Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

AI-Driven Digital Twins: A Theoretical Framework for Predictive Decision-Making in Manufacturing and Supply Chains

Rohan Joshi[1], Shreyash Ruikar[2], and Sagar Sapte[3]

[123]Department of industrial engineering, Arizona State University, AZ, USA
Corresponding author: Rohan Joshi, **Email**: rohanjoshi1094@gmail.com

| ABSTRACT

Manufacturing supply chains are increasingly faced with volatility such as demands, supply chain disruptions, and equipment breakdowns. Although organizations have modernized their approaches to digitalization and analytics, decision-making remains more reactionary and descriptive, making it more difficult to proactively detect and avoid obstacles. Digital twins are a dynamic virtual replica of physical assets and processes, but currently these twins are generally limited to monitoring and offline analytics, with less incorporation of more sophisticated artificial intelligence (AI) functions. This paper builds upon theoretical foundations concerning artificial intelligence-based digital twins functioning as predictive decision engines within manufacturing and supply chain domains. To commence, we gather a synopsis on theoretical foundations concerning digital twins, artificial intelligence/ machine-learning analytics, and predictive decision-making, and put forth a strategic two-tiered architecture concerning physical domains, information/data domains, artificial intelligence/modeling, and human-AI interaction. From this strategic architecture, we put forth a decision-centric theory concerning correlations between information value, digital twins' accuracy, artificial intelligence' capability to make predictions on manufacturing processes and domains to arrive at higher-quality decisions and multidimensional manufacturing outcomes such as efficiency, resilience, and sustainability. Using hypothetical examples concerning predictive maintenance, quality prediction, demand projection, and comprehensive end-to-end risk management, we formulate theoretical propositions concerning this innovative technology theory to serve as guidelines within future studies. This paper adds by shedding light on how artificial intelligence-driven digital twins are a socio-technical capability within organizations to enable proactivity within manufacturing domains to transition such organizations' processes and operations to more proactive and futuristic, and ultimately much more proactive manufacturing and supply chain management.

| KEYWORDS

AI-Driven Digital Twins; Predictive Decision-Making; Manufacturing and Supply Chains

| ARTICLE INFORMATION

ACCEPTED: 01 November 2025 **PUBLISHED:** 19 November 2025 **DOI:** 10.32996/jcsts.2025.7.11.39

1. Introduction: From Reactive Operations to Predictive, AI-Enabled Ecosystems

The present-day manufacturing and supply chain web faces increasingly high levels of uncertainty, influenced by variables such as varying customer demand, reduced product life spans, political instabilities, and regular disruptive effects on logistics and procurement. Against this background, it has been noticed that there is a continuation of organizations' employing decision-supporting mechanisms and strategies that are largely reactive and/or descriptive. This is because typical historical trending, static dashboard analytics, and isolated simulation analyses tend to serve up a retrospective or snapshot perspective on system behavior. As such, managers lack specific forewarnings about impending risks such as capacity constraints, drift trends, and delays [1].

Digital twins have appeared on the horizon as a kind of remedy to this complexity. A digital twin can be viewed as a live virtual replica of a physical entity, a process, or a network that is constantly harmonized with its corresponding physical counterpart via two-way flows of data. The reality is, though, that many applications of digital twins are currently no more than advanced visualizations, monitoring, and what-if analytics that take place offline and fail to live up to making optimized predictions and recommendations using artificial intelligence and machine learning to affect any kind of decisioning in real-time. The promise of digital twins acting as active, artificial-intelligence-driven decisioning engines has thus remained unrealized within such manufacturing and supply chain-related domains [2][3].

Despite these developments, this paper fills this research gap by proposing a theoretical foundation concerning AI-driven digital twins within a socio-technical capability facilitating a shift towards proactive and prescriptive manufacturing and supply chain management. Current literature generally investigates digital twins, AI-driven analytics, and resulting operational decision-making on an intersectionally independent basis. Moreover, there is a considerable gap concerning literature not exploring this comprehensive connection but rather dealing with very specific applications. The aim of this paper is to close this knowledge gap regarding this theoretical baseline by proposing its relevant architectural pillars, which can lead to theoretical propositions amenable to investigation within future empirical studies. To this end, this paper places AI-driven digital twins within this socio-technical capability facilitating this shift towards proactive and prescriptive manufacturing and supply chain management.

2. Conceptual Foundations: Digital Twins, AI, and Predictive Decision-Making

Digital twins have emerged as popular ideas within the realms of Industry 4.0 and Supply Chain 4.0, but they tend to get applied uniformly across varying technological platforms. For this paper, a digital twin can be defined generally as a virtual replica of a physical entity, such as a process, system, or network, that is continuously and bi-directionally interfaced with its corresponding physical entity. This is achieved via a flow of information that conveys the present state of machinery, assembly lines, storage units, and/or logistics processes, to name a few examples, to necessarily affect how their digital twins replicate the dynamically varying behavior patterns of the corresponding physical entities. Digital twins are distinct from other simulation technologies because they tend to operate on synchronous interfaces and work on refinement rather than being replicas operating on offline simulations [4].

Digital twins can also exist at different granularity sizes. At a granularity level that is specific to assets, a digital twin can be representative of specific equipment, such as a machine, reflecting its operating environment, degradation processes, and dynamics. At a system level, which can also be referred to as a granularity level that is specific to plants, a digital twin can represent an entire manufacturing line, reflecting interactions between workstations, buffers, and material flows. Finally, at a granularity level that is specific to a network, a supply chain digital twin combines information on suppliers, plants, warehouses, and logistics [5].

Artificial intelligence and machine learning raise the level of digital twins into the realm of predictive and prescriptive analytics, where they can offer recommendations that go beyond simple visualizations. Already operating in an operations and supply chain setting to offer value in forecasting, predicting breakdowns, quality anomaly detection, inventory management, and finding optimized routes, these applications represent a natural next step in analytics evolution, which first involved descriptive analytics to tell what has already occurred, proceed to diagnose by understanding the reasoning when it occurred, and finally decide on what may happen with estimates via predictive analytics to prescribe what to do next. The digital twins powered by artificial intelligence operate within these other two realms, making estimates and offering recommendations on what could happen and what to do [6].

To appreciate how digital twins enabled by artificial intelligence involve predictive decision-making, it is important to break down these twins into multiple related aspects. The information aspect deals with extracting, integrating, and preprocessing information that is gathered from sensors, business systems, and other business partners. The other aspect is model building, which could involve physics- or rule-based models about business processes augmented by artificial intelligence and machine learning approaches that entail extracting correlations, patterns, and systematic relations within business information. The interaction aspect is centered on how human stakeholders interact with these twins via interfaces, simulation platforms, notification mechanisms, and recommendation platforms influencing how decisions associated with predictions and recommendations are responded to. The final aspect is related to understanding that digital twins involve multiple stages concerning improving design, start-up, operation, and enhancement informed by feedback obtained after each phase [7].

These factors are not merely technical strata but rather part and parcel of a larger socio-technical system upon which predictive decision making relies. The quality and immediacy of available data boost the credibility of this virtual depiction, while reliable and properly developed AI models improve predictive precision, with interface design influencing what can and should be comprehended about it. Throughout an analytics-driven life cycle within a twin, constants related to assumptions and policy governance within these analytics-driven applications evolve according to observed results. The conceptual groundwork laid out within this section is accordingly constructive to what follows because these factors are systematically aligned to decision and execution quality within manufacturing and supply chain processes [8].

3. AI-Driven Digital Twin Architecture for Manufacturing and Supply Chains

To proceed from conceptual building blocks to design implementation, digital twins powered by artificial intelligence can be logically structured into a multi-layered architecture that stretches from physical entities to decision interfaces. The groundwork is formed by the physical layer, within which are included machines, manufacturing lines, material handling equipment, warehousing, and transport equipment. They constantly produce a flow of information about their state, including but not limited to temperatures, vibration intensity, rate of processing, inventory locations, and travel times. The next level is that of connectivity and integration, which involves sensors, IoT modules, edge node interfaces, and middleware that converters and transfer this information into the virtual space. This level is particularly important because it defines how much information about particular processes and equipment will be produced to ultimately input into the artificial intelligence architecture [9].

Above this connectivity layer is the layer responsible for data management and governance. The raw data obtained from different sources is warehoused, cleaned, curated, and enriched within these data lakes. Metadata and master data management processes offer definitions to common entities such as items, orders, suppliers, and equipment. This is where trustful preconditions for trustworthy AI are set. Without governed and standard data, any digital twin that uses AI is foreseen to produce erroneous results. This level is imperative because organizations can put into effect a whole technology stack that can result in exceptional business outcomes.

The second layer is comprised of Modeling & Artificial Intelligence, which is based on this foundation and comprises physics-based models, discrete-event/agent-based simulation, and machine learning & optimization models. Physics/process models elucidate the known mechanisms in manufacturing that relate to thermal effects during machining processes, assembly line flow processes, etc. Machine learning models identify trends during historic & real-time data to make predictions about machine forecasting, quality outcome classification, lead time estimation, etc. The Optimization & Reinforcement Learning Models analyze huge decision spaces to make recommendations about schedules, routing, & inventory to achieve defined goals & constraints, marking this layer as the analytical heart of the Digital Twin.

The heart of this structure is constituted by the digital twin core layer, which manages the synchronization between both worlds. This layer is responsible for keeping a consistent representation of the system state by integrating incoming information with results from mathematical models, monitoring differences between predicted and actual behavior, and launching system calibrations accordingly. The scenario and experiment engines are also contained within this layer, which enables decision-makers to formulate queries like “What will happen if a critical machine goes down tomorrow?” and “What impact will a spike in one region have on the system?” The Digital Twin Core layer combines state estimation and scenario simulation to animate the Digital Twin by turning a static model into a dynamic one.

The last part of this architecture is what is termed the decision and interaction layer, which is responsible for human-AI collaboration. The role of this layer is to show prediction results, recommendations, and scenario outcomes via dashboard interfaces, notification systems, control panels, and conversations. The layer can incorporate different decision mechanisms, whereby while in some instances, the digital twin automatically initiates control actions such as alteration of machine settings and order route change within policy and safety limits, while in other instances, options and risk evaluations are shown to decision-makers to aid executive choice. The architecture layer requires a heavy emphasis on transparency and ease of experience to ensure that human beings are informed about how recommendations produced by artificial intelligence can be implemented.

Most importantly, this solution can function on any scale. This is because this architecture can work on any level, such as a machine level, which can analyze equipment failure predictions. It can work on a plant level, such as optimizing manufacturing processes and managing material movement. This architecture can work on a supply chain level, which can analyze sourcing, inventory management, and other factors related to multiple stakeholders. This is achieved by making sure that every output produced by each lower level, such as line-throughput estimates and downtime estimates, is inputted into higher level planning processes.

4. Theoretical Framework for Predictive Decision-Making

From a view grounded in architecture, this theoretical structure sees the role of this digital twin, fueled by artificial intelligence, as being decision-centric, integrating data, models, and behavior to impact observed outcomes. The essence of this theoretical structure is its building blocks. Data richness and its timeliness speak to the availability and comprehensiveness of knowledge about the physical system and its environment. Digital twin fidelity indexes how well these virtual twins emulate their counterpart, physical entities, concerning their state and behavior. The role of artificial intelligence is defined by its prediction capability, which indexes effectiveness, strength, and adaptability. The construct called decision quality indexes factors like speed, precision, consistency, and strength concerning decisions reached concerning planning and control functions. Performance outcomes speak to outcomes obtained concerning value added, such as those concerning efficiency, responsiveness, resilience, services, and sustainability. This theoretical structure postulates that higher levels of these factors lead to better outcomes.

The processes that link these variables can be viewed as being comprised of a series of causal paths. First, there is the increased forecasting capability accomplished with the aid of digital twins powered by AI. The forecasting capabilities related to demands, machine degradation, and lead time can be predicted more precisely than could previously be achieved by more conventional analytical processes, which left a degree of uncertainty that could only be mitigated by hedging bets. Second, there is scenario validation, which enables enterprises to analyze what might happen if different variables, such as enterprise choices or market shocks, occurred rather than taking immediate action to effect change upon the environment. Managers can analyze how specific "what-if" scenarios related to manufacturing decisions, sourcing, and/or inventory management play out, and enable options which work best over multiple versions to proceed. Third, there is immediate synchronization and model-based management processes which allow immediate response to variables such as a delayed supplier, an unexpected order, or an erratic change within product quality specifications. These processes combine to comprise the foundation upon which a theoretical relationship exists between AI-driven twins and decision-making processes.

The framework is also equipped to distinguish between varying decision time horizons while being thoughtfully linked. Starting with an operational perspective, decision support relevant to predictive analytics encompasses short-run activities such as job assignment on a line, scheduling maintenance interventions, truck routing, and reallocating items within a day and a shift. Proceeding to a tactical perspective, decisions relate to weekly to monthly capacity allocation, medium-term sourcing agreements, and configuring the structure of replenishment and safety items on a network. Finally, a strategic perspective encompasses decisions about manufacturing and supply chain infrastructure, technology expenditures, and long-term partner arrangements. An artificial intelligence-infused digital twin can serve these varying perspectives appropriately while scaling up to shift time granularity and varying decision variables. The theoretical assumption is that entities incorporating digital twins thoughtfully across these perspectives have a better chance to align short-term activity with long-term strategies while sidestepping a pitfall where short-term activity conflicts with strategic visioning.

Uncertainty, risk, and resilience are part and parcel of this framework rather than afterthoughts. Manufacturing and supply chains are characterized by stochastic fluctuations and extreme but impactful events. The digital twin, augmented with AI models, can serve as an early warning system to identify abnormal patterns in sensor readings, supplier behavior, and demand signals that occur before failure events. It can assess risk by computing probability distributions associated with outcomes corresponding to alternative options and can aid in developing countermeasures such as dynamic buffers, contingency routes, and/or alternative sourcing arrangements. The theoretical hypothesis here is that companies with more developed AI-based digital twins will not only optimize their average outcomes but will also display reduced variability and quicker recovery trajectories during adverse periods. This work sees predictive decision-making as a tool to enhance resilience.

Finally, this analytical framework takes into account that there is no direct value added by artificial intelligence-based digital twins but is rather affected by certain organizational and human factors. The wealth of information and artificial intelligence capability does not automatically lead to better decision making but requires decision processes that can incorporate, understand, and make decisions on artificial model results. The level of trust in artificial intelligent capabilities, transparency in artificial model explanations, access to cross-functional teams informed about both business operations and analytics, and organizational incentives can impact these artificial intelligent recommendations to change business outcomes or continue to ignore them. Therefore, artificial intelligent digital twins can be perceived to exist within socio-technical systems whereby technical superiority and organizational readiness evolve simultaneously. This lays out the beginning of exploring artificial intelligent digital twins within the next contexts.

5. Application Scenarios and Propositions for Manufacturing and Supply Chains

The theoretical implications can become more precise and relevant when they are tied to generic decision-making contexts and problems typically faced by manufacturers and supply chain enterprises. Another specific and interesting example is the one related to both predictive and equipment health management processes. In a typical scenario, maintenance could happen on a reactive basis, when equipment actually breaks down, but more typically on a scheduled, preventative basis, which is not necessarily aligned with actual usage. Using an AI-based digital twins capability at the equipment/unit level, there is a continuous flow of vibration, temperature, energy, and cycle time sensor information into the digital representation. The digital twins can leverage this information, along with knowledge about degradation, to estimate remaining life and probabilities of failure. This information can, theoretically, leverage better-quality decisions due to less uncertainty about equipment usage to more reliable equipment up-time.

The second case is about predictive quality and process optimization. Production processes tend to work within certain nominal specifications pertaining to temperature, pressure, speed, or chemical composition, but subtle interactions between these factors may result in quality drift and increased scraps. The digital twin, with physics-based correlations and models trained on past process and quality historical trends, can identify early warning indications pointing to an impending drift outside acceptable limits before defects actually occur on finished goods. The digital twin can, within this virtual space, evaluate what other adjustments to parameters could optimize the process to return to a positive state. Humans can review and act on this advice on the shop floor. This second scenario illustrates how, theoretically, its ability to perceive and make predictions about quality outcomes improves decision making on process control to generate suggestions that corporations implementing an AI-driven digital twins technology can achieve fewer defects, less rework, and higher one-piece flow compared to corporations employing only inspection after-the-fact.

The third example is at the network level and is concerned with end-to-end visibility and predictive risk management. The contemporary supply chain is more complex due to its involvement with multiple tiers of suppliers, manufacturing plants, distribution nodes, and logistics companies, such that a disruption travels very quickly across these multiple nodes. The role of a supply chain digital twin is to consolidate information on orders and inventory, suppliers' performance, transport flows, and external influences such as weather and geopolitics into a single coherent entity. The AI models within this entity enable analysts to forecast impending stockout, congestion within definite routes, late shipment from specific suppliers, and mismatch between regions and regional demands. These analysts make adjustments to route orders, relocate inventory, shift manufacturing schedules, and activate contingency sourcing arrangements prior to inconvenient customers. The implications relate to improving the speed and resolve of analysts' decisions within uncertainty theory, thereby validating arguments that these organizations will excel within timed deliveries, reduced stockout, and resistance to disruption.

The fourth scenario is about predictive demand sensing and inventory management. The scenario describes how traditional forecasting is often done with coarse time buckets that don't necessarily reflect shifts in consumer behavior. The scenario describes how a digital twin can incorporate point-of-sale information, promotional schedules, and external factors such as social media sentiment or macroeconomic trends. The Digital Twin can leverage these more informative streams to make short-term predictions about demands on a more refined level. These predictions are inputted into inventory management and manufacturing planning equations within the Digital Twin that can evaluate how varying arrangements concerning inventory management and manufacturing will affect service and working capital. The scenario describes how managers can select approaches to trade off responsiveness and costs to make more informed decisions. The scenario illustrates how one can view technology advancing along a continuum that goes from Data Richness to Artificial Intelligence Capability to Decisions to Performance to Propositions like those put forth: organizations implementing demand-sensing capabilities into Digital Twins will observe better forecast accuracy, less excess inventory, and fewer losses due to out-of-stock conditions.

Despite these differing contexts, human and organizational aspects continue to play an important role. The results and predictions gained from these digital twins need to be assessed by maintenance engineers, process technologists, and managers, resulting in actions being taken or not being taken at all. The above-mentioned applications inherently cover ideas related to moderation effects because organizations putting more effort into training and designing aspects related to these digital twins could gain better results related to performance, which is theoretically postulated within this model. These applications can, thus, serve not only as examples to make one understand how these digital twins work but also aid in building a connection to empirically relate theoretical ideas within future studies.

6. Discussion, Implications, and Future Research Directions

The theoretical lens introduced above reframes digital twins not merely as innovative simulation technologies or visualization platforms. Emphasizing their role as prediction-driven technologies informed by artificial intelligence, this lens provides a unique socio-technical capability that connects data, analytical models, and human decision-making processes. This understanding goes beyond other conceptualizations of Industry 4.0 because it places decision quality at its forefront, such that the value proposition of digitalization is no longer simply about connectivity and transparency but about forecasting outcomes and making decisions that are resilient to uncertainty. As such, digital twins informed by artificial intelligence occupy a point within the intersection of operations management, information technology, and organizational theory studies, each benefiting distinctively from a decision-quality perspective.

From a practitioner perspective, one could view this structure and hierarchy as a roadmap to unlocking value through AI-enabled digital twins. The challenge is not merely to build a technology platform and reap immediate rewards but to, on one hand, continue to build upon enriched information assets, faithful twins, and smarter artificial intelligence while, on the other hand, change and evolve decision processes, roles, and workforce competencies. Initial applications could emphasize rather straightforward applications like predictive maintenance and/or demand sensing to name a couple, which offer short-term payoffs and build organizational knowledge. These applications can evolve over time to involve plant-scale and enterprise-wide digital twins to facilitate comprehensive planning efforts on short, medium, to long-term strategic operating planes. This can entail overcoming obstacles like information silos, aged infrastructure, a lack of analytical professionals, and resistance to recommendations informed by artificial intelligence.

The framework also has its limitations, which serve to open up opportunities for future work. The nature of this work is necessarily generic, aiming to abstract above specific-sector information, differing levels of digital maturity, and organizational cultures. Empirical work is required to confirm these putative linkages among data richness, fidelity to the twin, capability to employ the AI in these twins, decision making, and outcomes, and to measure how these relations change according to differing strengths and weaknesses. Comparative research might investigate how specific industries like process manufacturing, discrete manufacturing, and logistics-intensive industries implement digital twins having an underlying emphasis on artificial intelligence. Further research could also focus on extending into themes more specific to the advent of Industry 5.0, such as human design goals, sustainability, and circular economy goals within digital twins.

This paper contends that AI-driven digital twins represent an extremely rich conceptual and applications roadmap for moving manufacturing and supply chain management from a firefighting to a proactive, and ultimately prescriptive mode of operation. The implications here are those organizations finding ways to think about and work with AI-driven digital twins, not merely as technologies but also as evolving socio-technical capabilities, will gain a better OCRR to deal with VUCA environments, and to construct resilient and high-performing manufacturing enterprises.

7. Conclusion

Throughout this paper, it has been posited that while simulating physical processes is only one strength and capability of digital twins, their integration with AI provides them with a more predictive and decision-influencing capability, meaning they can serve not only as simulators but also as predictive engines because they can combine flows of data with high-fidelity digital twins and more sophisticated AI models to make organizations more anticipatory rather than merely descriptive. The contribution of this paper is to put forth a decision-centric paradigm that can link data intensity, the fidelity level of digital twins, and their predictive capabilities to decision outcomes and ultimately to multiple dimensions of outcomes such as efficiency, responsiveness, resilience, and sustainability.

The design principles and constructs developed herein aim to cover a wide range of applications extending to assets, plants, and networks. The paper, through prediction use cases and quality processes, end-to-end-risk management processes, and last but not least, demand-sensing applications, demonstrates how similar building blocks can be applied to very different domains. It is also evident across these examples that there is a constantly recurring message: being useful, value-creating, requires a symbiotic relationship between technology and organizational aspects. Well-structured information flows and very capable models are no more than half the story—if not less. They should and must be complemented by organizational aspects like governance and human-AI collaboration.

As a theory-based framework, it provides a starting point rather than a conclusion. Theoretical constructs, mechanisms, and hypotheses can serve to formulate and verify tests on how they can be challenged within an industrial setting. From this perspective, this theory provides a conceptual blueprint on how to align digital twin investments along goals concerning decision making rather than mere technology implementation. As manufacturing and supply chain organizations continue to grapple with volatility and complexity, artificial intelligence-enabled digital twins, which can be viewed as continuously developing socio-technical capacities, will play a crucial role within these organizations to anticipate and respond to change.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Katsaliaki K, Galetsi P, Kumar S (2022) Supply chain disruptions and resilience: a major review and future research agenda. Ann Oper Res 319:. https://doi.org/10.1007/s10479-020-03912-1

[2] Xu L, Proselkov Y, Schoepf S, et al (2023) Implementation of Autonomous Supply Chains for Digital Twinning: a Multi-Agent Approach. In: IFAC-PapersOnLine

[3] Akash Abaji Kadam, & Harshad Pitkar. (2025). Blockchain-Enabled Lean Automation and Risk Mitigation in Supply Chain 4.0 A Systematic Review and Future Directions. Journal of Economics, Finance and Accounting Studies , 7(3), 64-81. https://doi.org/10.32996/jefas.2025.7.7

[4] Thelen A, Zhang X, Fink O, et al (2022) A comprehensive review of digital twin — part 1: modeling and twinning enabling technologies. Structural and Multidisciplinary Optimization 65

[5] Zou S, Tao X, Tao B, Wu G (2022) A Preliminary Study on the Development and Application of Digital Twin Landscape Architectures in the Context of Smart City. In: Proceedings - 2022 Global Conference on Robotics, Artificial Intelligence and Information Technology, GCRAIT 2022

[6] Fuller A, Fan Z, Day C, Barlow C (2020) Digital Twin: Enabling Technologies, Challenges and Open Research. IEEE Access 8:. https://doi.org/10.1109/ACCESS.2020.2998358

[7] Lv Z, Xie S (2021) Artificial intelligence in the digital twins: State of the art, challenges, and future research topics. Digital Twin 1:. https://doi.org/10.12688/digitaltwin.17524.1

[8] Akash Abaji Kadam, Ramakrishna Garine, Supriya Akash Kadam (2024) Revolutionizing inventory management: A comprehensive automated data-driven model using power BI incorporating industry 4.0. World Journal of Advanced Research and Reviews 24:477–488. https://doi.org/10.30574/wjarr.2024.24.1.3035

[9] Akash Kadam, Diwakar Reddy Peddinti, & Aditya Gupta. (2025). The Evolution of Smart Factories: Integrating IOT and Machine Learning in Supply Chain and Manufacturing. Journal of Computer Science and Technology Studies, 7(5), 251-261. https://doi.org/10.32996/jcsts.2025.7.5.32