; Igbokwe & Nwamekwe, 2025). Others integrate process mining with lean principles (Khakpour et al., 2024). Still others propose multi-agent systems with IoT-enabled data collection (Huang et al., 2019). Each approach addresses specific aspects of the problem but lacks a comprehensive, standardized structure that practitioners across industries could adopt. The absence of a common framework creates fragmentation in both research and practice (Saad et al., 2023; Salvadorinho & Teixeira, 2021). Organizations attempting to implement intelligent VSM must piece together methods from different sources, often without clear guidance on how to sequence the steps or evaluate the results (Kumar et al., 2023; Peças et al., 2021). This gap is particularly acute for small and medium enterprises, which lack the resources to experiment with multiple approaches (Alsaadi, 2024). A standardized framework would need to specify data requirements, model selection criteria, integration protocols with existing lean tools, and performance evaluation metrics (Serrato, 2021; Shan et al., 2023). Developing and validating such a framework through cross-industry case studies represents one of the most pressing research needs in this field.

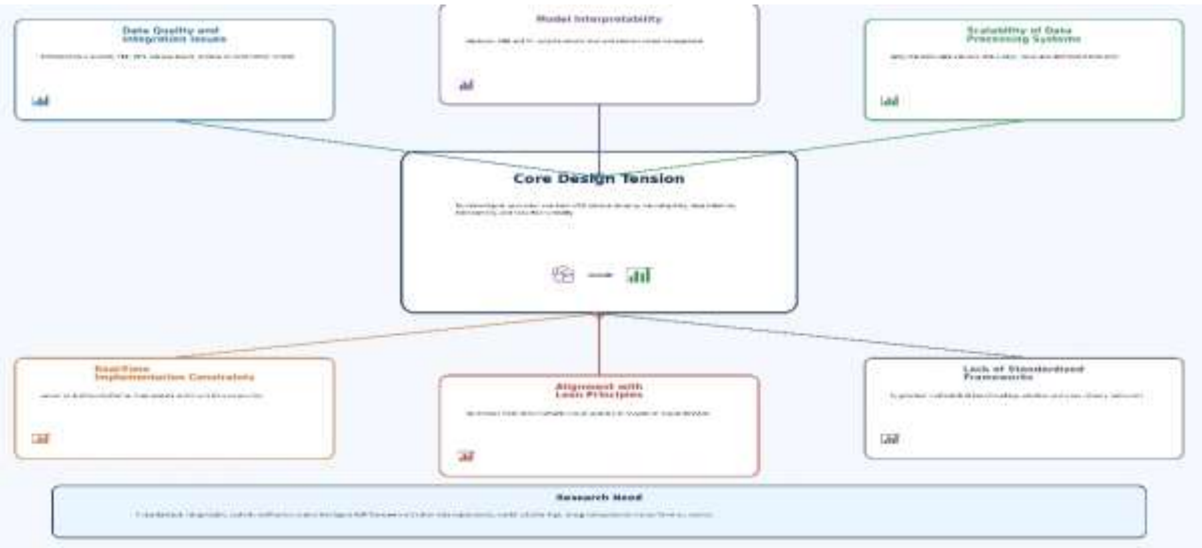

Figure 5: Challenges and Trade-offs in Intelligent Value Stream Mapping Implementation

Figure 5 summarizes the major implementation challenges associated with Intelligent VSM. Data quality issues, model interpretability limitations, scalability concerns, real-time processing constraints, alignment with lean principles, and the absence of standardized frameworks converge into a central design tension. The figure emphasizes the need for balanced solutions that simultaneously achieve analytical sophistication, operational simplicity, scalability, and sustainable lean performance.

6. Future Directions and Conclusion

6.1 AI-Driven Value Stream Optimization

Future research should move Intelligent Value Stream Mapping beyond descriptive visualization toward AI-driven value stream optimization. Conventional VSM identifies waste, bottlenecks, waiting time, excessive inventory, and non-value-added activities after they have already occurred. Intelligent VSM should instead predict these inefficiencies before they disrupt production flow. This requires stronger integration of machine learning, process mining, simulation, and real-time shop-floor analytics within the VSM structure.

AI models should be developed to forecast cycle-time variation, takt-time deviation, work-in-process accumulation, equipment downtime, production imbalance, defect risk, and demand fluctuation. These predictions can support proactive scheduling, resource allocation, bottleneck prevention, and kaizen prioritization. Artificial neural networks, regression models, classification models, time-series models, and system dynamics models already show strong potential in manufacturing forecasting. However, future systems must go further by embedding these models directly into live value stream maps that update continuously as new production data becomes available.

A major research need is the development of optimization engines that convert predictions into actionable lean decisions. Intelligent VSM should not only show where waste may occur; it should recommend how to reduce it, when to intervene, and which lean tool should be applied. For example, the system may recommend Kanban adjustment when inventory is predicted to rise, Heijunka revision when demand volatility increases, Andon activation when quality deviation is detected, or kaizen intervention when a bottleneck is projected. This would shift VSM from a static diagnostic tool to a predictive and prescriptive improvement platform.

6.2 Integration with Digital Twin Ecosystems

Digital twin integration represents a critical future direction for Intelligent VSM. The manuscript shows that modern VSM must capture dynamic production behaviour, real-time data flows, uncertainty, and future-state scenarios. Digital twins provide the virtual environment needed to achieve this. A digital value stream twin can mirror the physical production system, continuously synchronize with shop-floor data, and simulate how different process changes will affect lead time, inventory, throughput, resource utilization, and waste generation.

Future research should focus on developing digital twin ecosystems that connect VSM with sensors, IoT devices, RFID systems, MES, ERP, cloud platforms, and simulation models. Such integration would allow manufacturers to visualize current production conditions, test alternative future-state maps, and assess the operational impact of lean interventions before physical implementation. This is particularly important in environments with high product variety, fluctuating demand, machine breakdowns, and supply chain uncertainty.

Digital twins should also support what-if analysis and closed-loop improvement. Managers should be able to simulate changes in takt time, batch size, workstation capacity, machine availability, material arrival patterns, and operator allocation. The system should then quantify the expected effect on lead time, value-added ratio, process cycle efficiency, OEE, and inventory accumulation. This would make VSM more rigorous, evidence-based, and responsive to real manufacturing complexity.

6.3 Edge Computing for Real-Time Analytics

Real-time implementation remains one of the most important barriers to Intelligent VSM adoption. Predictive analytics can only support shop-floor decisions when data is collected, processed, interpreted, and displayed quickly enough to guide action before waste accumulates. Future research should therefore prioritize edge computing architectures that process manufacturing data closer to machines, sensors, and operators.

Edge computing can reduce latency, limit dependence on cloud connectivity, and enable faster response to production abnormalities. In Intelligent VSM, edge devices can preprocess sensor readings, filter noise, detect anomalies, calculate cycle-time deviations, and transmit only relevant insights to central dashboards or digital twins. This structure can improve real-time responsiveness while reducing bandwidth demand.

However, edge-based Intelligent VSM must balance local processing with plant-wide visibility. Local analytics may detect workstation-level problems quickly, but value stream optimization also requires system-level coordination. Future architectures should therefore combine edge analytics for immediate shop-floor action with cloud or enterprise analytics for strategic learning, model retraining, and cross-line optimization. This layered structure will be essential for scalable Intelligent VSM systems that operate across multiple machines, production lines, and manufacturing sites.

6.4 Human-Centric Decision Support Systems

Intelligent VSM must remain aligned with the human-centered philosophy of lean manufacturing. Lean systems depend on visual management, operator involvement, team-based problem solving, and practical simplicity. Predictive analytics can strengthen these principles only when its outputs are interpretable, accessible, and directly connected to improvement action. If the system becomes overly complex or difficult for frontline users to understand, it risks creating a new form of operational waste.

Future systems should therefore prioritize human-centric decision support. Dashboards should present predictions, warnings, and recommended actions in a clear visual format that supports fast interpretation by operators, supervisors, engineers, and managers. Model outputs should explain why a bottleneck, inventory surge, delay, or quality risk is predicted. This is necessary because black-box models may reduce trust, especially in lean environments where improvement decisions are traditionally based on visible facts and shared reasoning.

Human-centric Intelligent VSM should also support collaborative kaizen. The system should not replace operators or lean teams. It should guide them toward the highest-impact improvement opportunities. Recommended interventions should be traceable to data patterns, process conditions, and lean performance metrics. This will help practitioners connect predictive analytics with established lean tools such as Kanban, Andon, Poka-Yoke, Heijunka, standard work, and continuous improvement routines.

6.5 Standardization, Scalability, and Implementation Frameworks

The absence of a standardized methodology remains a major research gap. Existing Intelligent VSM approaches differ in data sources, modelling methods, digital technologies, simulation tools, visualization formats, and evaluation metrics. This fragmentation makes implementation difficult, especially for small and medium enterprises with limited technical resources.

Future research should develop a standardized implementation framework for Intelligent VSM with embedded predictive analytics. Such a framework should define the required data sources, data-quality checks, communication protocols, preprocessing steps, feature-engineering procedures, model-selection criteria, dashboard requirements, and performance metrics. It should also show how predictive analytics can be integrated with existing lean practices without weakening the simplicity and visual nature of VSM.

Scalability must also be addressed. Many current solutions work at pilot scale but become difficult to deploy across large production systems with multiple workstations, machines, sensors, and enterprise platforms. Future frameworks should support modular deployment, interoperability with legacy systems, and gradual digital transformation. This is important because many manufacturing firms cannot replace existing systems immediately. Intelligent VSM must therefore be practical, scalable, and adaptable to different levels of digital maturity.

6.6 Conclusion

This review has shown that Intelligent Value Stream Mapping with embedded predictive analytics represents a significant advancement in lean manufacturing. Traditional VSM remains valuable for visualizing material and information flow, identifying waste, and supporting current-state and future-state improvement planning. However, its static nature limits its usefulness in modern manufacturing environments characterized by real-time data generation, process variability, demand uncertainty, and complex production interactions.

Embedding predictive analytics into VSM transforms the tool from a periodic diagnostic map into a dynamic decision-support system. By integrating IoT sensors, RFID, ERP, MES, process mining, machine learning, simulation, digital twins, and real-time dashboards, Intelligent VSM can monitor current performance, forecast future system behaviour, and support proactive improvement. This capability strengthens bottleneck prediction, inventory and lead-time management, continuous kaizen, demand-driven production, and integration with lean tools such as Kanban, Andon, Poka-Yoke, and Heijunka.

The review also identified critical challenges that must be addressed before Intelligent VSM can achieve widespread industrial adoption. These include data quality and integration problems, limited model interpretability, scalability constraints, real-time processing delays, possible misalignment with lean principles, and the lack of standardized implementation frameworks. These challenges show that Intelligent VSM is not only a technological issue but also an operational, organizational, and methodological challenge.

Future development should therefore focus on AI-driven optimization, digital twin ecosystems, edge-enabled real-time analytics, human-centered decision support, and standardized scalable frameworks. These directions will allow Intelligent VSM to remain faithful to lean principles while taking full advantage of Industry 4.0 technologies. In conclusion, Intelligent VSM provides a pathway for transforming lean manufacturing from retrospective waste identification into predictive, adaptive, and data-driven value stream optimization.

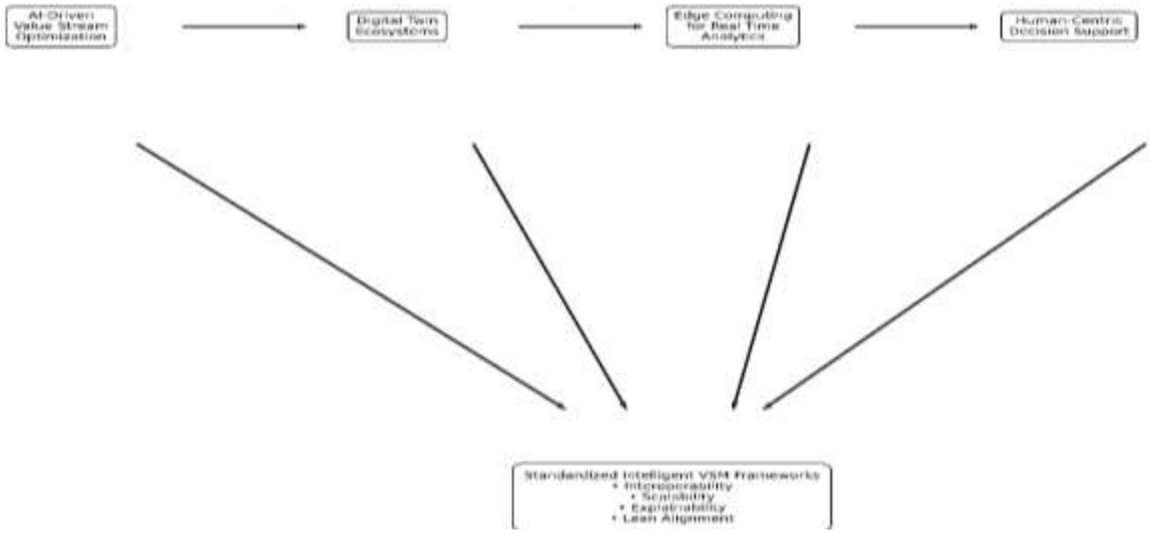

Figure 6: Future Roadmap for Intelligent Value Stream Mapping with Predictive Analytics.

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