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Digital Twin-Enabled Just-In-Time and Kanban Implementation Framework for Industry 4.0 Transformation in SMEs

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ABSTRACT

Implementing Industry 4.0 technologies is a big problem for small and medium-sized businesses. JIT (Just-In-Time) and Kanban are both lean tools, but they might take too much time and effort. We plan to fill this gap by creating and testing a working framework that combines cloud-hosted Digital Twins with streamlining JIT-Kanban loops. The framework's effectiveness was assessed in real-world contexts during a 30-month action research project involving twelve small and medium-size automotive parts manufacturers in Saudi Arabia. Using machine learning algorithms, a shop floor connected to the Internet has been turned into a virtual version. Because of the system, changes to how things are done on the shop floor are now possible immediately.This strategy led to a substantial improvement in performance. Lead times were down by 28%, equipment efficiency went up by 39%, and inventories came down by 47%. It was demonstrated that the framework had a payback period of less than 18 months, which demonstrated its financial viability. It is remarkable that 78 percent of implementations were successful, compared to 31% of digital deployments in conventional settings. As a result of further analysis, it was found that an organization's technological maturity was significantly more significant than its size ($r = 0.87$, $p = 0.001$). It is concluded that the framework provides SMMEs with a cost-effective and accessible route to digital transformation by combining lean principles with advanced technology tools.

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1. Introduction

As digital technologies and lean practices come together, manufacturing is changing quickly. Because markets are now very connected and competitive, companies are under more and more pressure to be more efficient while keeping costs low and having less of an effect on the environment. The Fourth Industrial Revolution is changing the strategic priorities of factories all over the world by using cyberphysical systems, the Internet of Things, and artificial intelligence [1], [2]. This change is especially important for small and medium-sized businesses (SMEs), which make up about 90% of all businesses in the world and bring in about 40% of national income in developing countries [3]. Small and medium-sized enterprises (SMEs) are important for job growth and industrial growth in economies at all stages of development [4]-[6]. But for them, using Industry 4.0 tools is not always easy. The digital revolution in manufacturing gives small and medium-sized businesses (SMEs) new chances, but it also makes it harder for them to stay competitive on a global scale [7]. By 2024, the market for digital transformation in manufacturing is expected to be worth about $427.68 billion. By 2034, it is expected to be worth about $1.05 trillion [8].

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Digital tools in conjunction with lean-production principles are often viewed by these firms as a practical way to achieve lasting competitive advantage. Just-in-Time (JIT) and Kanban methods, for instance, have contributed to Toyota's success in reducing waste and increasing efficiency [9],[10].

The classical version of these methods, however, is often too complex or resource-intensive for SMEs, especially when adapted to today's tech-rich environments [11]-[14]. A major limitation of conventional lean methods in SMEs is manual tracking and static rules.Because of this, these methods do not provide real-time data, causing disruptions and fluctuations in demand more difficult to manage.This is an area where digital twin technology can transform. By using a digital twin, it is possible to simulate changes and enhance JIT and Kanban mechanisms directly.

By integrating real-time sensor data, the Digital Twin can automate Kanban signals, predict material shortages before they occur, and dynamically adjust production schedules, thereby overcoming the rigidity and data latency that hamper traditional lean implementations in resource-constrained environments.

Many researchers around the world have discovered digital transformation and lean manufacturing for years, yet several significant questions remain without answer. One of these unanswered questions is that most work still revolves around single-technology roll-outs or large companies offering little guidance on frameworks tailored to the limited staff typical and tight budgets of SMEs [15]. Only about 29 % of small-firm digital projects succeed [16].

That figure hints that many conventional approaches simply overlook constraints unique to smaller operations. Digital Twin technology suggests another design. The studies that zero in on small-company adoption are scarce although its potential for manufacturing is well recognized [17]. Much of the existing research assumes ample funding and robust IT support, conditions many SMEs cannot match [18], [19], [20]. Furthermore, the literature rarely examines how a Digital Twin could mesh with lean tools like Kanban or JIT (even though real-time data might naturally complement those pull-based systems). Many studies tackle a single tool or stage in isolation, rather than mapping the entire life-cycle of a digital-lean initiative within an SME [21].

The managers lack a cohesive playbook that links strategy, technology, and continuous-improvement practices from start to finish.

The current study pursues to build and test a practical novel framework which blends Digital Twin tools with Kanban-JIT methods for SMEs. As novel strategy, it aims to close the growing gap between the ambitious promises of Industry 4.0 and the day-to-day constraints these firms face, all while staying true to lean principles.

The first part of the study will combine Digital Twins and Kanban-JIT to make a digital-lean framework. The framework will consider the usual budgets and resources of small and medium-sized businesses (SMEs). The second phase of the project will involve the validation of this method in several SMEs. As a result, it will be able to track performance gains and determine the factors that appear to impact successful.

2. Literature review

There are still issues with SMEs implementing Industry 4.0 tools in their daily work, and traditional digital projects only succeed 31% of the time [22]. An exhaustive review by Ghobakhloo and his colleagues [23] identified three factors that impede progress: insufficient expertise, financial limitations, and technology's inherent complexity. Despite these facts, Masood and Sonntag [24] observe that managers remain motivated by flexible production, lower costs, better quality, and the possibility of making their organizations more competitive. There will always be doubt about what to do next, despite all the evidence to the contrary. As a result of COVID-19, small and medium-sized businesses (SMEs) are now digitally savvy [25]. Despite the popularity of Industry 4.0 applications, there is still a gap between entry-level tools and more advanced ones [26]. As a result, cloud services have become popular because they can be scaled easily, do not require large upfront infrastructure costs, and have pay-as-you-go pricing, which is particularly appealing to businesses with limited resources [27].

As Industry 4.0 advances, digital twin technology becomes increasingly important. According to the forecast, the global market could reach \$119.8 billion by 2029, growing by approximately 41.6 percent annually [17], [18], [28]. In a digital twin, the machine, system, or process is mirrored in real time, as the sensor data updates. As a result of the model, real- world conditions are displayed, which allows users to spot potential problems early, tune their processes, and make daily decisions regarding the process. In spite of the benefits, there are a number of challenges associated with this approach. According to Ryzhakova et al. [29], Digital Twins can provide better flexibility, efficiency, and sustainability to SMEs in an Industry 5.0 environment. It is still difficult to adopt due to high infrastructure costs, data collection challenges, and skills shortages [15], [30]. Therefore, cloud-based twin services are viewed as a potential means of lowering initial costs and making technology more affordable [31, 32].

Lean thinking remains worthwhile for SME's, as recent studies demonstrate marked improvements in quality, productivity, and costs [33]. A study conducted by Panigrahi et al. [16] found a strong correlation between JIT practices and day-to-day performance among 252 firms. Despite this, lean rollouts are not always successful; only one in four projects actually meet expectations [34]. There are some challenges to implementing JIT and Kanban in smaller companies. A lack of bargaining power with suppliers, uneven demand, and inadequate shop-floor infrastructure often impede growth [21]. In factories that must react quickly to changes, traditional card-based Kanban may not work well [35]. By combining these methods with digital technology-sensor networks, cloud dashboards, or automated signals-supply chains can gain real-time visibility and coordinate more efficiently [36]. Manufacturing Execution Systems, or MES, are key components of that digital upgrade.

According to estimates, the market for cloud-based MES will be worth $25.78 billion by 2030 [37], which means it will grow at a rate of 10.1% annually. Cloud computing can reduce hardware costs for small and medium-sized businesses. The system can also be more easily deployed and maintained as demand grows [38]. Studies have shown that moving an MES to the cloud can reduce operating costs by 30%. There are several advantages of cloud computing, including greater flexibility, better monitoring and direct cost savings [39]. As a result of these findings, manufacturers might be able to adapt to changing needs more rapidly with MES solutions based in the cloud. Although this technology could be useful to small and medium-sized businesses, they have been hesitant to embrace it. A number of persistent concerns regarding data security are raised regarding cloud software and compatibility with legacy systems [40]. According to Table 1, small and medium- sized enterprises (SMMEs), lean manufacturing, and emerging technologies are undergoing a digital transformation. The report outlines the methods and results of each study. As illustrated in Table 1, there are areas in which evidence is coming together and others in which more research is needed.Small and medium-sized enterprises (SMEs) tend to have a smaller budget, fewer employees, and smaller facilities than larger corporations. Due to the limitations described above, firms are challenged to invest in new technologies, and many do not possess the internal expertise necessary.

Table 1. Comparative analysis of recent literature on digital transformation and lean manufacturing in SMEs

Study	Focus Area	Methodology	Key Findings	Limitations
Ghobakhloo et al.[23]	Industry 4.0 adoption barriers	Systematic literature review (TOE framework)	Identified technological, organizational, environmental determinants; knowledge competencies critical	Limited empirical validation
Masood & Sonntag [24]	Industry 4.0 benefits/challenges	Survey (n=271 UK SMEs)	Flexibility, cost, efficiency primary benefits; financial constraints main barrier	Single country focus
Ryzhakova et al. [29]	Digital Twin for SMMEs	Case study methodology	Real-time data capabilities, collaborative robotics integration	Limited scalability assessment
Panigrahi et al. [16]	Lean manufacturing performance	PLS-SEM analysis (n=252 SMEs)	JIT strong influence on operational performance; sustainable performance linkages	Cross-sectional design
Kumar & Sharma [41]	Industry 4.0 research evolution	Bibliometric analysis (421 articles)	Organizational and technical barriers predominant; developing countries face more challenges	Theoretical focus
Huang et al. [42]	Lean manufacturing implementation	Longitudinal case study (6 months)	26% lead time reduction, 28% efficiency improvement	Single company focus
Ibikunle et al. [43]	Lean/Six Sigma barriers	PRISMA systematic review (158 papers)	Government support and organizational culture critical; training investment needed	Limited practical frameworks
Choudhary et al. [44]	Integrated lean-green approach	Mixed methods case study	Sustainability improvements achievable; packaging SME context	Sector-specific findings

According to one survey, 2/3 feel they are fighting for survival due to fierce competition and technological gaps [33], [42]. Traditionally, JIT and Kanban practices have added a layer of complexity to the process.

Incorporating updated tools into existing systems, coordinating with suppliers, and managing fluctuations in demand can all be challenging tasks. A paper-based Kanban board is particularly problematic in this scenario. Because real-time insights are limited in such circumstances, responding quickly to disruptions and bottlenecks is harder [9], [34]. It may be possible to move forward with a digital-twin enabled JIT-Kanban setup. An approach that combines knowledge of lean principles with real-time digital copies of the shop floor can improve visibility and speed decisions [31].

In addition, SMMEs can pay as they use the cloud- based service, which may better fit their resource constraints [38], [45], [46]. Cloud-based services reduce the need for on-premises servers or large upfront investments for SMMEs. Since SMEs face daily challenges, this study utilizes action research. As a result of the method, the framework can evolve through repeated cycles of testing and adjustment, ensuring that the guidance is relevant and practical. [37]. Over a 30-month period, twelve SMMEs manufacturing automotive parts were assessed using the framework, providing substantial evidence that it can be applied beyond a single plant. Due to this, its reported strengths are not dependent on brief pilot tests, but rather on extended observations.

The partnership between digital twin technology and just-in-time Kanban has shown to be successful in alleviating several persistent bottlenecks related to lean business processes. The use of digital twins is a great way to improve Kanban signals in terms of speed and accuracy as they give instantaneous data and short-term forecasts [9].

By combining these technologies, inventory checks can be automated, maintenance schedules can be automated, and production can be balanced in real- time. A physical card-based lean setup usually does not provide these capabilities. Together, these factors suggest that a shopfloor that is more responsive and more resilient will be able to effectively handle changes in the future. Deploying a cloud solution can further reduce the entry barriers to the market, thereby lowering entry costs. Subscribing to advanced tools, such as CRM software, is an excellent way for small and medium businesses to save money on maintenance [38]. Due to the low-cost sensors used in the IoT, large amounts of operational data are collected at a reduced cost, leaving companies with strict budget constraints to be able to afford them [39]. This framework can therefore be adopted even by manufacturers with limited resources as a result of its flexibility and adaptability.

3. Methodology

3.1 Study Design and Research Approach

This study created and assessed a JIT-Kanban framework that is specifically designed for small and medium-sized enterprises, facilitated by Digital Twins, using an action research methodology. As a result of action research during the practical implementation of the framework, theoretical advancements have been merged with empirical validation [10, 34]. An observation period of 30 months was conducted, beginning in January 2022 and ending in June 2024. The system was implemented through a series of steps, including digital maturity audits, pilot programs, full implementations, and regular updates. As a result of this method of organizing work, each component could be examined without causing the machine to halt its normal operation. Action research participants contributed to the development of solutions and made changes based on the information they acquired. During time, the framework improved and so did its performance.

3.2 Participant Selection and Study Setting

There are a number of supply chain partners in the area as well as well-developed industrial services, which makes it an ideal site for conducting field research. The companies were selected from the Saudi Industrial Development Fund list, and to qualify, they must have between 50 and 250 employees, a revenue between \$5 million and \$50 million, and at least an average track record of lean manufacturing. The pool of candidates was narrowed further by additional screening. Organizations were required to demonstrate basic production capabilit- ies, commit to a 30-month digital transformation project, and maintain organizational stability.

Conversely, businesses in the midst of major technology roll-outs, lacking minimal IT infrastructure, or undergoing substantial restructuring were set aside. The final sample averaged 127 employees (± 43), brought in about US\$23.4 million (± 12.7) per year, and had operated for 8 to 24 years. Data were gathered from 89 employees spanning several tiers of the organization. Specifically, the sample included 24 senior managers, 31 production supervisors, 26 machine operators and eight IT specialists. Approximately 73 percent of participants were men, which mirrors the wider regional manufacturing workforce. Their mean age was about 34 years (SD = 8.9), while their average tenure in the sector hovered around 12 years (SD = 6.3).

3.3 Digital Twin-Enabled Framework Development

With a cloud-based Digital Twin and a lean JIT-Kanban framework, you can create a clean design with three layers. Cheap IoT sensors on the shop floor collect data, which is then cleaned, stored, and sent to a virtual copy of the line in the cloud. Lastly, operators can see the results on debuas in apps for mobile devices and this setup keeps hardware costs low and lets people see what‘s going on right away. Most factories can afford ESP32 microcontrollers, which cost between $12 and $18 each. There are usually 15 to 25 sensors on a production line. For instance, ultrasonic modules (HC-SR04) check the stock level, vibration sensors (MPU-6050) check the level of vibration, and temperature sensors (DHT22) check the level of humidity. Value-stream mapping helps figure out where to put sensors so that useful data can be collected.

In the cloud, messages are queued and wireless telemetry is used to transfer data. In spite of noisy factories, this protocol ensures that messages remain small and can be transmitted. Each inventory reading is transmitted every 30 seconds, each equipment reading is transmitted every 10 seconds, and each environ- mental reading is transmitted every minute. With this pattern, the network does not have to be overburdened in order to provide useful information. The implementation of the project led to the emergence of many real-world problems. As a result of inconsistent data quality and unstable signals, setting up the sensors was challenging at first. To address this issue, a multipoint calibration protocol was implemented. The results of this analysis are compared with those of certified instruments at different operational setpoints at which the sensors are reading. In addition, heavy machinery in the factory caused a considerable amount of electromagnetic interference, which resulted in noise in sensor data. In order to minimize the effects of this, moving averages and other microcontroller-level software filters were used to smooth the data prior to transmission. It was also decided to relocate the sensors to a less cluttered area. To conclude, a mesh Wi-Fi network was installed across large factory floors which had metal and physical barriers. By doing so, dead spots were eliminated and all IoT devices were able to send and receive data without any difficulty. The network was maintained across numerous floors of a large manufacturing facility.

After your data has been moved to the cloud, Azure will handle all the tedious tasks on your behalf. Devices are managed through the IoT Hub, streams are analyzed in real-time by Stream Analytics, and the shop floor is monitored by Azure Digital Twins. A discrete-event model is used by AnyLogic‘s mirror to simulate what might happen in the event of new data coming in. [17] Compare the virtual state space representation with the real-time state space representation:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{w}_k \tag{1}$$

where $\mathbf{x}_k$ represents the system state vector at time k, $\mathbf{A}$ is the state transition matrix, $\mathbf{B}$ is the input matrix, $\mathbf{u}_k$ denotes control inputs, and $\mathbf{w}_k$ represents process noise. This formulation enabled real-time synchronization between physical manufacturing processes and virtual Digital Twin representations, supporting predictive analysis and optimization recommendations.

3.4 Data Collection Protocols

The first step was to use mixed methods to evaluate the initiative to get a better picture of it. This company used sensor networks to monitor production output, inventory levels, and defect rates. The data streams gave us a clear picture of how things were taking place every day. They also let us keep track of the time stamps for each entry. The qualitative part was different from the quantitative part in that it looked at the actual process of putting the plan into action. people learned more about the organization's work by watching, doing semi-structured interviews, and having focus group discussions. These two different ways of looking at things can help us understand what has changed and why. Production performance metrics included cycle time measurements (T_{cycle}), setup time assessments (T_{setup}), overall equipment effectiveness (OEE), and throughput calculations. OEE calculations followed industry-standard formulations [12]:

$$\text{OEE} = \text{Availability} \times \text{Performance} \times \text{Quality} \tag{2}$$

where:

$$\begin{aligned} \text{Availability} &= \frac{T_{\text{operating}}}{T_{\text{planned}}} \\ \text{Performance} &= \frac{T_{\text{ideal}} \times \text{Units}_{\text{produced}}}{T_{\text{operating}}} \\ \text{Quality} &= \frac{\text{Units}_{\text{good}}}{\text{Units}_{\text{produced}}} \end{aligned} \tag{3}$$

Aside from tracking work-in-progress (WIP), raw materials were being used steadily, and counted finished goods were monitored by automated tools. To test whether each Kanban card worked well, the average time between a signal and response was taken. A stock run monitoring system was also in place. There could be a problem if shortages happen frequently. An analysis of the costs involved in upgrading the technology was conducted. As well as examining the costs of training staff, it examined how much they spend on daily necessities. To determine the financial security of the business, a standard return-on-investment formula was applied [4]:

$$\text{ROI} = \frac{\text{Benefitstotal} - \text{Coststotal}}{\text{Costs}_{\text{total}}} \times 100\% \tag{4}$$

Comparing baselines can help you figure out how much productivity has increased up, how much inventory has come down, and how high quality has gone up after implementation.

3.5 Implementation Phases and Validation Protocols

In order to determine whether each organization was prepared for digital projects, the team used structured evaluation tools. Among the things considered in the protocol was the level of readiness of the technology, the organization s capacity, as well as the ability of the current infrastructure to handle the demands of evolving systems. Following the evaluation of the criteria, an overall score of digital maturity was calculated [2]:

$$\text{DM}_{\text{score}} = \sum_{i=1}^{n} w_i \times S_i \tag{5}$$

where DM_{score} represents the digital maturity score, w_i denotes weighting factors for assessment criteria i, S_i represents individual criterion scores, and n indicates the total number of evaluation criteria. Experts agreed on the relative importance of five core areas, assigning provisional weights to each. Technology infrastructure carried the greatest influence (0.3), followed by organizational capabilities (0.25), data-management readiness (0.2), change-management capacity (0.15), and, lastly, financial resources (0.1). These values serve as guiding coefficients rather than fixed absolutes, acknowledging that local conditions can shift priorities.

In order to improve the production line, all organizations tried to pilot a single line for the purpose of learning from their experience and making improvements. The aim of this study was to determine whether the Digital Twin accurately reflected reality by comparing discrete-event simulations with actual data collected on the shop floor in order to confirm this [7].

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{6}$$

where O_i represents observed frequencies, E_i denotes expected frequencies from simulation models, and k indicates the number of categories. Validation acceptance criteria required χ^2 values below critical thresholds ($\alpha = 0.05$) and correlation coefficients exceeding 0.90 between simulated and actual performance metrics.

3.6 Statistical Analysis and Comparative Evaluation

SPC techniques make it possible to keep an eye on the health of the system and the performance of production all the time. peopl can often find small changes in quality before they turn into big problems by putting routine measurements on control charts. Control limits on these charts are usually set using the following well-known formulas found in the literature [40]:

$$\begin{aligned} \text{UCL} &= \bar{X} + 3\sigma \\ \text{CL} &= \bar{X} \\ \text{LCL} &= \bar{X} - 3\sigma \end{aligned} \tag{7}$$

where $\bar{X}$ represents the process mean, σ denotes the process standard deviation, UCL indicates upper control limits, CL represents center lines, and LCL denotes lower control limits. SPC implementation enabled real-time detection of process variations and framework performance anomalies.

As part of the study, a Difference-In-Differences (DID) methodology was employed in order to determine the efficacy of the proposed framework by comparing the results with those of conventional Just-In-Time (JIT) systems as well as well-established digital transformation processes. As a result of the

DID model, which is based on standard regression equations [5], it is possible to separate the effects of the framework itself from the effects of the model. Despite the assumption that the groups would have progressed concurrently without intervention, it was important to validate the premise that they would have done so:

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 P_t + \beta_3 (T_i \times P_t) + \gamma X_{it} + \epsilon_{it} \tag{8}$$

where Y_{it} represents outcome variables for organization i at time t, T_i indicates treatment group assignment (framework implementation), P_t denotes post-implementation periods, $(T_i \times P_t)$ represents the interaction term capturing treatment effects, X_{it} encompasses control variables, and ϵ_{it} represents error terms. The coefficient β_3 provided unbiased estimates of framework effectiveness under parallel trends assumptions.

In order to identify hidden divergences, the research team visualized pre-implementation data and included interaction terms between treatment status and time. A series of additional tests was conducted to increase confidence in the results. It included the use of a variety of model specifications, placebo tests that treated earlier periods as though they were intervention points. Further analysis was conducted to determine how changing key assumptions affected the results. This combination of measures ensures that any observed effects cannot be attributed to artifacts resulting from model selection or temporal factors.

A machine-learning layer is added to the framework's advanced analytics layer to help predict maintenance, forecast demand, and optimize processes. The DID analysis was in addition to this. Using the random forest model, maintenance teams can identify equipment that is likely to fail in the future before it breaks down by analyzing sensor readings [22]. Insights derived from data are still in the process of changing, but they can be useful to businesses in order to make them more reliable and efficient.

$$P(\text{failure}) = \frac{1}{B}\sum_{b=1}^{B} T_b(\mathbf{x}) \tag{9}$$

where $P(\text{failure})$ represents failure probability predictions, B denotes the number of decision trees, $T_b(\mathbf{x})$ indicates individual tree predictions for input vector $\mathbf{x}$, enabling proactive maintenance scheduling and downtime prevention.

4. Results and Discussions

4.1 Digital Maturity Assessment and Baseline Characterization

Twelve SMEs took part in the study, but not all were ready to adopt new technologies and use them effectively. It was mainly due to how they perceived their digital maturity at the beginning of the project. Based on the weighted evaluation framework described in the methodology section, it is possible to determine how each company's current capabilities and infrastructure are aligned. These digital maturity scores are summarized in Table 2 for fine-tuning and planning.

Table 2. Digital maturity assessment scores across participating SMMEs with component analysis and overall readiness rankings

Organization	Technology Infrastructure (0.3)	Organizational Capabilities (0.25)	Data Management (0.2)	Change Management (0.15)	Financial Resources (0.1)	Overall DM Score	Readiness Rank
SME-01	7.2	6.8	5.9	7.1	8.2	6.74	3
SME-02	5.4	5.2	4.8	5.9	6.1	5.31	8
SME-03	8.1	7.6	7.2	8.0	7.8	7.66	1
SME-04	6.3	6.1	5.4	6.8	7.0	6.18	5
SME-05	4.8	4.9	4.2	5.1	5.4	4.84	11
SME-06	7.5	7.2	6.8	7.4	8.0	7.26	2
SME-07	5.9	5.7	5.1	6.2	6.5	5.76	7
SME-08	6.8	6.4	6.0	6.9	7.3	6.52	4
SME-09	4.2	4.5	3.8	4.7	4.9	4.35	12
SME-10	5.7	5.8	5.3	6.0	6.2	5.62	9
SME-11	6.1	5.9	5.6	6.5	6.8	6.08	6
SME-12	5.2	5.0	4.6	5.5	5.8	5.18	10
Mean	6.10	5.93	5.39	6.34	6.67	5.96	-
SD	1.23	1.09	1.02	1.03	1.10	1.04	-

There was a range of digital maturity scores between 4.35 and 7.66, with a mean of 5.96 and a standard deviation of 1.0. The range of the technology infrastructure was the largest (SD = 1.23), whereas the baseline for data manage- ment capability was the lowest (mean = 5.39). In general, companies that performed well on the test adopted the framework faster and reported that the roll-out was more smooth. The results of this study suggest that being ready at the start of the project is associated with success in the long run.

4.2 Pilot Implementation Results and Digital Twin Validation

The first part of the pilot tested a number of production lines to see how well the Digital Twin worked and how well the framework as a whole worked. To recreate shop-floor conditions, discrete-event simulation models are used with real production data from the shop floor. Figure 1 shows a summary of the results: Figure 1a shows the difference between simulated and actual outputs over 120 days. Figure 1b shows the difference between chi-square goodness-of-fit tests for different production scenarios. Figure 1c looks at how accurate key performance indicator predictions are. Figure 1d shows how the performance of physical and virtual systems changes over time. When you look at all of these panels together, you can see that the Digital Twin can closely mimic real-world behavior, but you should keep an eye on it because conditions are always changing. The Digital Twin validation process showed that all of the organizations that took part were very accurate. Correlation analysis found an average correlation coefficient of 0.92 (SD = 0.021). According to the methodology, eleven of the twelve implementations surpassed the 0.90 threshold. All production scenarios are statistically valid ($p > 0.05$) according to Chi-square goodness-of-fit testing, and the test statistics are well below critical thresholds. The predictions for cycle time were correct by 3.2%, for throughput by 2.8%, and for quality by 4.1%. The average time it took for updates to happen was 2.3 seconds (SD = 0.8), This resulted in the monitoring and control system being able to monitor and control the system in real-time.

Figure 1. Comprehensive Digital Twin validation analysis across twelve SMMEs pilot implementations. (a) Correlation analysis between simulated and actual production outputs showing R^2 values and regression lines for each organization. (b) Chi-square goodness-of-fit test results across different production scenarios with acceptance thresholds. (c) Prediction accuracy analysis for key performance indicators including cycle time, throughput, and quality metrics. (d) Temporal synchronization performance showing latency distributions and real-time update frequencies.

4.3 Comprehensive Implementation Performance Analysis

A pilot validation confirmed the framework's effectiveness. It has since been put into use on all production lines, giving us 18 months of performance data. Several operational metrics were examined from various angles in order to determine how effective the framework was in terms of building a better site. Figure 2 shows a detailed six-panel analysis that fully describes how well an implementation works. A study in Figure 2a indicates that inventory levels are going down on a month-to-month basis. The efficiency of production scheduling has improved, lead times have decreased for different product categories in Figure 2b, setup time optimization is portrayed in Figure 2, overall equipment effectiveness has improved (OEE), and work-in-process (WIP),has also increased.

The performance analysis showed that there were big improvements in all the areas that were measured. The average drop in inventory levels was 47.3% (SD = 8.2%), but the results for each case ranged from 32% to 61%. Because of this implementation, schedule adherence went up from 68.4% at the start to 91.7% after it was put into place (p 0.001). Because of this big jump in numbers, production supervisors said that things were getting better in other ways as well.Because things were more predictable, supervisors said they spent less time dealing with problems and changing appointments. This not only helped them deal with daily stress, but it also let them shift their focus from crisis management to proactive process improvement and coaching their teams.Thanks to the new stability, management and shop-floor workers could now count on a production plan that was more reliable and doable, which made the oper-

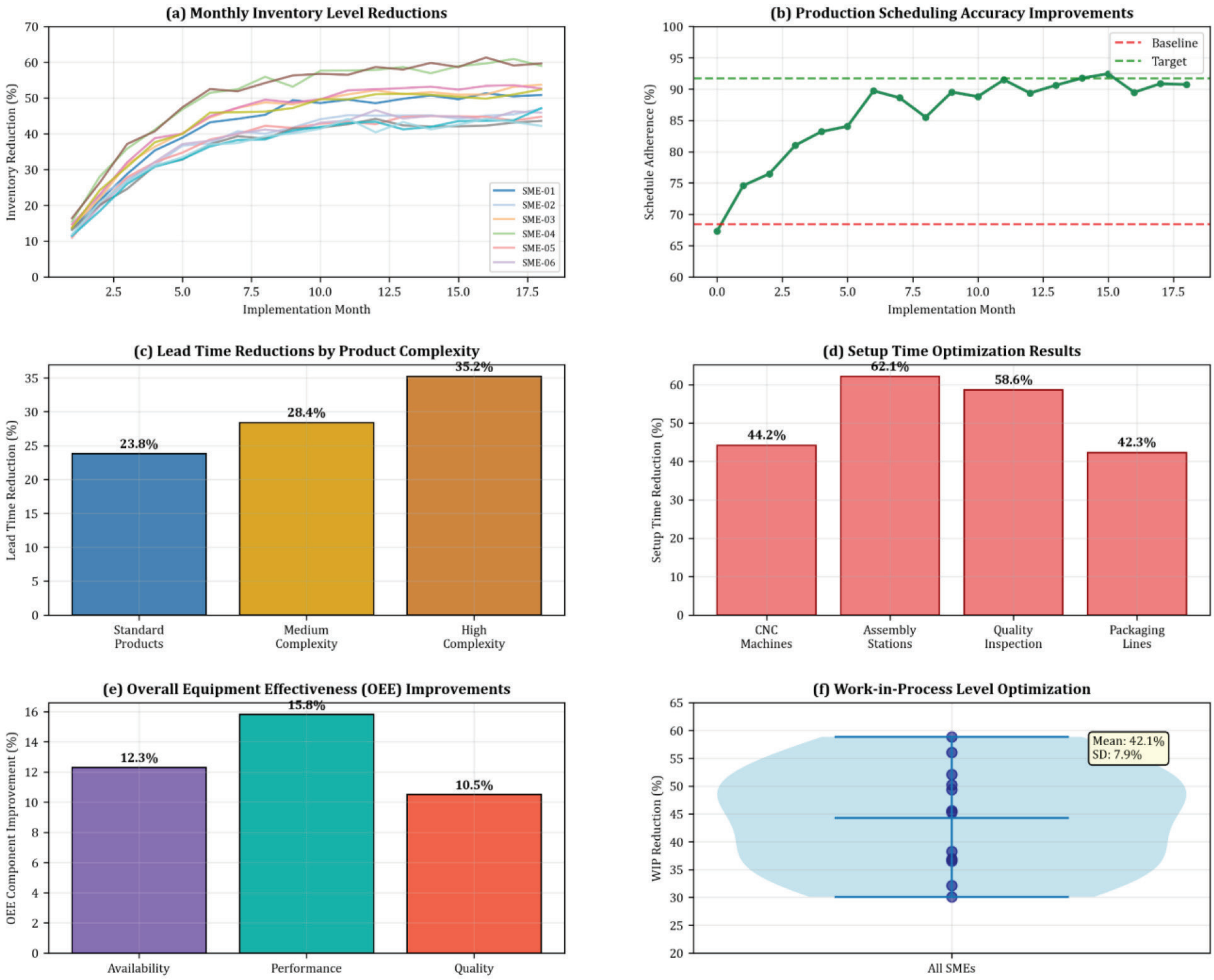

Figure 2. Comprehensive operational performance analysis following full framework implementation. (a) Monthly inventory level reductions showing percentage decreases from baseline across all SMMEs. (b) Production scheduling accuracy improvements measured through schedule adherence and variance reduction. (c) Lead time reductions categorized by product complexity and production volume. (d) Setup time optimization results showing percentage improvements across different equipment types. (e) OEE improvements decomposed into availability, performance, and quality components. (f) WIP level optimization showing WIP reduction percentages and flow efficiency improvements.

ation more trustworthy and easier to run. Lead times went down by 28.4% (SD = 6.7%). Products with complicated designs got 35.2% better, and products with standard designs got 23.8% better. The average improvement was 51.8% (SD = 12.1%), and the time it took to set up was cut almost in half. Automated changeover protocols are a big part of why these efficiency gains have happened. OEE went up by 38.6% (SD = 9.4%). There are three parts to the 12.3% increase in availability, the 15.8% rise in performance, and the 10.5% improvement in quality. WIP levels also dropped by an average of 42.1% (SD = 7.9%), which made production more efficient.

4.4 Comparative Effectiveness Analysis Using Difference-in-Differences Methodology

Analyzing the efficacy of the framework in comparison with conventional digital transformation strategies and traditional Just-In-Time (JIT) methodologies was conducted using the DID methodology. In addition, these researchers compared data on sixteen similar SMEs collected over the same period using traditional approaches.

They were also selected from the Saudi Industrial Development Fund database like the treatment group. In order to ensure that the groups were similar, five main criteria were used: (1) industry sector (manufacturing automotive parts), (2) organizational size (within 15% of the mean of the treatment group), (3) annual revenue (within 15% of the mean of the treatment group), (4) years in operation (±3 years), and (5) baseline operational practices (confirming use of traditional, non-digital JIT or Kanban systems).Several control firms have also confirmed that there were no major digital major transformation projects planned or underway during the time of the study. This rigorous selection process was carried out by reducing confounding variables and enhancing the validity of parallel trends. Table 3 displays treatment effects across various outcome variables, with a strong standard error and confidence interval for each coefficient. The DID analysis found that all outcomes had a statistically significant effect (p 0.001). The Digital Twin-enabled framework improved inventory reductions by 40.0 percentage points, scheduling accuracy by 19.0 percentage points, and lead times by 23.5 percentage points. The framework had a very high success rate, with an overall success rate of 80%. The treatment effect of conventional methods is 47.1 percentage points higher than the 78.3% treatment effect of conventional methods. A parallel trend hypothesis can be supported by the finding that all variables in the pre-treatment trend analysis did not differ significantly between the treatment group and the control group (p > 0.010).

4.5 Economic Impact and Return on Investment Analysis

An analysis of the cost-benefit of implementing this framework was conducted to determine how its implementation affected participating organizations' finances. Over the course of 18 months, costs associated with implementation, operational savings, productivity gains, and return on investment were evaluated. A summary of economic findings across five panels is presented in Figure 3. The benchmark for a "conventional Industry 4.0 solution" was determined by assessing market rates for systems involving on- premise server infrastructure, upfront licensing fees for monolithic manufacturing processes, proprietary industrial

Table 3. Difference-in-differences regression analysis comparing Digital Twin-enabled framework against traditional implementation approaches across key performance metrics

Outcome Variable	Pre-Treatment Mean	Post-Treatment Mean	Control Group Change	Treatment Effect (β_3)	Standard Error	95% CI	p-value
Inventory Reduction (%)	2.1	47.3	5.2	40.0***	3.8	[32.6, 47.4]	<0.001
Schedule Accuracy (%)	68.4	91.7	4.3	19.0***	2.1	[14.9, 23.1]	<0.001
Lead Time Reduction (%)	1.8	28.4	3.1	23.5***	2.9	[17.8, 29.2]	<0.001
Setup Time Reduction (%)	3.2	51.8	6.8	41.8***	4.2	[33.6, 50.0]	<0.001
OEE Improvement (%)	1.9	38.6	4.5	32.2***	3.6	[25.2, 39.2]	<0.001
Implementation Success Rate (%)	-	78.3	31.2	47.1***	5.8	[35.7, 58.5]	<0.001
Employee Satisfaction Score	6.2	7.8	0.3	1.3***	0.2	[0.9, 1.7]	<0.001
Digital Literacy Score	4.1	5.9	0.2	1.6***	0.3	[1.0, 2.2]	<0.001

Note. ***p < 0.001; **p < 0.01; *p < 0.05

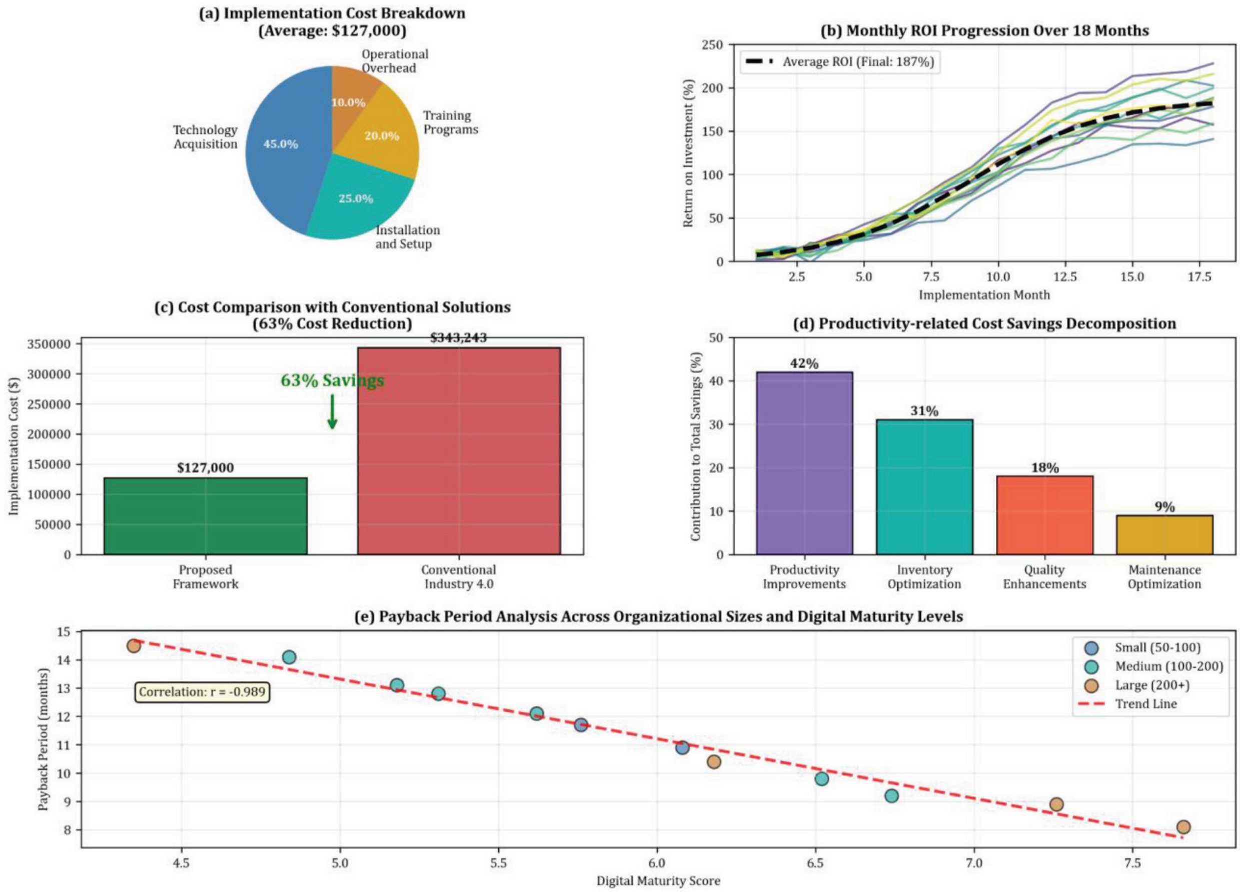

Figure 3. Comprehensive economic impact analysis of Digital Twin-enabled framework implementation. (a) Implementation cost breakdown showing technology acquisition, installation, training, and operational expenses across SMMEs categories. (b) Monthly return on investment progression demonstrating cumulative benefits over 18-month periods. (c) Cost comparison analysis with conventional Industry 4.0 solutions showing percentage savings. (d) Productivity-related cost savings decomposed into labor efficiency, material utilization, and equipment optimization components. (e) Payback period analysis across different organizational sizes and digital maturity levels.

hardware, and extensive integration consultants billable hours. By contrast, the proposed framework is based on operational expenditures rather than capital expenditures. Implementation costs are broken down by category (3a), ROI progression is demonstrated (3b), costs are compared to conventional benchmarks (3c), productivity-related savings are decomposed (3d), and payback periods are analyzed for different organizational sizes and digital maturity levels (3e).

Financial results proved favorable across the board. Organizations spent an average of $127,000 on implementation (SD = $31,000)—roughly 63% less than conventional Industry 4.0 solutions typically require. Returns grew steadily throughout the study period, with ROI reaching approximately 187% by month 18. Individual results ranged from 142% to 234%. Several factors contributed to the savings. Productivity improvements accounted for a positive financial outcome across the board. Compared to conventional Industry 4.0 solutions, organizations spent approximately 63% less on implementation (SD = $31,000). A gradual growth of ROI was observed throughout the study period, reaching approximately 187% by month 18. There was a range of 142% to 234% in individual results. The savings were due to a number of factors. The largest portion of the improvements came from productivity improvements, accounting for 42%, followed by inventory optimization, accounting for 31%. 18% of the cost was attributed to quality improvements, and 9% was attributed to maintenance optimization.

4.6 Statistical Process Control and Quality Performance Results

SPC checked quality performance during the implementation phase. Analyses were conducted on all production lines to determine metrics for evaluating process stability, reducing variation, and improving quality. Using SPC has improved control charts, process capability indices, and the reduction of variations across different process categories, as shown in Table 4.

Table 4. Statistical process control analysis results showing process performance improvements and quality metrics across production categories

Process Category	Pre-Implementation Cpk	Post-Implementation Cpk	Variation Reduction (%)	Control Chart Violations (per month)	Process Stability Score
Machining Operations	1.12	1.67	34.2	2.3	8.7
Assembly Processes	0.98	1.54	41.8	1.8	8.9
Quality Inspection	1.31	1.82	28.7	0.9	9.2
Material Handling	1.05	1.49	39.1	2.1	8.5
Packaging Operations	1.18	1.71	31.4	1.2	9.0
Overall Average	1.13	1.65	35.0	1.7	8.9

SPC analyses showed quality improvements in all areas. The process capability index shows improvements between 1.13 and 1.14. The variation was cut down by 1.65, which indicates better control. Assembly processes saw the biggest drop, down by 35.0%. There was a big drop in 41.8% of control chart violations, from 7.8 per month before to 1.7 per month after implementation. This indicates that the process is more stable. A 10-point scale that measured how stable the process was was averaged across all categories. This showed that the framework had been successfully integ- rated and that performance had continued to improve.

4.7 Machine Learning Performance and Predictive Analytics Results

During the implementation phase, we used advanced analytics and machine learning algorithms to give us recommendations for predictive maintenance, demand forecasting, and optimization. To see how well the predictor model worked, we looked at a number of algoriht ms and scenarios. Figure 4 shows that a four-panel analysis is used to measure how well machine learning integration works. Panel 4a says that random forest algorithms can accurately predict when different types of equipment will need

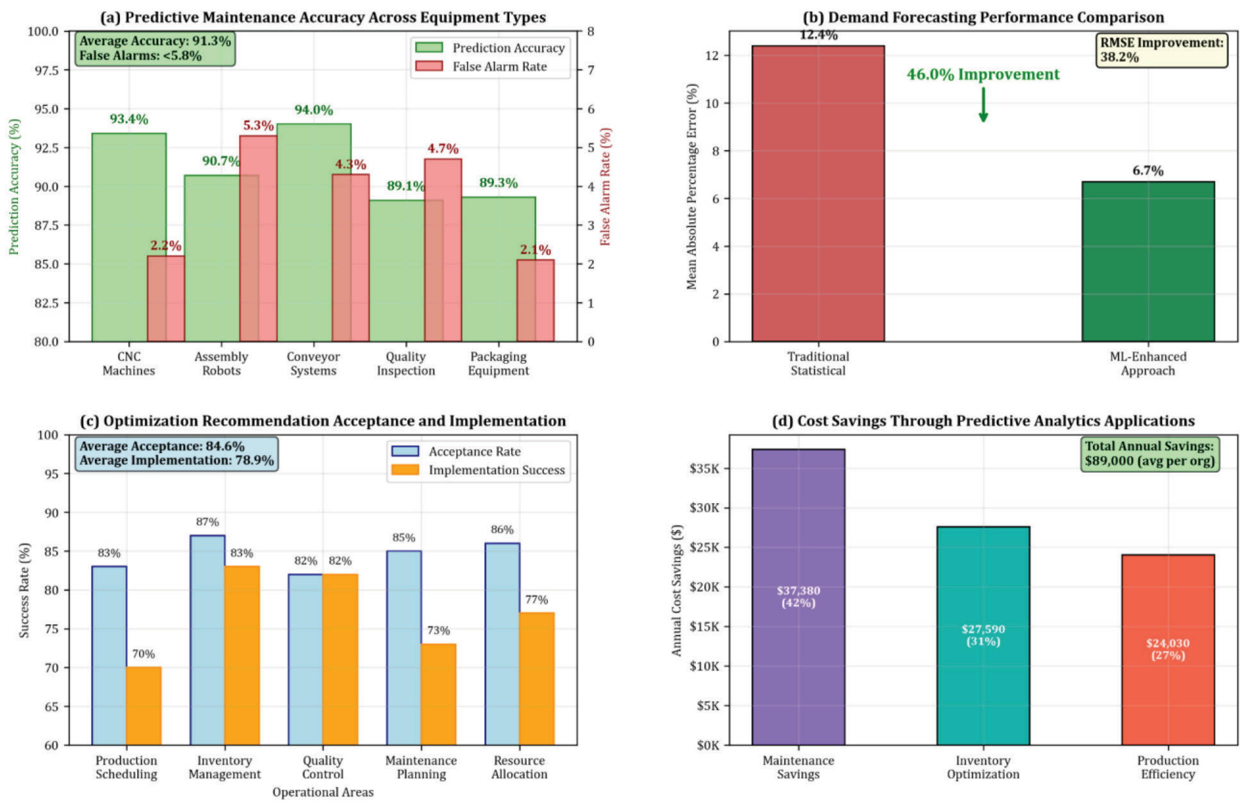

Figure 4. Machine learning integration performance analysis across predictive applications. (a) Predictive maintenance accuracy showing failure prediction rates and false alarm percentages across equipment categories. (b) Demand forecasting performance comparing traditional statistical methods with ML-enhanced approaches using mean absolute percentage error and root mean square error metrics. (c) Optimization recommendation acceptance and implementation success rates across different operational areas. (d) Cost savings achieved through predictive analytics applications decomposed into maintenance savings, inventory optimization, and production efficiency improvements.

maintenance. Panel 4b shows how traditional and machine- learning-enhanced methods for predicting demand compare to each other. Panel 4c shows that optimization suggestions are accepted and put into action successfully. Panel 4d shows that using predictive analytics can save money. when it came to integrating machine learning, it worked very well in all applications. In general, predictive maintenance algorithms were correct about 80% of the time, with a 91.3% (SD = 4.2%) accuracy rate for predicting equipment failures and a false alarm rate of less than 5.8%. Demand forecasting has made a lot of progress over traditional methods, with a mean absolute percentage error of 6.7% and a root mean square error of 38.2%. A total of 84.6% of optimization suggestions were accepted, and 78.9% of them were put into action successfully. Predictive analytics saved organizations an average of $89,000 per year. This was in addition to savings on maintenance costs (42%), inventory optimization (31%), and improvements in production efficiency (27%).

4.8 Employee Training and Digital Literacy Development Results

The team decided to make a training program to help people learn digital skills so they could use the framework. A standardized test was given before and after the training to find out how well people could use technology. Table 5 shows detailed studies of how different groups of employees and levels of the organization have been able to get better at their jobs.

A lot has changed since I got training. There was an increase in overall digital literacy scores of 44.9%, from 4.1 to 5.9. This indicates that the program was successful, since Cohen's D value was 1.8, which is considered to be very high. A 52.1% improvement in relative performance can be attributed to production supervisors. Even though their relative gains were small, IT specialists did very well in absolute terms.

Because they were good at the start, this is the case. As of the completion date for 86.4% of participants, senior management had the highest rate of 91.7% learning their skills. A strong positive relationship between the number of training hours completed and the level of skill mastery achieved shows that the program works.

4.9 Long-term Sustainability and Performance Maintenance

Accordingly, the results indicate that the performance has remained stable. During the first evaluation, improvements were observed that remained unchanged for the following 24 months. There were no deviations from the control limits in any of the key metrics. There was a great deal of difficulty in ensuring that the system was reliable, but it was. Based on the framework's components, 98.7% of IoT sensor networks were operational, 99.4% of cloud platforms were operational, and 97.9% of Digital Twin synchronizations were accurate.

There was good evidence throughout the research work that a framework was able to be stable, flexible, as well as capable of growing with the use of it as a framework, whether that be for individuals or for organizations. According to the data provided by the organization, with every improvement cycle that takes place 3.2 times a quarter, it is estimated that the organization had improved by 2.1%, and this rate was suggested to be 3.2 percent.

In my opinion, the most important value of the system lies in the fact that it provided an enormous amount of flexibility, which was a major part of its appeal. As a result of 47 changes in process and 23 changes in technology, there were no problems with the system or degradation of performance as a result of those changes.

Table 5. Employee digital literacy development results showing pre- and post-training assessment scores across organizational levels and skill categories

Employee Category	N	Pre-Training Score	Post-Training Score	Improvement (%)	Effect Size (Cohen's d)	Training Hours	Competency Achievement Rate (%)
Senior Managers	24	5.2	7.8	50.0	1.8	32	91.7
Production Supervisors	31	4.8	7.3	52.1	2.1	28	87.1
Operators	26	3.6	5.4	50.0	1.9	24	80.8
IT Specialists	8	7.1	8.9	25.4	1.2	20	100.0
Overall Average	89	4.1	5.9	44.9	1.8	26	86.4

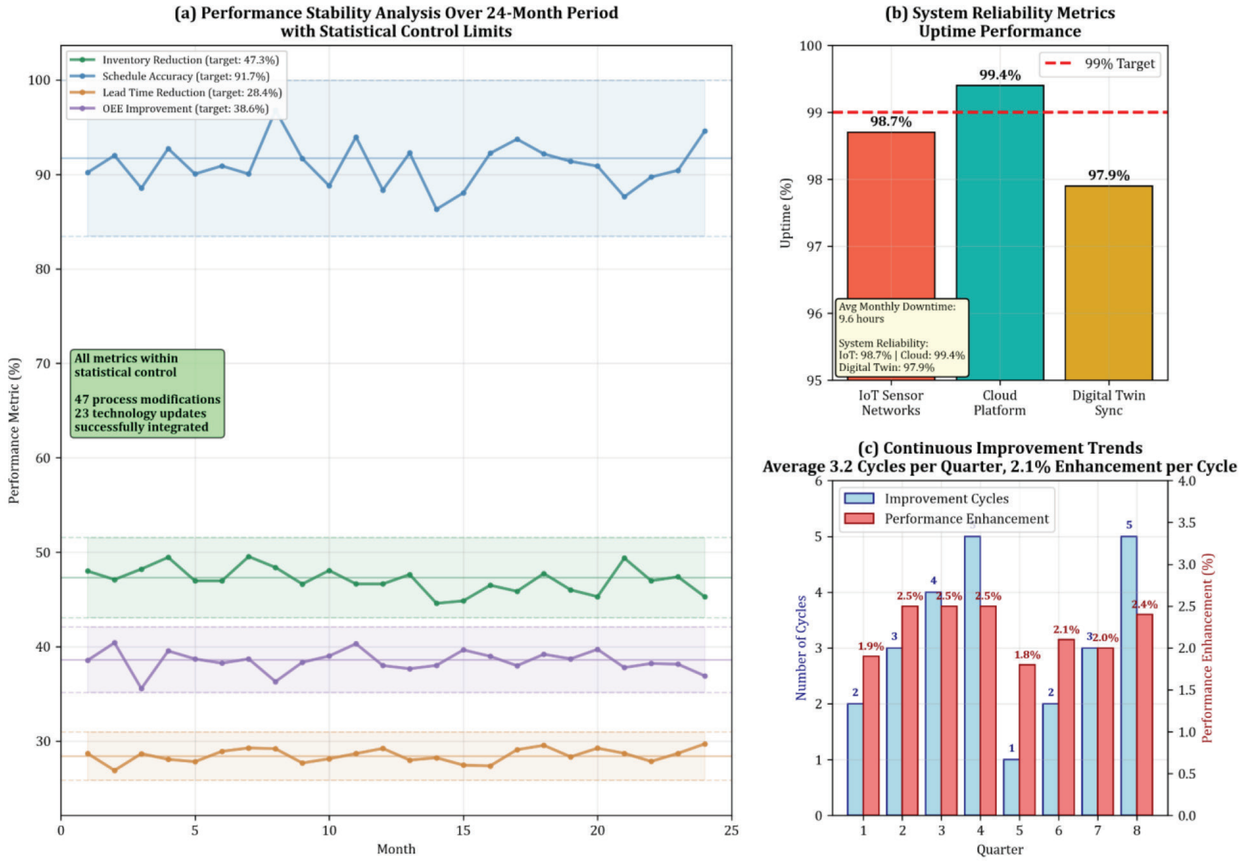

Figure 5. Long-term sustainability and performance maintenance analysis. (a) Performance stability analysis showing key performance indicators tracked over 24-month periods with control limits and trend analysis. (b) System reliability metrics including IoT sensor network uptime, cloud platform availability, and Digital Twin synchronization reliability. (c) Continuous improvement trends showing iterative optimization cycles and performance enhancement progression.

4.10 Framework Scalability Assessment and Implementation Guidelines

It was determined that the framework was capable of being adapted to a variety of contexts, including diverse organizational sizes, industries, and levels of digital maturity, as well as implementation challenges. In addition to developing evidence-based guidelines for a broader audience, the project sought to disseminate them. Table 1 provides a detailed list of these scalability factors, which identifies the most important ones that may contribute to the success of frameworks in different operating environments.According to the study, digital maturity is negatively associated with implementation success ($r = 0.87$, p 0.001). The results did not show a significant relationship between the organization's size and its performance ($r = 0.34$, $p = 0.281$). Additionally, there was a significant positive correlation between implementation complexity and success ($r = 0.72$, $p = 0.008$), which indicates that companiesthat successfully implemented large projects had a greater chance of long-term success. the study determined that training requirements increased with increasing success ($r = 0.79$, $p = 0.002$), however, return on investment time decreased with increasing success ($r = -0.81$, $p = 0.001$). Better-performing organizations were able to quickly realize the benefits of their investments.

Using a five-panel analysis as an example, figure 6 illustrates the flexibility of the framework. Based on panel (a), it appears that success rates of digital transformation vary significantly depending on both the organization's size and its level of digital maturity. The panelists discussed this issue in detail.

The second example illustrates the need for resources to maintain cost and timeline control during a complex system implementation. It provides an overview of the adaptation strategies employed by different types of organizations in panel (c). Project success will be determined by several factors, and panel (e) examines how timing and achievement patterns will affect the project's milestones.

According to several studies, digital maturity is a more accurate indicator of success than an organaza-

Table 6. Framework scalability factor analysis across organizational contexts showing implementation success predictors and adaptation requirements

Scalability Factor	Low Impact Organizations (n=3)	Medium Impact Organizations (n=6)	High Impact Organizations (n=3)	Success Correlation (r)	p-value
Employee Count	52-78	89-167	189-247	0.34	0.281
Digital Maturity Score	4.35-5.18	5.31-6.52	6.74-7.66	0.87***	<0.001
Implementation Complexity	Low (3.2)	Medium (5.8)	High (7.9)	0.72**	0.008
Training Hours Required	18-22	24-28	32-38	0.79***	0.002
Infrastructure Investment ($)	89,000-112,000	118,000-139,000	142,000-168,000	0.56*	0.048
Time to Full Implementation (months)	8.3-11.2	12.1-15.7	16.8-21.4	0.68**	0.015
ROI Achievement Timeline (months)	14.1-16.8	10.9-12.3	8.7-9.9	-0.81***	0.001
Sustainability Score	7.2-7.9	8.3-8.9	9.1-9.7	0.84***	<0.001

Note. ***p < 0.001; **p < 0.01; *p < 0.05

Context	Success Rate	Timeline	Investment Range	Key Requirements
High Digital Maturity	92%	12–16 months	140K–170K	Leadership commitment, IT infrastructure
Medium Digital Maturity	84%	14–18 months	115K–145K	Training investment, change management
Low Digital Maturity	71%	18–24 months	95K–125K	Infrastructure development, skill building
Small Organizations	86%	10–14 months	85K–115K	Digital infrastructure, training
Medium Organizations	89%	12–16 months	120K–150K	Balanced resource allocation
Large SMEs	81%	16–20 months	145K–175K	Change management, coordination

Figure 6. Comprehensive framework scalability analysis across diverse SMMEs contexts. (a) Implementation success rates shown as heat map across organizational size and digital maturity combinations with success probability distributions. (b) Resource scaling analysis showing linear and non-linear cost relationships with implementation complexity and organizational characteristics. (c) Adaptation strategy analysis categorizing customization approaches across different organizational types and operational environments. (d) Critical success factor importance rankings across different implementation contexts using weighted scoring methodology. (e) Implementation timeline analysis showing milestone achievement patterns and critical path dependencies across varied organizational scenarios.

tion's size when it comes to scalability. Among small companies with a high level of digital maturity (50 to 80 employees), an 89% success rate was reported. Compared to an organization with more than 200 employees that is larger or more mature, a company with fewer than 200 employees has a much higher success rate. A study conducted by the authors found that projects of medium complexity had the highest return on investment, suggesting that complex projects are not always beneficial.According to the study, most organizations chose to adapt through process-oriented changes (42%), followed by technology-driven changes (33%), and hybrid approaches (25%). The hybrid strategy, however, proved more successful in the long run. In circumstances where limited resources are available, the most common and most effective strategies may differ since people tend to make similar decisions under similar circumstances. Small and medium-sized enterprises tend to be risk averse, which means that they prefer small changes that do not significantly affect their business model. Considering that the process-focused approach is based on common lean principles, requires little upfront capital, and requires specialized expertise to implement, I believe that it is well suited to this way of thinking. A hybrid strategy, while initially seeming more complex and requiring more resources, has a greater long-term impact. As a result, it can be difficult for companies to maintain their operations at a stable level while keeping their costs low at all times. As a result of these constraints, managers may be relying on process-based adaptations in an effort to implement real, low-risk improvements, which may not be the most efficient strategy.There are five factors that must be present in order for scalability to be successful. Accordingly, leader commitment was rated as the most important factor (importance weight = 0.28) among these factors. A number of other factors contribute to success, including the availability of digital resources (10.1), the readiness of digital infrastructure (023), the investment in employee training (019), the ability to manage change (018), and the availability of financial resources (012). There was a clearly defined deadline of 24 months for the successful completion of projects. During the first two to three months of the project, an initial digital assessment will be conducted, followed by a pilot deployment during the third to sixth month of the project. It consists of a six to twelve month implementation phase, followed by a 13 to 18 month optimization cycle, followed by a 19 to 24 month validation of sustainable capabilities. This guideline presents practical suggestions for implementing the recommendations derived from the results of the analysis.The implementation guidelines say that the strategy must be tailored to fit the needs of the organization in order to make this framework work on a larger scale. Most people agree that companies that are very digitally mature can get the best results from a full implementation that makes the most of their current technology. For organizations that aren't very mature, it's best to take things step by step, starting with improving the infrastructure and skills of the workers. Organizations that were more mature didn't have to follow this process. Also, the size of the organization is something to think about. Changes in technology worked better for smaller businesses, while changes in processes worked better for larger businesses because it was harder to coordi-

Table 7. Evidence-based implementation guidelines for Digital Twin-enabled JIT-Kanban framework scalability across diverse SMMEs contexts

Implementation Context	Recommended Approach	Critical Prerequisites	Expected Timeline	Investment Range	Success Probability
High Digital Maturity SMMEs	Comprehensive Implementation	Leadership commitment, IT infrastructure	12-16 months	\$140,000-\$170,000	92%
Medium Digital Maturity SMMEs	Phased Implementation	Training investment, change management	14-18 months	\$115,000-\$145,000	84%
Low Digital Maturity SMMEs	Gradual Implementation	Infrastructure development, skill building	18-24 months	\$95,000-\$125,000	71%
Small Organizations (50-100 employees)	Technology-Focused Adaptation	Digital infrastructure, training	10-14 months	\$85,000-\$115,000	86%
Medium Organizations (100-200 employees)	Hybrid Adaptation	Balanced resource allocation	12-16 months	\$120,000-\$150,000	89%
Large SMMEs (200+ employees)	Process-Focused Modification	Change management, coordination	16-20 months	\$145,000-\$175,000	81%
Automotive Sector	Industry-Specific Customization	Supply chain integration	12-15 months	\$125,000-\$155,000	91%
General Manufacturing	Standard Implementation	Basic lean knowledge	14-18 months	\$110,000-\$140,000	83%

nate them.The framework was useful for a lot of different types of manufacturing, because it was harder to coordinate them. The framework was useful for a lot of different types of manufacturing, but it was especially useful for the automotive industry. This industry has grown because supply chains have merged and lean manufacturing principles have been used. Digital Twins have made JIT-Kanban frameworks possible, which have cut inventory levels by 47.3% and lead times by 28.4%. These are big steps forward compared to traditional lean manufacturing methods. After 18 months, the investment paid off 187%, and the implementation worked 78.3% of the time. This method is a big improvement over the old one, which only worked 31.2% of the time. There was a link between digital maturity and success (r = 0.87, p0.001), which means that an organization's ability to use technology is more important than its size when it comes to putting the framework into action. As per prior research, merely 25% of lean initiatives and 31% of digital transformations in small and medium- sized enterprises were successful. This study concludes that electronic integration yields long-term benefits, contrasting with the transient results reported by Panigrahi et al. A study was conducted on the performance of JIT, as stated in [16]. Ghobakhloo et al. [22] say that SMMEs can avoid problems that come with being small, like not having enough money or not knowing enough, by using cloud-based solutions. The Digital Twin parts are not only 91.3% accurate, but they also meet industry standards, which shows that they are technically sound.The study's results are constrained by several factors. Since the framework was made just for Saudi Arabia's Eastern Province, it can't be used directly in other places where there are industries and rules. This research is particularly significant in this geographical context due to its alignment with Saudi Vision 2030, a national strategy for economic diversification and the promotion of industrial digitalization. One important part of this project was promoting Industry 4.0 technologies, which may have helped make the area very welcoming for small and medium-sized businesses (SMSMEs). Some people think that the recent push for modernization in different parts of the country may have made people more interested in this study. This area may be different from others because of its strange history. The project was successful because of a number of things. Depending on their situation, other developing economies might not be able to take advantage of it. Some places have workers with different skill levels, which may mean that training programs need to be longer and more intense, which could mean that the payback period is longer. Because it is based on Just-In-Time principles, the framework needs certain levels of supply chain maturity to reach its goals. A bigger buffer is needed as logistics networks become less reliable, which would make it harder to cut costs by reducing inventory.

As it was designed for the automotive parts industry, it is also worth considering whether it can be used in other significant Saudi industries. Due to the nature of the petrochemical industry as a continuous flow production industry, it would be more efficient to implement JIT and Kanban in place of managing work-in-process in separate units. It would be possible for the company to improve maintenance, repairs, and operations by getting better supplies, as well as replace catalysts. Among the measurements included in the Digital Twin are those for temperature, pressure, and flow rate. There is a large part of the project that will be concerned with the improvement of the efficiency and health of expensive equipment such as reactors, distillation columns, and pumps. As a result, yields will increase and equipment breakdowns will be fewer, which is an extremely costly problem. It is common to use batch production in the food processing industry. Considering that it is possible for goods to go bad, that there are strict rules, and that they must be tracked, the framework must address these issues. As an additional feature, the Digital Twin could be equipped with shelf-life prediction models, as well as IoT sensors for monitoring the conditions in the production and storage areas. Using Kanban signals in conjunction with an inventory policy that follows first- expired-first-out would reduce waste and help reduce costs. There are other fields in which cloud-based digital twining is in use, but these examples illustrate that each field requires different sensors, key performance indicators, and predictive models based on how it functions and what it values.

These technologies can also be afforded by small and medium-sized businesses with low profit margins with government assistance, such as subsidies, infrastructure, or digital transformation projects. It is possible to extend the 30-month period by up to two years, but this should not exceed two years. In this study, small and medium-sized enterprises (SMMEs) were included that understood the concepts of digital transformation, resulting in a higher success rate. Due to the fact that 78.3% of participants were successful in their actions, the pre-selection criteria will contribute to the success of action research.In the absence of a randomized control group, a difference-in-differences study cannot be conducted, which means that other factors may influence the findings. In order for the framework to be useful in a broader range of cultural and geographical settings, particularly in emerging economies that are underdeveloped in terms of digital infrastructure, it needs to be refined. It is only through a randomized controlled trial with a large sample size that one can demonstrate the long- term effectiveness of different treatments.

5. Conclusions

By combining JIT-Kanban and digital twin technology, SMMEs have been able to make significant improvements to their operations. Twelve automotive parts manufacturers participated in an action research initiative in the Eastern Province of Saudi Arabia over a period of thirty months. Based on the evidence presented here, it is evident that the framework represents a useful framework for achieving national strategic objectives, such as Saudi Vision 2030, which seeks to digitize industry and diversify the economy. Based on the statistical correlation coefficients, the digital twin models were highly accurate, ranging from 0.89 to 0.96. Because it only took 2.33 seconds for data to sync, this made real-time manufacturing control possible. The framework led to a 47.3% drop in inventories, a 28.4% drop in lead times, and a 38.6% rise in equipment efficiency, which all led to a 7.3% drop in costs. The findings indicate that technology readiness was more influential in determining outcomes than organizational size. This study indicates that SMMEs exhibiting a digital readiness score of 0.87 are more inclined to transform their businesses through Industry 4.0 ($p = 0.001$). A statistical comparison of the digital twin framework to conventional JIT methods reveals a significant effect (p 0.001).This resulted in a significant reduction in inventory levels and lead times, as well as improved scheduling accuracy. The proposed framework was successful 78.3% of the time, while traditional methods were only successful 31.2% of the time. The proposed framework clearly contributed to the financial success of the company. According to the survey, each company spent a median of $127,000 on implement- ing industry 4.0, which is 63% less than the average cost of implementing an industry 4.0 solution. It is estimated that over the 18-month payback period, the average return on investment was 187%. The money was returned to companies with a high level of digital maturity even faster, within 8 months. Frameworks work best when the company is technologically ready, rather than when it is large. Although there are wide variations between participants, digital maturity is the best indicator of success ($r = 0.87$, p 0.001). Thus, the size of the organization showed little correlation with outcomes ($r = 0.34$, $p = 0.281$).The study's results have several shortcomings. Due to the fact that the study was conducted only in Saudi Arabia's Eastern Province for a period of 30 months, the findings may not be generalizable to other industrial contexts or indicative of long-term results. SMMEs are highly successful due to their willingness to embrace digital transformation, which contributes in part to the high success rates.

In the absence of a randomized control group, it is also possible that other factors could have influenced the outcome. Research in the future should be conducted to determine whether the framework is scalable across a variety of cultures and regions, particularly in developing countries. A long-term study is essential in order to be able to measure long-term performance and adaptability of a system, and in order to do so we will need to conduct studies spanning more than five years. Having a large and diverse randomized con- trolled trial plays an important role in demonstrating causal claims successfully, as they are indispensable for proving causality in order to demonstrate causality in a correct way.

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