Shakil Al Jabir

AI-RPA Integration in Cloud-Based MES for Smart Production

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Author: Shakil Al Jabir
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Abstract

The integration of AI and RPA in cloud-based MES opens up new possibilities for smart production in industries. Therefore, AI and RPA must interoperate within cloud based MES to achieve smart production but the real-world integration still remains fragmented. Literature on subject is still strewn and there isn't one clear framework that brings it all together.

This study formulates and empirically validates a requirement of holistic model that integrates AI analytics, RPA task execution MES orchestration with-in the cloud infrastructure. Explains how the technological fit, cloud trust and human factors shape the operational performance.

Grounded in TTF, TOE, RBV, and STS theories, the current study employs a quantitative, explanatory, cross-sectional survey (n=210) analyzed via Partial Least Squares Structural Equation Modelling (PLS-SEM), with standard screening procedures including duplicate removal, missing data treatment, outlier detection, VIF checks, and CMB assessment.

The results of study analysis, leads to the cloud trust substantially that shows improve MES performance ($R^2 = 0.57$, $p < .05$). Compatibility ($\beta = .32$, $p < .01$) and cloud trust ($\beta = .27$, $p < .05$) significant. Furthermore, study show that the Integration challenges have an indirect effect through habitual barriers, highlighting the socio-technical aspect of digital transformation.

A theory integrated framework (TTF-TOE-RBV-STS) that clarifies fit, thus this study validates theoretical contribution by connecting environment, resources and human adaption guidance for readiness/barriers, and practical contribution i.e. helping manufacturers to use AI → RPA → MES feedback blueprint that improve efficiency, adaptability and the operational resilience and decision to action latency reduction.

Keywords: AI-RPA Integration, Cloud-Based MES, Smart Production, Industry 4.0, Task-Technology Fit, Predictive Maintenance, Manufacturing Execution System, Automation, Closed-Loop Control, Digital Transformation.

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Abbreviations

AI	Artificial Intelligence
AI-RPA-MES	Integrated AI, RPA, and MES Smart Production Ecosystem
API	Application Programming Interface
AVE	Average Variance Extracted
β	Standardized Path Coefficient (Beta)
CBM	Condition-Based Maintenance
CFA	Confirmatory Factor Analysis
CI	Compatibility
CR	Composite Reliability
DV	Dependent Variable
EFA	Exploratory Factor Analysis
ERP	Enterprise Resource Planning
H1-H7	Hypothesis numbers defined in the research model
HOB	Habitual Barriers
HTMT	Heterotrait-Monotrait Ratio
IC	Integration Challenges
ICT	Information and Communication Technology
IaaS	Infrastructure as a Service
Industry 4.0	Fourth Industrial Revolution (Digital Manufacturing Paradigm)
Industry 5.0	Human-Technology Collaborative Manufacturing Paradigm
IoT	Internet of Things
IV	Independent Variable
IT	Information Technology
KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
M	Mediator Variable
MES	Manufacturing Execution System
OEM	Original Equipment Manufacturer
OP	Operational Performance
OR	Organizational Readiness
PaaS	Platform as a Service
PLC	Programmable Logic Controller
PLS-SEM	Partial Least Squares Structural Equation Modeling
p	Probability Value (Significance Level)
R^2	Coefficient of Determination
RBV	Resource Based View
RPA	Robotic Process Automation
SaaS	Software as a Service
SD	Standard Deviation
SEM	Structural Equation Modeling
SME	Small and Medium Enterprise
SPSS	Statistical Package for the Social Sciences
STS	Socio-Technical Systems Theory
TTF	Task-Technology Fit Theory

TOE	Technology-Organization-Environment Framework
TRA	Trust in Cloud Reliability
VIF	Variance Inflation Factor

1. Introduction

1.1 Background and Motivation

The global manufacturing is undergoing a reflective transformation pushed by advent Industry 4.0. In a paradigm is to merges digital technologies with a physical production processes for create smart production systems (Kagermann et al., 2013). In the major shift and transformation of it, the main and core ping is the integration of AI and RPA into cloud-based MES. It serves as the digital nervous system of modern factories (Zuehlke, 2010; Schuh et al., 2017). The manufacturing sectors are traditionally characterized by rigid, hierarchical structures and the siloed operations. As for now, to maintains competitiveness the critical point is to transitions toward agile and the data driven environments that helps in the real time decision making, predictive analytics, and autonomous task execution (Lasi et al., 2014; Schuh et al., 2017).

AI and RPA have great potential but even thus, their use as a composed structure with MES is still not well developed or sometimes not properly connected. Due to this, lack of integration causes inefficiencies, duplication of work, and major productivity losses in the production environments. According to some industry reports available, manufacturers can lose about 20 to 30% of their productivity as the AI and RPA tools often work separately instead of together (McKinsey, 2023). These reports and results shows the requirement to complete and standardized framework that brings together all components. Fundamentally , AI's data analysis power with RPA's automation abilities in a smooth but further the cloud-based MES system would be optimum solution to these problems.

This thesis addresses the key gap. It suggests model that joins data-driven decision tools with RPA for smart manufacturing. Keeping in view the TTF theory by Goodhue and Thompson (1995) the idea is simple. Match the "task" of making decisions with the "technology" that executes them. When this application would fit well the factory

performance improves. Thus making the equipment to runs more efficiently an less errors with systems respond faster in real time.

My professional exposure to with manufacturing data pipelines and the automation exposed persistent gaps between AI analytics and execution to the shop floor. I saw that AI models were insightful but underused, while routine tasks still consumed operator time. Integrating AI for detection, RPA for execution, and MES for orchestration offered a practical path to stabilize throughput and reduce downtime. This experiences lead me to study aiming to engineer a testable bridge where AI decisions and RPA task execution are orchestrated within the MES. The goal to reduce the decision to action latency and translate insights into reliable actions.

Fields of science: Industrial System Analytics, Information Systems (Technology management focused)

1.2 Defining Smart Production

Modern manufacturing systems now transformed into a data driven and flexible systems as they quickly adapt to changing market needs through smart production. These data driven approaches has bring together the big data analytics and the cyber-physical systems (CPS), and the Internet of Things (IoT). This smart production is enabling factories to use adaptive scheduling, predictive maintenance and more better automated decision making (Kagermann et al., 2013; Lasi et al., 2014).

This type of Smart production systems have the following key features:-

1. Integrated Digital and Physical Layers: The required data is gathered in real times from sensors, machines, and systems from the production floor (Zuehlke, 2010).
2. Closed Loop Control: This provides the continuous feedback cycles to maintained whereas, the RPA agents perform corrective actions and the AI models provide insights furthermore, IoT devices also collects data (Schuh et al., 2017).

3. Human Machine Collaboration: Automation handles repetitive tasks on auto in work whereas, the employees focus on creative and high value tasks while interacting with AI tools (Porter & Heppelmann, 2014).

This concept aligns with the vision of smart factories systems that optimize themselves continuously helping them to makes decentralized decisions and thus, produces customized good. However, the vital benefit of smart production remain unrealized somehow, as there is still no standardized framework that effectively connects AI's thinking abilities with RPA's operational power.

1.3 Cloud-Based Manufacturing Execution Systems (MES)

MES are software platforms designed to manage, monitor and control the manufacturing operations in a real time (Kärkkäinen et al., 2018).

In the past, MES solutions were installed and run on local company servers. This arrangement completed them for expensive to maintain, difficult to scaleup, and often it was inefficient when it came for the sharing or integrating data across systems. In the era of cloud technology MES has undergone with major transformation. Cloud based MES platforms are able to provide flexibility, lower costs and with global access for manufacturers to utilize (Culot et al., 2020). The popular examples in this regards is Siemens Opcenter, Oracle Cloud MES, and PTC ThingWorx.

These platforms allow manufacturers to monitor production data from anywhere. Furthermore, they are also connected with other helpful business systems like ERP and PLM solutions. Additionally, it uses advanced analytics and AI for smarter decisions and able to adjust computing resources as production needs change at runtimes.

Most of the cloud based MES platforms and solutions, despite of these advancements are still struggles with wholly integration via AI and RPA. In many cases, AI systems that analyse and predict outcomes remain separate from the RPA tools that perform

automated action. Furthermore, the RPA itself often relies on simple rule based operations (Sobczak & Ziora, 2021; Schuh et al., 2017).

To overcome these limitations, there is a need for a unified architectural model. That model should able to bring AI decision-making and RPA execution together within the MES environment. This integration when successful, would enable manufacturing systems to make and implement real-time decisions. The results would be leading to more efficient, adaptive and intelligent production processes.

1.4 Artificial Intelligence in MES

AI is now playing an important role in the manufacturing industry. It helps companies predict problems before they happen. It also helps in to find mistakes during production, maintain quality and manage schedules of task in a more affective manner. Advance techniques like Machine Learning, Deep Learning, Natural Language Processing and Reinforcement Learning allows systems to study the past and current data patterns of systems to make production better and faster (Bousdekis et al., 2020).

In manufacturing systems, AI is used in several ways, e.g. predictive maintenance uses models to warn when a machine might break down (Zhang et al., 2019). Defect detection components and tools uses image based technique to spot faults in products during inspection (Zhao et al., 2021). In the demand forecasting and scheduling it helps the managers to plan production based anticipated demands (Shao et al., 2020). Anomaly detection section is able to finds any unusual patterns in the process that may cause any issues in the systems (Mourtzis et al., 2020).

Keeping this in view, AI may alone cannot take direct action. AI is able to give insights, predictions, and suggestions but it usually needs a human or another tool to take the action. This is where automation tools like RPA come in as they are capable to take the actions that AI recommend. This is making the process smoother and even more efficient.

1.5 Robotic Process Automation in MES

RPA is a type of simple automation mechanism that uses software-based robots to perform tasks just like a human would do on the computer screen (van der Aalst et al., 2018; Reijers et al., 2020). These robots follow a set of instructions and interact with systems through their normal interfaces such as buttons and forms as to complete routine work.

In manufacturing systems, RPA is very useful for several reasons. It can automate data entry and transfer, further moving information between different systems like MES, ERP. Furthermore, it can linked with other databases of companies without manual effort (Osman, 2019).

It has the capacity to generate the reports, collecting data from various sources and then able to prepare very well structured production summaries for managers to view and analyse. One of another important use is to processing orders where RPA is to help manage approvals, check inventory levels, and schedule production automatically.

RPA can handle alerts and notifications, and capable of sending messages when certain conditions or problems rise at production systems (Sobczak & Ziora, 2021).

Although RPA improves efficiency and reduces human workload but it is often used in scattered or isolated technique. This means that each RPA setup usually works alone and don't connect smoothly with other systems. Due to this requirement and issue, when problem is detected by data systems, a person may still needs to step in or manually run RPA scripts/codes to fix the problem. This lack of coordination limiting the full potential of automation in modern manufacturing operations.

1.6 Task-Technology Fit (TTF) Theory

The Task-Technology Fit (TTF) theory, introduced by Goodhue and Thompson (1995). His theory explains that technology improves performance only when the technology's features match the specific needs of the task. In simple standings, the better the results will be only when there is better fit between what a job requires and what a tool can do.

In the case of manufacturing systems, this idea means that each part of the setup plays a special role. AI is used for thinking, type tasks such as analysing data, making predictions, and supporting decisions. Robotic Process Automation (RPA) is used for doing-type tasks such as sending commands to machines, updating system records, or sending alerts. In this regards, the MES connects both parts, allowing AI insights and RPA actions to work together smoothly and improve production processes.

Current study applies the TTF concept by developing a structure where both AI and RPA are designed to work side by side. And they will be connected modules inside a cloud based MES system. The goal of this model is to shorten the time between decision making and action, help to increase in efficiency of equipment, furthermore helps to improve overall production performance.

1.7 Integration Challenges and Research Gaps

These problems together form the main practical issue that this study aims to explore through a cross-sectional explanatory model, which will be tested and explained in the following chapters. Although the concepts of modern manufacturing and automation appear well-aligned in theory, several real-world challenges make it difficult to connect these systems effectively within Manufacturing Execution Systems (MES).

One of the major issue is data silos as where AI and automation tools work on different sets of data, causing errors and inconsistencies. The lack of standardization is another challenge as there is no common framework that guides how these technologies should be built and, connected within MES workflows (Schuh et al., 2017).

Scalability is also a problem since automation scripts often fail to handle the complex and constantly changing nature of modern production environments. Similarly, real-time adaptability remains limited because analytical tools cannot easily perform instant actions without automation support. Another important bottleneck is the vendor lock-in that restricts flexibility, as due to many MES platforms are proprietary and provide limited access to their systems, preventing smooth integration of other tools (Culot et al., 2020).

Due to such types of challenges many manufacturers continue to use AI and automation separately rather than like single-connected system. This separation prevents them from achieving the true benefits of smart and efficient production.

Recent studies mainly remained focused either on using AI in manufacturing or on applying automation to office-related tasks. Few studies have examined how these two can work together within MES frameworks (Sobczak & Ziora, 2021; Osman, 2019). Therefore, current study focuses on understanding and addressing this gap through a structured research model.

1.8 Research Objectives and Contributions

This study's primary objective is to develop and evaluate a transparent framework for integrating digital systems and automation tools with cloud-based Manufacturing Execution Systems (MES). The goal is to assist factories in their transition to more intelligent and effective production. Task-Technology Fit (TTF), Technology-Organization-Environment (TOE), Resource-Based View (RBV), and Socio-Technical Systems (STS) are the four main tenets upon which the study is built. These aid in the explanation of how people, organizations, and technology collaborate to ensure successful integration and enhance factory performance.

The following are the goals of the study:-

1. To construct a basic framework that explains how automation interacts with MES in a cloud configuration and integrates concepts from TTF, TOE, RBV, and STS.
2. To determine how well manufacturing companies' current MES systems integrate with contemporary automation technologies.
3. To investigate the relationship between successful integration and organizational readiness, including leadership, IT systems, and employee skills.
4. To investigate how confidence in cloud systems affects confidence in teamwork, dependability, and data security.
5. To recognize and comprehend the main obstacles to adoption, such as cost, data management, and system compatibility.
6. To investigate how the relationship between integration and factory performance is impacted by human-related problems, such as a lack of digital training or a fear of change.
7. To verify the connections b/w primary factors then mapping it on the suggested framework with survey data and statistical analysis (PLS-SEM).
8. To help in actionable suggestions for managers to expedite the adoption of digital automation and increase the sustainability of production.

1.9 Structure of the Thesis

This study overall comprises of five chapters. Chapter 1 defines the research context, problem formulation, objectives and research questions after that chapter 2 defines data from multiple sources on MES, AI, RPA, cloud manufacturing and socio-technical integration is also explained for identification of the research obligation. Chapter 3 defines the methodology and it includes research design, measurement development, sampling and data collection and the PLS_SEM approach. After that chapter 4 defines the empirical findings that encompassing data screening, descriptive statistics, measurement model (CFA), structural model, hypothesis testing and predictive relevance. At last the chapter 5 discussions are about the results, it showing the improved integration framework and talks about the consequences for managers and

policymakers, the limitations and the directions for future research. In the Figure 1, it demonstrates the comprehensive research process, encircling by theoretical foundation, empirical validation, and policy recommendations.

2. Literature Review

2.1 Introduction

The integration of AI and RPA with-in cloud based MES represents union of transformative technologies in the manufacturing sector. Present study is to critically examines existing research, identifying trends, challenges, and gaps in the current body of knowledge. By out-lining the evolution of MES, AI, and RPA in manufacturing and then explores their interactions, integration frameworks and challenges. Initially it explains that how MES and automation technologies developed over time in the field of manufacturing. Afterwards, it discusses how these technologies can work together. What frameworks available for their integration and what challenges still to face. The review drawn from the scholarly articles, industry reports and some case studies from 2018 to 2025. It helps in establishing solid foundation for the research problem identified.

2.2 Manufacturing Execution Systems (MES) in the Cloud Era

2.2.1 Evolution of MES

MES had played vital role in factory operations since 1980s. They help monitor production in real time and connect the actual work is happening on the production floor (Kärkkäinen et al., 2018). Previously, most of the MES systems were installed locally. They were expensive and sometimes hard to extend and lacked in major flexibility (Zuehlke, 2010).

The rise of cloud computing has an impact on how MES functions. Present-day MES solutions are service-based and much more efficient in scaling-up. The obvious advantages are that the price is lower, the access is global and the flexibility is better

(Culot et al., 2020). The examples in this respect can be Opcenter, Oracle Cloud MES, and PTC ThingWorx. These systems allow companies to manage operations from anywhere. It also links information from several factories that change their data with the usage of advanced tools to make better decisions (Schuh et al., 2017). But, a number of issues are still remaining such as data delays, risks of cybersecurity, and problems in connecting old systems with new cloud platforms (Bousdekis et al., 2020).

Present-day research indicates that cloud-based MES has become even more significant as it facilitates the connection with advanced automation tools. Such devices are not only capable of taking data but also they can make real-time operations and easily integrate the data. In addition, they enable the use of predictive instruments that support planning and give back-time by lowering the demand for the production process (Culot et al., 2020; Mourtzis, Doukas, & Psarommatis, 2020). The flexibility feature is just one of the primary advantages revolved around such systems. With Cloud MES, factories have the ability to ramp up or scale down their computing power as per the requirement of the production. Moreover, it allows them to maintain their effectiveness and also to be able to give a quick response to the changing market demands (Rodrigues, 2025). In addition, research sources point out that interoperability is not only the different systems being capable of communicating technically, but also being able to understand each other's semantics and being of the same organizational level, so this end to end integration entail getting common models and having processes that are in line with each other (Evaluation of interoperability challenges in computer-integrated manufacturing systems, 2022).

2.2.2 Role of MES in Smart Manufacturing

MES is digital backbone of smart production systems. MES let you collect data in real time, plan resources and manage quality (Mourtzis et al., 2020). When you design to combine it with IoT, big data and AI it turns regular factories into smart factories. It can

do things like predictive maintenance, autonomous scheduling and adaptive control (Porter & Heppelmann, 2014). As the, MES platforms often don't have built-ins features that should make it easy to add AI decision making and RPA driven execution. This situations sometimes leads to systems that don't work together and missed-up chances to optimize processes from start to finish (Zuehlke, 2010).

Recent studies combine the state of cloud manufacturing (CMfg), outlining architectures, platforms, interoperability and migration challenges that mirror our empirical barriers (latency, vendor lock-in, heterogeneity). These syntheses strengthen the rationale for cloud trust/readiness in our model (Gharibvand et al, 2024)

2.3 Artificial Intelligence in Manufacturing: Applications and Trends

2.3.1 AI Techniques and Tools

One of the most significant and impactful innovations in AI in the industrial sector is the implementation of the following technologies: machine learning, deep learning, natural language processing, and reinforcement learning (Zhao et al., 2021). These are highly evolved AI tools that assist factories in analyzing data and making better decisions about their production. As an illustration, long short-term memory (LSTM) networks are able to foresee the time when a machine will probably be out of order and therefore maintenance can be done before it actually breaks down (Zhang et al., 2019). In the same way, convolutional neural networks (CNNs) are the most rapid and accurate defect detection methods in product visual inspection systems (Shao et al., 2020).

These digital instruments are able to assist in demand forecasting, production scheduling as well as in the recognition of the unusual patterns in operations. When these tools are coupled, they elevate equipment efficiency and decrease the times when the manufacturing processes are on hold (Bousdekis et al., 2020). The service offerings on the cloud platforms serve as a very significant factor in providing the

required computing power to execute these highly advanced models. Nevertheless, the extent to which they are leveraged in the daily production systems and SMEs like MES is still minor (Sobczak & Ziora, 2021).

Recent studies point to an increasing relationship between b/w automation and process control systems. This type of integration b/w tools helped to improve the predictive maintenance, through the real-time monitoring within manufacturing of production environments. Rodrigues (2025) noted that this connection increases production efficiency by automatically identifying potential problems and thus its reducing system interruptions. In addition to this, the combination of automation tools with adaptive technologies allows systems to handle complex decision-making tasks. This further eliminates the required human involvement. This shift marks a significant step toward smarter and more reliable industrial operations.

2.3.2 Challenges of AI Adoption in MES

These are the major hurdles in AI adoption about the MES despite and its effective potential, here the main points are given below:-

- Data availability and quality:- MES data is often heterogeneous, unstructured, and incomplete, hindering AI model training (Schuh et al., 2017).
- Model interpretability:- Black-box AI models can lead to mistrust among operators and managers (Bousdekis et al., 2020).
- Deployment scalability:- Scaling AI across multiple MES instances and production lines remains complex (Culot et al., 2020).
- Real time integration:- The outputs from AI models often require manual interpretation before execution so making slowing response times (Mourtzis et al., 2020).

These challenges highlights need for frameworks that embed AI as a core component of MES, furthermore it works as integral part instead of only as an external analytic layer. KPI oriented MES deployments in SMEs demonstrate that disciplined monitoring and

data pipelines are central to measurable operational performance (Bianchini, A., et al. 2024). A recent internet-scale scan of OPC UA endpoints reports widespread misconfigurations (outdated software, weak certificates, broken access control), underscoring why governance and cloud-trust controls materially affect integration outcomes (Bui, T., Wernli, S., & Fettweis, G, 2025).

2.4 Robotic Process Automation (RPA) in Manufacturing

2.4.1 RPA Fundamentals and Tools

RPA helps use of software robots that performs routine, rules based tasks by doing same way the humans can interacts with computer systems (van der Aalst et al., 2018). These robots can do clicks, typing and navigate screens just same like a person would do on duty. Moreover they can do it faster and without mistakes. Popular RPA tools such as UiPath, Automation Anywhere, and Blue Prism are already widely used in sectors like banking, insurance, and shared business services (Syed et al., 2019; Osman, 2019).

In the manufacturing field, RPA is now being used in several important ways:

- Data extraction from MES and ERP
- Order processing and scheduling
- Quality control documentation
- Alert and report generation (Sobczak & Ziora, 2021).

RPA offers benefits such as cost savings, error reduction, and faster processing times, but its adoption in manufacturing has lagged behind other sectors, partly due to integration challenges (Schuh et al., 2017).

2.4.2 RPA in Smart Production: Current Status

Recent studies in literature highlighted that automation tools are becoming more common in manufacturing industries. As an example study, the KAS Bank used robotic automation to handle its financial operations. This major change helped bank to savethe time and reduce costs by removing repetitive manual works (Oshri & Plugge, 2021). In another study by Sobczak and Ziora (2021) showed how the same technology was used successfully in local government services. These examples shows that the automation can work in many different areas, including the industries that aim to become more efficient and technology-driven, e.g. smart cities and smart factories.

Even beside these achievements use of automation in manufacturing industries and factories still faces limitations. In most factories, it is applied only to simple or back-office tasks, such as data entry or report generation. Rarely it is connected to the main production lines where the materials are processed or machines are operated. Due to these limitations and hurdles the impact overall remains limited. Manufacturing units need the systems that can automatically adjust to changes required in the production without depending on regular human input (Reijers et al., 2020).

In the studies recent, also show that automation is gradually expanding into more complex zones of production. Now it can be used to manage inventory, plan schedules, and monitor compliance with production rules. These applications help factories respond more quickly to production needs, reduce errors, and make better use of available resources (Rodrigues, 2025; Zhang & Wen, 2021). Recent TOE-based studies confirm that technology, organization, and environment jointly shape, Industry 4.0 adoption and performance supporting our inclusion of compatibility and cloud trust pattern. Case evidence from SMEs indicates that smart MES architectures can be phased in over legacy control systems, enabling gradual data-driven operations (Simůnek, J et al, 2021). Furthermore, recent systematic review links manufacturing operations initiatives to SME performance outcomes, reinforcing our operational KPIs and measurement model (Madau, 2024)

2.5 AI-RPA Synergies and Integration Challenges

2.5.1 Conceptual Synergies

In recent era the automation and process technologies has bring together different strengths to manufacturing. One focuses on thinking and analysis, while the other focuses on performing actions. Analytical tools help in understanding data, finding patterns, and making predictions. Automation tools, on the other hand, carry out the required tasks by following set rules or the outcomes of those analyses (van der Aalst et al., 2018). When both of these components work together in a system, they can form a connected system where one identifies an issue or opportunity and the other immediately responds to fix it (Schuh et al., 2017).

In a monitoring system it may predict that a machine is likely to fail soon. Once this prediction is made, next is that an automated process can take-over and then it can schedule maintenance, prepare purchase orders for spare parts, and update records in the production system without human involvement (Osman, 2019). This self-processing approach in the system can saves time, prevents production delays, and ensures smoother operations.

In addition, the recent developments had led to Intelligent Process Automation (IPA). In this approach, analytical systems and automation tools are combined more closely to create smarter and faster workflows (Patrício, 2024; Rodrigues, 2025). This integration allows manufacturing systems to make quick decisions during production and take corrective steps automatically. As a result of it, the factories experience higher productivity with very fewer mistakes, and furthermore better use of resources (Venigandla & Vemuri, 2022). Meta analysis integrates 47 studies on I4.0 technology acceptance, highlighting consistent determinants that complement TOE and TTF in manufacturing contexts as mentioned by Zou, W., et al, 2025)

2.5.2 Integration Barriers

Conceptually its fit for implementation but still AI and RPA integration faces several barriers as explained below.

- Siloed architectures: AI and RPA systems are often developed and deployed independently, with limited communication (Sobczak & Ziora, 2021).
- Lack of standardized frameworks: No universal architecture exists for embedding AI decision engines within RPA workflows in MES (Schuh et al., 2017).
- Scalability issues: RPA scripts are often fragile and requiring manual updates when processes change, on the other side, the AI models need retraining to maintain accuracy (Syed et al., 2019).
- Latency and real-time execution: AI outputs may not trigger RPA actions immediately due to system delays or human approvals (Reijers et al., 2020).

Combining automation and process control systems in cloud-based MES offers many benefits but on the other hand it also brings several challenges. Studies point out important barriers such as poor data management, difficulty in connecting different technologies, and problems in expanding systems for large-scale use (Afrin, 2024; Rodrigues, 2025).

One of the major concern is related to ethics and regulations. Organizations are required to ensure that data is handled dutifully. Furthermore, automation to follows clear rules and ethical standards (Patrício, 2024). Therefore, without proper governance, there is a risk of misuse, privacy violations, or lack of accountability in automated decision-making. OPC UA's information model and transport options have been evaluated for IIoT scenarios, evidencing scalability and suitability for heterogeneous shop-floors (Aboushady, A., et al, 2021). Furthermore, on similar lines for security best practices guidance for OPC UA underscores authentication, certificate handling, and secure channels, all relevant to our cloud-trust pathway (OPC Foundation, 2018). There are several further issues where worked by survey on OPC UA products and security

configurations highlights practical implementation issues and attack surfaces that inform reliability concern (BSI, 2022).

These combined challenges are reason to slow down the transfer toward truly self-managing factories. For such systems to work effectively, the information produced by analytical tools should directly lead to automated actions. However, the current gaps in coordination, standardization, and regulation still prevent manufacturing from reaching this fully connected and adaptive stage.

2.6 Research Trends (2018–2025): A Thematic Synthesis

In the recent studies, in synthesis of literature from 2018 to 2025 reveals several trends:-

Table 1. Research trends - A thematic synthesis

Year	Representative Studies	Key Themes
2018 & back	Schuh et al. (2017), Osman (2018)	Exploration of AI-RPA synergy
2019	Syed et al. (2019), Osman (2019)	Emergence of RPA applications in MES
2020	Culot et al. (2020), Mourtzis et al. (2020), Reijers et al., (2020); Bousdekis et al., (2020); Mourtzis et al., (2020)	Cloud-based AI-RPA integration models, Shift from isolated AI and RPA studies to integration-focused research. Gap in standardize frameworks.
2021	Zhang & Wen (2021), Sobczak & Ziora (2021); Oshri & Plugge, (2021)	Expansion into manufacturing & finance, Using AI to enhance RPA bots' adaptability and error-handling capabilities
2022	Venigandla & Vemuri (2022)	AI-driven automation in software (DevOps)

2023	McKinsey (2023); Oshri & Plugge (2021)	Predictive analytics and scalability
2024	Patrício (2024), Afrin (2024)	Sustainability and ethical governance
2025	Rodrigues (2025)	AI-enhanced RPA for complex problem-solving

2.7 Identified Research Gaps

The review of past and recent, research highlights several important gaps in the available studies. Most current work does not provide enough practical evidence or clear models for how automation and process systems can be effectively joined within modern manufacturing.

First, there are very few detailed studies that examine how these technologies work together inside Manufacturing Execution Systems (MES) for smart production. Second, there is a lack of well-structured frameworks that combine analytical systems with automated task execution in a cloud-based environment.

Another missing area is the measurement of results after integration. Studies rarely focus on performance indicators such as equipment efficiency, error reduction, or production speed. In addition to this, the more real world test cases and validations are required by using the actual industrial data and real production settings.

There are limited theoretical studies that explains how tasks or processes and technologies can be fit together e.g. by using the TTF model. Furthermore the ethical aspects like fairness, transparency, and accountability in automated processes are also overlooked often. Additionally, some industries may still faces the practical problems related to scaling these systems. Further, to ensuring that different technologies can communicate smoothly within framework of complex production environments.

2.8 Conclusion

The review of existing studies shows that research on automation and process systems in manufacturing is still disjointed. These technologies in combination both improves efficiency on their own but there is limited research on how they can work together as one system. The goal of achieving fully autonomous and adaptive smart factories remains unfriendly in production systems due to this gap. Identified gaps makes the present study valueable as it aims to design and propose a complete integration framework that improves productivity and supports real-time adaptability in modern production systems.

The review from literature also shows that research in this area is expanding but lacks in clear direction. Couple of recent studies has focuses either on decision support systems or on automation tools but as combine its rarely examine how both can operate together in cloud environments. In addition, most research does not test its models with real data or consider the role of human and organizational readiness alongside technical factors. This study addresses these issues by developing and validating a combined framework that links technology, organization, and social-technical aspects with measurable production performance outcomes.

Overall, this discussion provides the foundation for building a unified model that connects automation and process systems within cloud-based MES. The proposed framework will be tested and validated through practical evidence in Chapter 4.

3. Methodology

This chapter explains the methodological framework used to analyse AI-RPA integration in cloud based MES. This section builds upon the theoretical foundations of TTF, TOE, and RBV. It also includes testing through statistical analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM).

3.1 Introduction

This chapter describes the framework that guided the investigation of how automation and process tools can be combined within cloud-based MES. The main goal is to understand how technology, organization, and human factors together influence operational performance also determine the readiness for modern smart production. Furthermore, the discussion covers the research philosophy, study design, theoretical background, data collection, variable measurement, and analytical techniques applied in the study.

In social and technical research, the methodology is not only about the steps taken but it also discuss about the way knowledge is built. Furthermore, it is a way to check how the results can be trusted and how they agree with the theory that is being tested. This research is in line with a quantitative, evidence-based approach, where ideas are operationalized by indicators derived from the previous studies and industry practices.

To a large extent, manufacturing systems are being linked with cloud-based instruments for the purposes of elevating production, quality, and maintenance processes. However, such integration often faces problems as given below:-

- System incompatibility
- Slow data transfer
- Security concerns.
- Outdated software

- Lack of skilled staff
- Resistance to change.

The issues raised here are clear enough to show that they may result in the suspension of work and monetary losses. Hence, this research understands the association of technological and organizational factors, integration issues, and human-related problems with the operational results of MES during the automation phase and further development.

3.2 Philosophical Assumptions

The study follows a positivist approach by this, meaning that it, focuses on measurable facts and evidence rather than subjective opinions. Furthermore, the abductive reasoning is also used, which combines theory testing and insights gained from real observations. The study assumes that reality exists independently and can be measured through data.

- Ontology:- Reality exists objectively. Manufacturing performance and integration outcomes can be measured using quantitative data.
- Epistemology:- Knowledge comes from careful observation, data collection, and statistical testing rather than personal interpretation.
- Axiology:- Researcher bias is reduced by using structured tools, standard methods, and objective statistical analysis.

The positivist approach aligns with the technological nature of the study, emphasizing measurement, prediction, and generalization rather than interpretive meaning-making.

3.3 Research Onion and Design Framework

Keeping in view the above explained philosophical foundation, the overall design of the study follows the Research Onion framework developed by Saunders et al. (2019). The

study uses a quantitative, explanatory, and cross-sectional design. Present study seeks test hypotheses that come from the TTF, TOE, RBV, and Socio-Technical Systems (STS) theories. With the combination of these all theories we can provide a broad view of how technology, organizational factors and human elements. Those elements that interact to determine the success of automation integration in smart manufacturing.

The cross-sectional design of the study is to explain that how data collected at same timeframe by giving snapshot that how manufacturing firms currently handle automation and system integration. This approach helped in identification of readiness levels, existing barriers and performance results. These identifications to contribute both in the theoretical understanding and practical improvements.

Selected survey method to collect standardized data from a wide range of participants efficiently. Structured questionnaires designed with Likert-scale questions. Questionnaire has helped to measure factors such as technological compatibility, organizational readiness, integration challenges, cloud trust and human barriers. Current study approach ensures reliable, analogous and generalizable findings across the different manufacturing sectors.

Furthermore, the research design follows logic of explanatory modelling, where relationships b/w variables are tested to identify cause and effect links that effect MES performance. The research model as shown in figure 1 shows the structure of this methodological decisions, moving from broad philosophical views to more explicit research techniques.

The outer layer of the Research Onion represents a practical philosophy that combines objective technology-based research, and it provides with detailed on the managerial insight. The next layer involves the abductive approach which is to joining the theory testing with learning and outcomes from actual data. The inner layers give the details and explains about the survey method, quantitative analysis and furthermore, supported by some qualitative interpretation, a cross-sectional timeframe, and data analysis using PLS-SEM.

Overall, the Research Onion and the study design provide a clear and systematic structure. This is aligned in a way that it, ensures the methods are aligned with both the theoretical foundation and the practical goals which will be helpful in creating an effective, measurable, and applicable framework for integrating automation and process systems in cloud-based MES for smart manufacturing.

- *Philosophy → Positivism*
- *Approach → Abductive (Deductive hypothesis testing with inductive refinement)*
- *Methodological Choice → Quantative*
- *Strategy → Survey with PLS-SEM, Time Horizon → Cross-sectional*
- *Techniques & procedures → Structured questionnaire, data screening, CFA, structural model, bootstrapping*

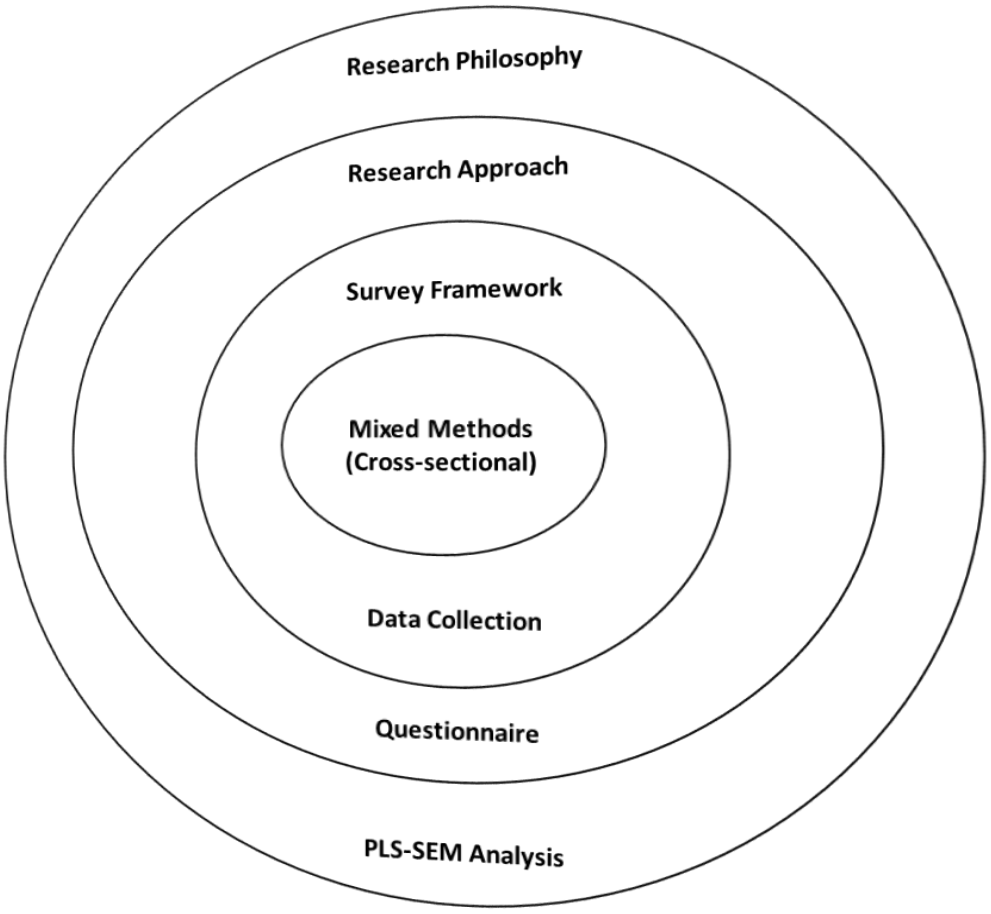

Figure 1. Research Onion for AI-RPA-MES Integration Framework (Saunders et al., 2019).

3.4 Conceptual Framework and Model

The conceptual framework of this study as shown in the figure 2, it brings together ideas from several key theories like TTF, TOE, RBV, STS. These theories as a combined factor, helped to explain how technology, organization, and human factors together influence the success of integrating automation tools within MES.

From the perspective of TTF theory the match between the features of a technology and the tasks it supports is very crucial in overall system. When automation tools work well with MES functions, they defiantly helps to improve production monitoring, increase automation efficiency, and support better decision-making. Therefore, technological compatibility in overall linked system, is viewed as a main factor and that directly affects how well integration works and how much it improves MES performance.

The TOE framework expands this understanding by highlighting that new technologies succeed only when supported by the right organizational and environmental conditions. The current study is to identify the organizational readiness includes leadership commitment, IT infrastructure, and employee skills needed to implement automation systems. The external factors such as competition, digital policies and industry standards are also to shapes the readiness levels. Thus they are also important and included in overall system. The external elements are represented indirectly through perceived integration challenges. As the overall result helps in framework that can assumes both organizational readiness and contextual challenges. Furthermore, it helps to identify that how deeply systems are integrated and how much users are in trust with cloud-based operations. OPC UA (IEC 62541) provides the de-facto vendor-neutral information model for secure, semantically rich shop-floor data exchange (International Electrotechnical Commission, 2020). At the communication layer, “OPC UA combined with Time-Sensitive Networking (TSN) is emerging as a next-generation open stack that replaces legacy industrial buses, enabling deterministic, interoperable and vendor-neutral data exchange, central to our operationalization of compatibility” (Trifonov, H, et al, 2025).

In addition to this, the RBV theory adds a strategic perspective by suggesting that long-term competitive advantage comes from resources that are valuable, rare, difficult to copy, and hard to replace. Keeping in view the ability to effectively combine data analytics, automation and MES coordination represents a strategic resource and appears as a important pillar. The integration capability of overall system may acts as a bridge that connects technology compatibility, organizational readiness and trust to better operational performance. Interoperability requirements in MES stacks are concretely defined by ISA-95/IEC 62264 i.e. which models enterprise control integration layers used in Industry 4.0 deployments

The STS theory introduces human aspects and emphasizing that how technology adoption depends and requires the balance b/w technical systems and people. Issues such as resistance to change, lack of digital skills and employee involvement can affect in smooth integration and automations. In this framework, human-factor barriers are seen as influences that can strengthen or weaken the relationship between integration capability and MES performance.

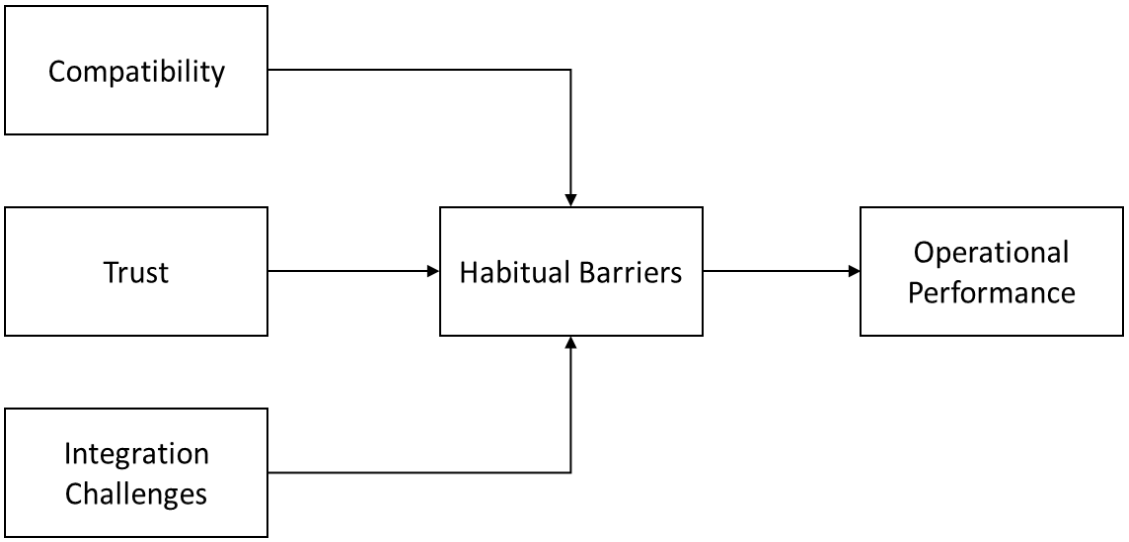

Figure 2. Conceptual framework

TTF provides the fit mechanism between analytical - AI and execution - RPA tasks within MES (Goodhue & Thompson, 1995). TOE positions adoption within organizational and

environmental realities (e.g., cloud reliability and policy constraints), (Tornatzky & Fleisher, 1990). RBV explains why data & automation capabilities and skills behave as VRIN resources discussing advantage (Barney, 1991, Wernerfelt, 1984). STS integrates the human and organizational adaptation needed to realize technical benefits. Together they explain why compatibility and trust strongly predict outcomes where as human barriers temper understood advantages.

3.5 Hypotheses Development

Keeping in view the proposed framework in current study, it formulated the following hypotheses:-

Table 2. Hypothesis

Code	**Hypothesis**
H1	Technological compatibility (CI) positively influences operational performance (OP) of AI–RPA–MES integration.
H2	Trust in cloud reliability (TRA) positively influences operational performance (OP).
H3	Integration challenges (IC) negatively influence operational performance (OP).
H4	Organizational readiness (OR) positively influences operational performance (OP).
H5	Habitual barriers (HOB) mediate the relationship between technological compatibility (CI) and operational performance (OP).
H6	Habitual barriers (HOB) mediate the relationship between organizational readiness (OR) and operational performance (OP).

H7	Habitual barriers (HOB) mediate the relationship between integration challenges (IC) and operational performance (OP).

3.6 Operationalization of Constructs

The measurement scale for the construct was through multiple Likert-scale items (1 = Strongly Disagree → 5 = Strongly Agree).

Table 3. Construct Measurement and Operationalization

Construct	Code	Definition	Example Indicators	Source(s)
Compatibility	CI	The degree to which MES, AI, and RPA technologies are interoperable and functionally aligned to support production tasks.	CI1: Our MES and AI/RPA systems exchange data seamlessly. CI2: Integration between automation and analytics platforms is technically feasible. CI3: System interfaces support real-time synchronization.	Adapted from Goodhue & Thompson (1995); Venkatesh et al. (2012)
Organizational Readiness	OR	The extent to which an organization possesses the resources, skills, and leadership commitment necessary to implement AI-RPA solutions.	OR1: Employees are adequately trained to work with AI/RPA tools. OR2: Our IT infrastructure can support additional AI/RPA workloads. OR3: Top management actively supports digital-automation projects.	Tornatzky & Fleischer (1990); Zhu & Kraemer (2005)
Trust in Cloud Reliability	TRA	Confidence of users and managers that the cloud platform is secure, stable, and reliable for	TRA1: We trust the reliability of our cloud service provider. TRA2: Data confidentiality is well protected. TRA3: System uptime meets	Gefen et al. (2003); Lankton et al. (2015)

		AI-RPA operations.	our operational expectations.	
Integration Challenges	IC	Technical and organizational barriers that complicate or delay AI-RPA-MES integration.	IC1: Legacy systems are difficult to automate. IC2: Integration costs are high. IC3: Data formats between systems are inconsistent.	Zhu et al. (2006); Oliveira & Martins (2011)
Habitual Barriers	HOB	Behavioral and process-level resistance that reduces adaptation to new AI-RPA workflows.	HOB1: Employees resist changes to automated routines. HOB2: Departments are reluctant to share data. HOB3: Existing procedures are difficult to modify.	Besson & Rowe (2012); Oreg (2006)
Operational Performance	OP	The measurable improvement in efficiency, quality, and throughput resulting from AI-RPA-MES integration.	OP1: Production efficiency has improved after automation. OP2: System downtime has decreased. OP3: Decision-making speed has increased.	Gunasekaran et al. (2018); Hair et al. (2019)

The constructs and indicators presented in Table 3 correspond directly to the latent variables examined in the PLS-SEM model.

In this framework, OP is the main outcome variable and represents the overall result of successful integration between automation and MES systems. It serves as the dependent variable for all hypotheses developed in the study.

The variables Compatibility, Trust, Integration Challenges and Organizational Readiness are treated as independent factors. Every variable in it, plays a role in shaping that how effectively the integration process functions within a manufacturing environment.

Habitual Barriers is included as a mediating factor that reflects human and behavioral resistance to change. This construct helps explain how employee habits, attitudes, and

readiness for change can either reduce or strengthen the direct impact of technological and organizational factors on operational performance.

By combining all the factors, these constructs form the analytical foundation for testing how technical alignment, organizational support, and human behavior interact to influence. Furthermore, gives the overall efficiency and performance of cloud-based MES integration.

3.7 Instrumentation Development

In the study a structured questionnaire used, as given in the Appendix-A to document, that was divided into three main sections. The first section collected general information about the respondents and their organizations. Details included are about their job role, the type of industry they worked in and the size of company and their years of experience.

The second section focused on measuring the main research constructs that includes, Compatibility, Trust, Integration Challenges, and Habitual Barriers.

The third section gathered data on key performance outcomes such as the frequency of downtime, estimated financial loss per hour and the percentage of those losses linked to system integration problems.

To ensure that the questionnaire accurately reflects the study objective and the items were adapted from previous research and further refined through discussions with three experts in manufacturing and automation.

A pilot study was then carried out with 20 participants to test the clarity of the questions, the reliability of the measures and the average time required to complete the survey. Based on the feedback received several items were reworded to remove ambiguity. Furthermore, the technical terms were simplified to ensure, that respondents from

different backgrounds in the industry such as engineers, analysts and managers could easily understand them.

The reliability of the questionnaire was assessed using Cronbach's alpha. The pilot results showed values between 0.70 and 0.85 for all constructs. This is indicating that the measurement items are internally consistent and suitable for use in the main study.

3.8 Population and Sampling

The target population targeted for this study are consisted of professionals who are involved in MES, automation processes and system management within manufacturing firms of different sectors.

The participants were individuals with practical and hands-on experience in areas of filed, such as MES operations, automation deployment, and production data handling. The common job roles among the respondents are included like automation engineers, IT managers, operations executives, and data analysts.

A goal-directed sampling technique was applied to ensure that only respondents with relevant experience and expertise participate in the survey. The appropriate sample size was determined using Cochran's formula, which assumes a large population of 95% confidence level and 5% margin of error. The calculation indicated that at least 196 responses were required. However, to enhance the accuracy and statistical reliability of the results total 210 of valid responses were collected and used in the analysis.

Table 4. Sample Composition by Sector and Role

Industry Sector	**Percentage**	**Primary Roles Represented**
Pharmaceuticals	42.3%	QA Managers, Process Engineers
Electronics	17.4%	Automation & Control Engineers
FMCG	14.3%	IT / MES Coordinators
Automotive	9.8%	Production Supervisors

Textiles & Others	16.2%	Data Analysts / Project Leads

In the Table 4 as shown, provides an overview of the sample composition by industry sector and professional role. The pharmaceutical sector accounted for the largest share of participants i.e. of 42.3% and followed by electronics i.e. of 17.4% and the fast-moving consumer goods are about 14.3% furthermore, automotive is about 9.8%, and textiles and other industries are about 16.2%. The key roles that participated and represented within these sectors included quality assurance managers, process engineers, automation and control specialists, MES coordinators, production supervisors, data analysts, and project leads.

The distribution in the roles and industry experts shows that the study achieved a balanced participation from well, established and developing technology oriented industries. Furthermore, It also highlights the increasing importance of MES and automation technologies in enhancing production efficiency and operational performance across diverse manufacturing sectors in Finland.

3.9 Data Collection Procedure

Data collection for this study was carried out over a two-month period i.e about from May to August 2025. Furthermore, the process involved distributing an online survey forms through Google Forms and sending email invitations to professional networks and manufacturing associations. The email include the detailed importance and guidance about the research. This way has helped reach a wide range of professionals working in different manufacturing sectors.

Several steps were taken to ensure the quality and reliability of the data collection and maintenance. Duplicate data and responses were identified and removed using IP address and timestamp on forms fillings. Each respondent was required to confirm their direct involvement with MES and, or automation related activities before proceeding to conduct and respond to the survey. Additionally, incomplete and inconsistent responses

were excluded from the dataset collection on identification. After applying these filters the total number of 210 records are complete and valid responses were retained for analysis.

Ethical approval for the study was obtained from the university. All participants were well informed about the purpose of the study and the confidentiality of their responses and their right to withdraw at any time. The informed consent was collected digitally before participants began the survey to ensure compliance with ethical research standards. Discriminant validity is assessed via HTMT with thresholds and inference per Henseler, Ringle, and Sarstedt Henseler (2015).

3.10 Data Preparation and Screening

The raw survey data was first exported in CSV format for processing and analysis. The Initial data pre-processing steps were carried out and the cleaning was done using Python and SPSS to remove errors. Thus, prepared the dataset for further analysis. The cleaned data was then imported into SmartPLS 4, which was used to perform the main statistical and structural equation modelling analyses in detail.

Only respondents with direct MES-AI-RPA responsibility proceeded past the screening item. We prevented duplicates via IP plus timestamp deduplication, flagged speeders by completion-time thresholds, and removed straight-liners/long-strings. An attention-check item ensured engagement.

Missing values accounted for less than three percent of the total responses and it was settled by using mean substitution to maintain data completeness. Outlier detection was performed using the Mahalanobis distance method in Python script, which helped in identify responses that significantly differ from the overall data pattern. Based on this analysis five of the extreme cases were identified and removed to ensure the accuracy and reliability of the results. We follow current PLS-SEM practice on model estimation and quality criteria (e.g., HTMT, SRMR, predictive relevance), consistent with the 3rd-edition prime (Hair, J. F et al, 2022),

Descriptive statistics of data is including the mean, median, and standard deviation. All was calculated for all variables to examine data distribution and check for skewness. Variance Inflation Factor (VIF) values were also computed for each construct therefore and all were found to be below 3.3 which is fine. This is confirms that multicollinearity was not an issue and thus meeting the recommended threshold suggested by Kock (2015). In the industry standards 4.0, while noting the manufacturing performances different impacts being noticed. In these studies the TOE based manufacturing studies validates the firm level adoption determinants relevant to our structural model (Amin etl, 2024).

3.11 Data Analysis Techniques

3.1.1 Data Analysis Techniques

The study used Partial Least Squares Structural Equation Modelling (PLS-SEM) as the main analytical technique. This method was chosen because it is well-suited for exploratory studies that include latent constructs and the data that may not follow a normal distribution furthermore as moderate sample sizes (Hair et al., 2019). PLS-SEM allows for the simultaneous assessment of measurement reliability. Beside this the testing of relationships among multiple variables within a single model is supported.

The data analysis was conducted in several stages to ensure accuracy and validity thus the step by step sequence is given below:-

1. **Descriptive Analysis:-** This analysis is involved in examining demographic profile of respondents and summarizing the indicators related to organizational readiness and integration factors.
2. **Measurement Model:-** The Reliability, convergent validity and discriminant validity of the constructs are tested at this stage to confirms that measurement items truthfully represented in their respective variables.

3. **Structural Model:-** The theorized relationships among the constructs analysed using bootstrapping method and 5000 resamples attuned to determine the stability and significance of the path estimates.
4. **Model Fit and Predictive Relevance:** The model overall performance was evaluated using key statistical indicators, as given below:-
    i. R^2 (explained variance).
    ii. Q^2 (predictive relevance)
    iii. f^2 (effect size)
    iv. SRMR (Standardized Root Mean Square Residual).
5. **Path Coefficient Interpretation:** The last and the final step in sequence is involved to interpreting the direction, strength and significance of the relationships between variables to determine their practical and theoretical implications.

Figure 3 as given below, shows the complete data analysis workflow, showing the sequence of steps from data preparation to hypothesis testing and model validation.

Figure 3. Data Analysis Workflow

3.12 Ethical Considerations

Ethical integrity was maintained at all stages. All the participants were fully informed about the purpose of the study, also informed about their rights to withdraw at any time if desired. Therefore, no identifiable personal or organizational information was recorded nor published. The researcher adhered to the University Research Ethics Code

of conduct and ensuring voluntary participation, secure data storage, and anonymization before analysis.

Limited AI-assisted tools were used for grammar (Grammarly) help and checks and in citation formatting. All empirical analysis, result interpretations and conclusions are conducted and verified. The sources are cited where applicable.

3.13 Summary of Methodological Framework

Table 5. Summary of Methodology Components

Component	Description
Research Philosophy	Positivist, quantitative
Design	Cross-sectional, explanatory survey
Theoretical Framework	TTF, TOE, RBV, STS
Sample	210 manufacturing professionals
Data Collection	Structured questionnaire
Analysis Tool	SmartPLS 4 (PLS-SEM)
Ethics	Confidential, voluntary participation

3.14 Limitations and Bias Controls

Despite the careful design and methodological rigor of this study still there are several limitations need to be acknowledged. These limitations are to provide the important direction for future research and may also help clarify the scope of the study's findings.

The first is the cross-sectional design limits the ability to draw strong causal conclusions between variables. Since the data was collected at approx same point in timeframe, it might reflects existing conditions only rather than long-term effects. Futuremore, the

studies could apply longitudinal research designs i.e. to observe how relationships evolve over time and can provide stronger evidence for causality. Secondly, the study relied on self-reported data which may introduce personal or response bias. To minimize this issue the respondents were assured of complete anonymity. They are also briefed about the survey questions were worded in a neutral and non-leading manner. Thirdly the sample composition focused mainly on small and medium-sized manufacturing enterprises (SMEs) in Finland. Where as, this ensures depth and contextual relevance in the results but may not be directly generalizable to larger corporations or to manufacturing environments in other countries. Broader and very large sampling across regions and industries would might help more to strengthen the external validity of future research. At number four there are some variables such as trust and organizational readiness, were measured based on respondents' perceptions rather than objective data. Although these perceptions are valuable but there is possibility that they may not fully capture the actual state of technology readiness or integration quality.

At last, the future research could enhance the robustness of findings by adopting mixed-method approaches. They can use the combining quantitative surveys with qualitative case studies from multiple countries would allow for deeper insights and cross-validation of results. Therefore, its may strengthening both theoretical and practical understanding of automation integration within manufacturing systems.

4. Results

4.1 Introduction

This chapter presents the empirical findings and analytical interpretations i.e. based on data collected from 210 professionals working in various manufacturing firms including major FMCG, Automotive, Textile, Pharmaceuticals, Electronic manufacturing and others. People playing pivotal role in industries participated including IT Manager, MES Managers, Operation Managers, and Data Analysts, SMEs. The main purpose of this chapter is to evaluate how technological, organizational, and human factors influence the integration of automation and process systems within cloud-based MES.

The chapter start with the data screening and then with preparation procedures, ensuring that the dataset is accurate, reliable, and suitable for analysis. Then it provides the demographic overview of the respondents and presents descriptive statistics for the main study constructs. Then the, subsequent sections describe the evaluation of the measurement model through Confirmatory Factor Analysis (CFA) and, also the testing of the structural model using Partial Least Squares Structural Equation Modelling (PLS-SEM). This chapter concludes by interpreting the results through the theoretical frameworks of TTF, TOE, RBV and STS.

4.2 Data Validation and Preparation

Prior to analysis the dataset underwent a rigorous cleaning and validation process, as explained in the chapter 3. In short, data validation included duplicate filtering, mean imputation for <3% missing values, Mahalanobis outlier removal, multicollinearity checks (VIF < 3.3), and CMB testing (Harman's single factor < 50%). This was to ensure accuracy, reliability and suitability for multivariate modelling.

Furthermore, the participants eligibility required direct involvement with MES & automations, which was verified by occupational relevance, and also targeted specified roles.

4.2.1 Missing Data and Outliers

Few responses were excluded, because they contained more than 20 percent missing data. For the remaining records, missing values represented less than three percent of the total dataset which was addressed. These minor gaps was addressed using mean substitution to maintain the overall representativeness of the data. The outliers were identified using the Mahalanobis distance method, and three extreme cases exceeding the critical chi-square value ($p < 0.001$) were removed as well from the dataset. This process helped improve the accuracy and stability of the final analysis of the study.

4.2.2 Normality and Multicollinearity

The dataset is examined for normality by assessing skewness and kurtosis of the values. All variables were found to fall within the acceptable range of ±2, i.e. indicating satisfactory univariate normality. The Variance Inflation Factor (VIF) values were also checked to detect, if any multicollinearity between variables is present. Therefore, the VIF values ranged between 1.21 and 2.87 and it tells that below the accepted upper limit of 3.3 (Kock, 2015). This confirms that multicollinearity not a concern in current dataset.

4.2.3 Common Method Bias (CMB)

The Harman's single factor test revealed that the first factor accounted for only 32.6% of variance. This is below the 50% threshold therefore it, implys no major CMB. Furthermore, the CMB risks are minimized by including anonymous participation and randomization of questions helping in imitation.

4.2.4 Data Readiness for PLS-SEM

Given the non-normality of some variables and the model's complexity, Partial Least Squares Structural Equation Modeling (PLS-SEM) was deemed appropriate (Hair et al., 2019). The cleaned data imported into SmartPLS 4 and the bootstrapping was later applied using 5000 subsamples to estimate significance levels for structural paths.

4.3 Demographic Profile of Respondents

The table 6 shows the sample representation in diverse cross-section of manufacturing sectors, professional roles and showing the external validity of the findings.

Table 6. Demographic Distribution of Respondents

Category	Classification	Frequency	Percentage
Gender	Male	168	80.0%
	Female	42	20.0%
Age	20–30 years	92	43.8%
	31–40 years	64	30.4%
	Above 40 years	54	25.8%
Role in Organization	Automation Engineer	49	23.4%
	IT Manager	34	16.2%
	Operations Manager	23	10.9%
	Data Analyst	33	15.5%
	Others	71	34.0%
Type of Industry	Pharmaceuticals	89	42.3%
	Electronics	37	17.4%
	FMCG	30	14.3%
	Automotive	21	9.8%

	Textiles & Others	33	16.2%
Company Size	< 50 Employees	97	46.4%
	50–250 Employees	61	29.1%
	251–1000 Employees	21	9.8%
	> 1000 Employees	31	14.7%
Experience Level	1–3 Years	123	58.5%
	4–6 Years	36	17.0%
	7–10 Years	51	24.5%

Interpretation:

The majority of respondents is approx about 75% that works in small to medium enterprises (SMEs) mainly into the pharmaceutical and electronics sectors. Most of them are technical or analytical roles and it aligning with the study's focus on AI-RPA-MES. This composition is provided a balanced perspective across both operational and managerial levels.

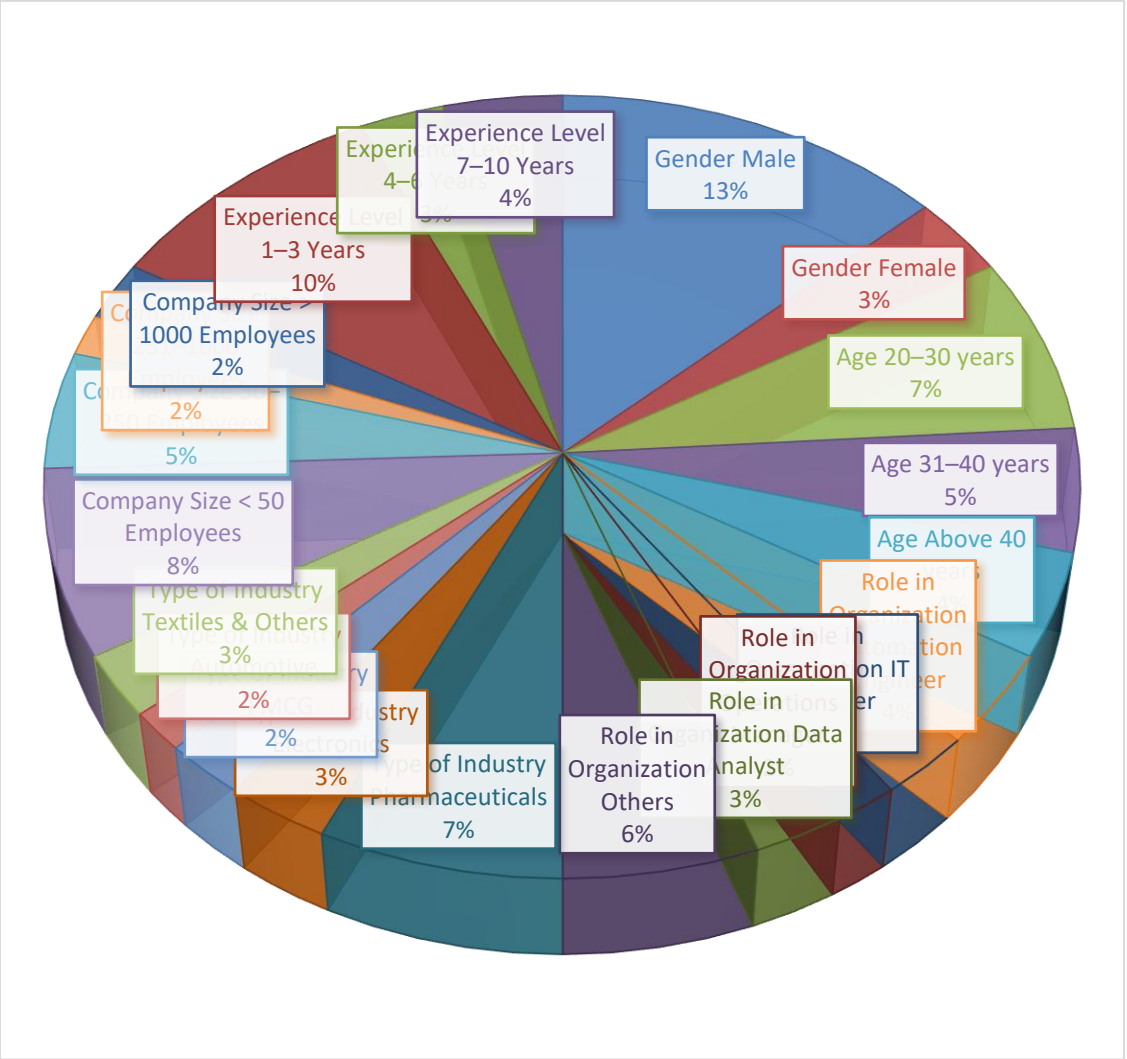

Figure 4. Demographic Overview

4.4 Descriptive Analysis of Study Constructs

The descriptive analysis provides initial insights into respondent perceptions. This explain about the organizational readiness, integration challenges, trust in cloud infrastructure and human factors influencing AI-RPA-MES adoption.

4.4.1 Organizational Readiness

The survey outputs from the findings of results shows a strong level of organizational readiness and adoption toward integrating automation technologies within the MES environment. A large majority of respondents i.e. about 71.4% either agreed and 37.4% or strongly agreed about 34.0% as that their organizations are prepared to integrate such systems. Only the 28.7% disagreed. This is suggesting that most participants hold a positive view of their company's readiness.

The findings to the extent also signal that this change is welcomed by the employees. Nearly 79.6% of the participants and 65.3% of the participants 14.3% of the participants generally agreed and 14.3% strongly agreed to the statement that employees have received enough training to work with automation tools. When talking about infrastructure, the confidence level is even higher. Almost 87.1% of the respondents (61.1% agreeing and 26.0% strongly agreeing) indicated that their organizations have the required IT infrastructure to support cloud-based automation.

Moreover, progress toward implementation is already visible. The significant 85.3% of respondents i.e about the 63.4% agreeing and 21.9% strongly agreeing are confirms in results that automation technologies have already been introduced at least partially within their organizations at different stages. This indicates that most manufacturing firms are not only ready but have already begun the process of integration across multiple operational sites.

As shown in the table 7, it presents the mean and standard deviation for each readiness indicator. The results show high mean scores across all items, with the strongest performance seen in infrastructure readiness i.e. (Mean = 4.27, SD = 0.75). The overall readiness score i..e of (Mean = 4.09 out of 5) suggests that firms are both technologically and organizationally equipped to advance toward deeper automation integration.

Table 7. Mean and Standard Deviation of Readiness Indicators

Statement	Mean	SD	Interpretation
Our organization is ready to integrate AI and RPA into MES.	4.06	0.83	High Readiness
Employees are adequately trained to work with AI-RPA tools.	3.92	0.88	Moderate-to-High
We have sufficient IT infrastructure for cloud-based automation.	4.27	0.75	Very High
AI and RPA technologies have already been partially implemented.	4.11	0.81	High

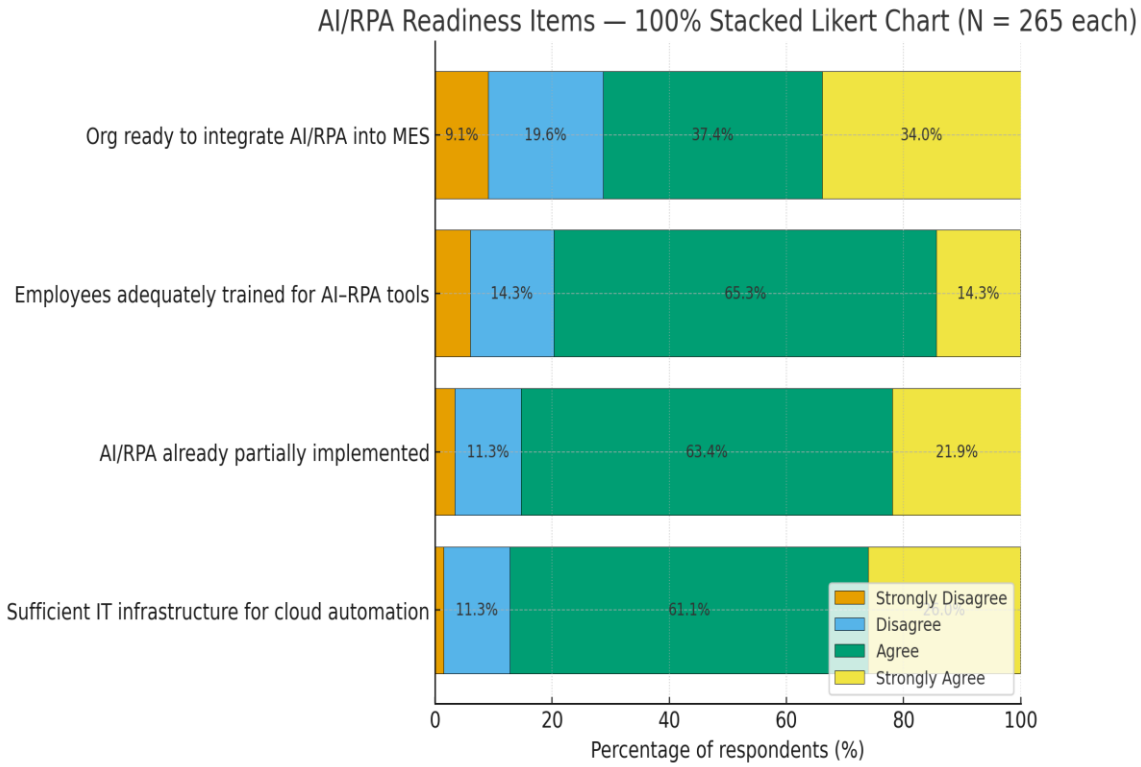

Figure 5. Combined Likert chart for AI-RPA readiness indicators

These results, as illustrated in figure 5, reflect a good level of preparedness consistent with the TOE framework. This implies that the internal conditions, such as managerial

support, infrastructure capability and, workforce skill are well aligned to support ongoing and future automation initiatives in manufacturing.

4.4.2 Integration and Technical Challenges

The results as shown in table 8 identify two main challenges that are to cause a continue limit in smooth integration of automation technologies with MES. The first major issue is data compatibility between MES and automation tools and other related systems. 64.6% of respondents reported this as either as significant of 55.5% or as major 9.1% concerns. Findings show that many organizations have adopted or actively adopting these technologies. The inconsistencies in data structures and communication setups remains serious barrier to effective integration.

The second major challenge is lack of standardized APIs and integration protocols. This can identified from results that 75.8% of respondents (67.5% significant and 8.3% major) mentioned these points. It can be noted as the deep rooted interoperability problem. Beside that strong technological readiness and modern infrastructure in many of organizations still face difficulties connecting various systems. Therefore, they are unable to ensure consistent data flow across platforms.

Findings of study indicate that technical integration is main limitation factor in achieving seamless automation within cloud-based MES. Therefore, without stable data structures and unified communication standards along with reliable APIs it will be struggling to share accurate and synchronized data. This is not only disrupting the workflows but also affecting the system efficiency and operational continuity.

The same problem is reflected in downtime patterns as due to integration delays and mismatched data transfers cause the downtime in production. To resolve these issues organizations need to invest in interoperability frameworks along with standardized integration protocols. These type of measures would allow automation tools and MES

platforms to work together more effectively and thus it would leading to higher productivity and fewer disruptions.

Table 8. Perceived Integration Challenges

Challenge	**% Reporting Significant/Major**	**Interpretation**
Data compatibility between MES, AI, and RPA tools	64.6%	Major issue
Lack of standardized APIs or integration protocols	75.8%	Critical issue
Latency and real-time synchronization problems	58.0%	Moderate
Legacy system complexity	49.5%	Moderate
High cost of integration and licensing	45.0%	Moderate

4.4.3 Cloud Reliability and Trust

The results presented in Table 9 shows, how respondents perceive the reliability and security of their cloud infrastructure. The main surveys and experiments' overall results revealed that the respondents generally had a high level of trust in cloud service providers. The statement "Our cloud provider ensures adequate uptime for MES workloads" was rated on average 3.98 (SD = 0.91), which reflects the strong trust of the respondents in the stability and performance of cloud services. The majority of the respondents are of the opinion that their providers fulfill service level agreements and hence, maintain a steady uptime which is very crucial for the smooth running of MES activities.

Table 9. Perceived Trust in Cloud Infrastructure

Statement	**Mean**	**SD**	**Interpretation**
Our cloud provider ensures adequate uptime for MES workloads.	3.98	0.91	High
Security and compliance issues prevent full cloud adoption. (R)	2.34	1.02	Moderate Concern
Integration with edge devices (sensors) is unstable. (R)	2.61	0.97	Moderate Concern

(*R = reverse coded*)

However, there is major concerns remain regarding the security, compliance, and edge connectivity. The item “Security and compliance issues prevent full cloud adoption” recorded a mean of 2.34 with SD = 1.02, suggesting moderate concern but not a major obstacle to adoption. Similarly, on the other note, the statement “Integration with edge devices (sensors) is unstable” had a mean score of 2.61 and the SD = 0.97. This indicates that connection problem exists but they are not viewed as serious limitation.

Overall, these findings suggests that manufacturing industries and factories trust their cloud providers to deliver stable and reliable services. On the other hand, they remains cautious about potential vulnerabilities related to data security and real-time integration with connected devices.

This pattern of results supports the TOE framework. It shows that out of technical infrastructure it is a key factor for successful system integration. It is also aligned with the RBV point of view, which considers reliable and secure IT infrastructure a valuable strategic asset. This asset to enhance the operational efficiency and long-term competitiveness.

4.4.4 Human and Change-Management Factors

The results in Table 10 shows that there is significant role that human and organizational factors play in the integration of automation technologies within the boundaries of MES environments. As seen from the technical readiness are generally high and the several non-technical barriers continue to affect smooth implementation.

The most common challenge identified is collaboration difficulties across functions is as reported by 80.3% of respondents and thus making it the highest-ranked human factor issue. From this we can suggests that communication gaps between departments such as IT, production and operations often slow down the progress of integration projects. On other similar notes, job replacement concerns were noted by 79.6% of participants and its indicating that a strong sense of insecurity among employees who fear about automation i.e. that may threaten their positions.

A lack of in-house expertise is also a major issue as about the 69.8% of respondents agreeing that is, their organizations face shortages in technical knowledge related to automation systems. Furthermore, resistance to the change is shown as 66.4% and poor change-management implementation is about almost 72.1%. It is highlighting the wider organizational challenges where employees and management struggle to adapt for new processes and technologies.

Table 10. Human-Factor Barriers

Factor	**Agree + Strongly Agree (%)**	**Interpretation**
Resistance to change among employees	66.4%	High
Lack of in-house AI/RPA expertise	69.8%	High
Collaboration difficulties across functions	80.3%	Very High

Poor change-management implementation	72.1%	High
Job-replacement concerns due to RPA	79.6%	Very High

These finding tells that human factors remains considerable barrier in successful integration. These results are align with the STS theory, which explains that technological progress alone is not enough to ensure success. Therefore, the organizational culture, employee attitudes and management practices also play vital role.

In conclusion the effective integration requires not only strong technical interoperability. This also necessitates to focus on human adaptability, workforce training and proactive change management strategies. Building trust, improving collaboration and addressing employee concerns are essential for long term success in automation driven manufacturing. These actions help in securing the adoption and sustain the performance for longer time.

4.5 Operational impact of AI/RPA-related downtime

4.5.1 Frequency of downtime incidents

The reported AI-RPA-related MES downtime per month is right-skewed with a mode of 2 incidents (22.3%) and a median about the ~4 incidents (cumulative 50.6% at 4.00). About 64.9% of sites report ≤8 incidents per month, and yet extreme outliers (e.g., ≥200) are present. This indicates most plants experience occasional disruptions, with a small group experiencing chronic instability.

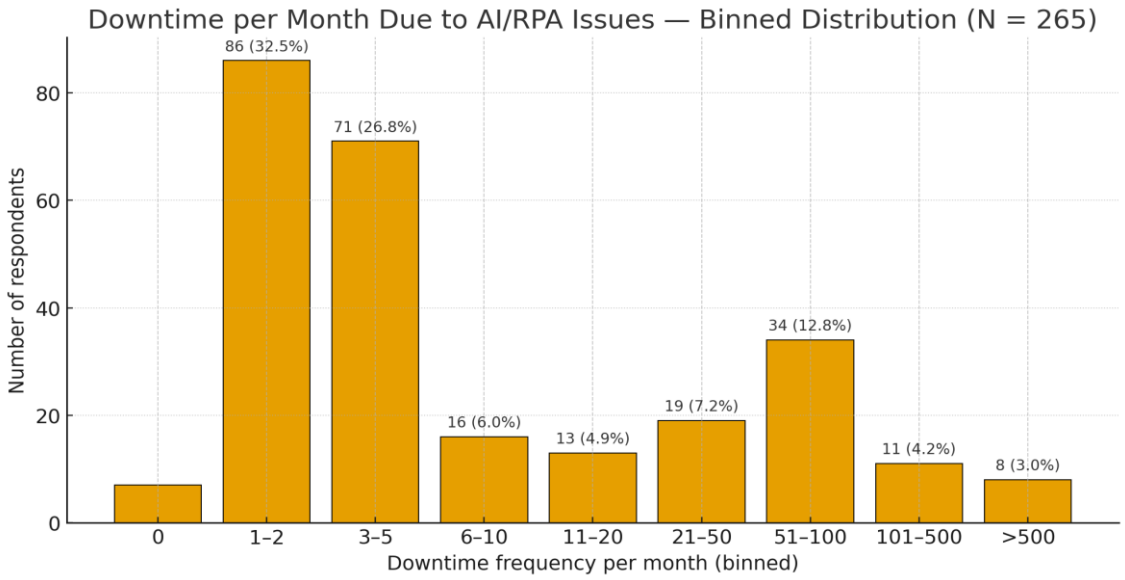

Figure 6. Downtime per month due to AI-RPA Issues

4.5.2 Financial loss per hour of downtime

Estimates range from 0 to 500,000 (currency units as reported), with notable spikes at 50 (6.0%), 500 (5.3%), 400 (4.2%), 1,000 (3.8%), and 200 (3.8%) (Table 4.12). The distribution is highly right-skewed with large outliers; in such cases, medians or binned summaries are more informative than means. Practically, many plants perceive losses in the tens to hundreds per hour, but a non-trivial tail expects thousands to hundreds-of-thousands, likely reflecting high-value continuous processes or stringent service-level penalties.

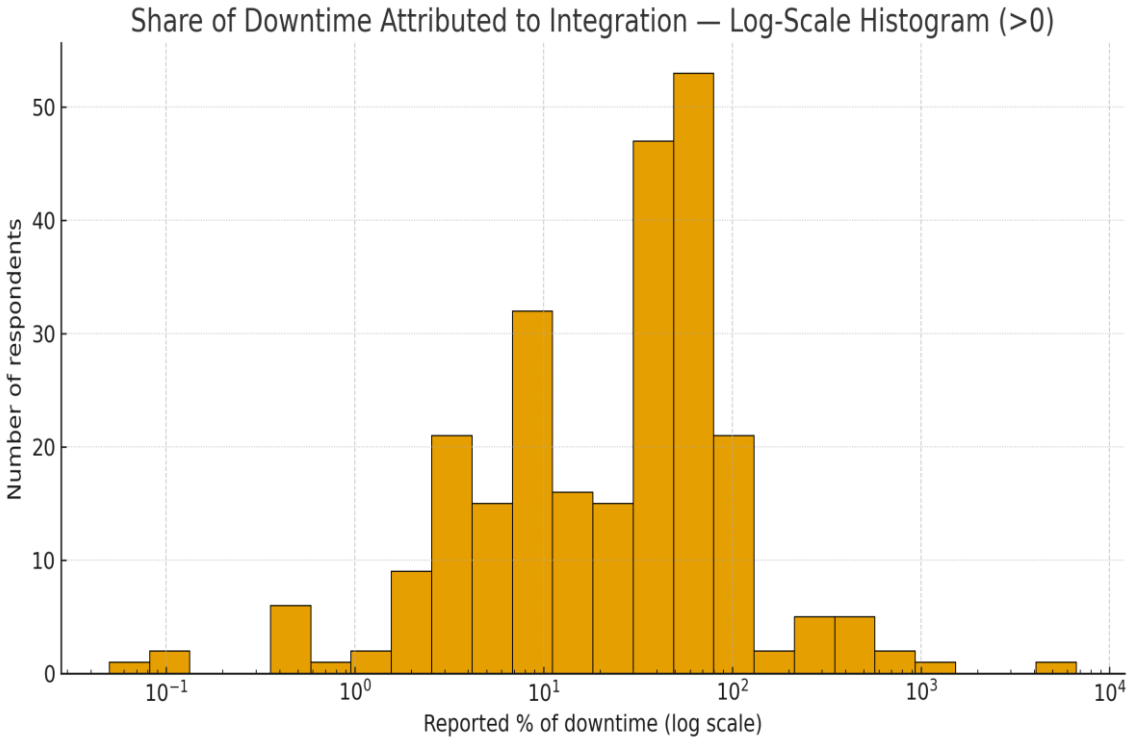

Figure 7. Share of downtime attributed to integration

4.5.3 Production units lost per incident

Losses per incident span from 0 to 30,000 units (Table 4.13). The median is ~30 units (cumulative 52.8% at 30.00). The mode is 5 units (7.2%), with secondary peaks at 10, 40, and 60 units (each 5.3%), and 50 units (5.7%). Again, the distribution is skewed, suggesting most events are relatively small but the tail risk of large batch losses is meaningful.

Auto-Recovery Mechanism & SLA Coverage — Graphical Summary

Summary (counts, N = 265 each):

- Auto-recovery mechanism present — Yes: 176 (66.4%), No: 89 (33.6%).
- SLA covers loss recovery — Yes: 157 (59.2%), No: 108 (40.8%).

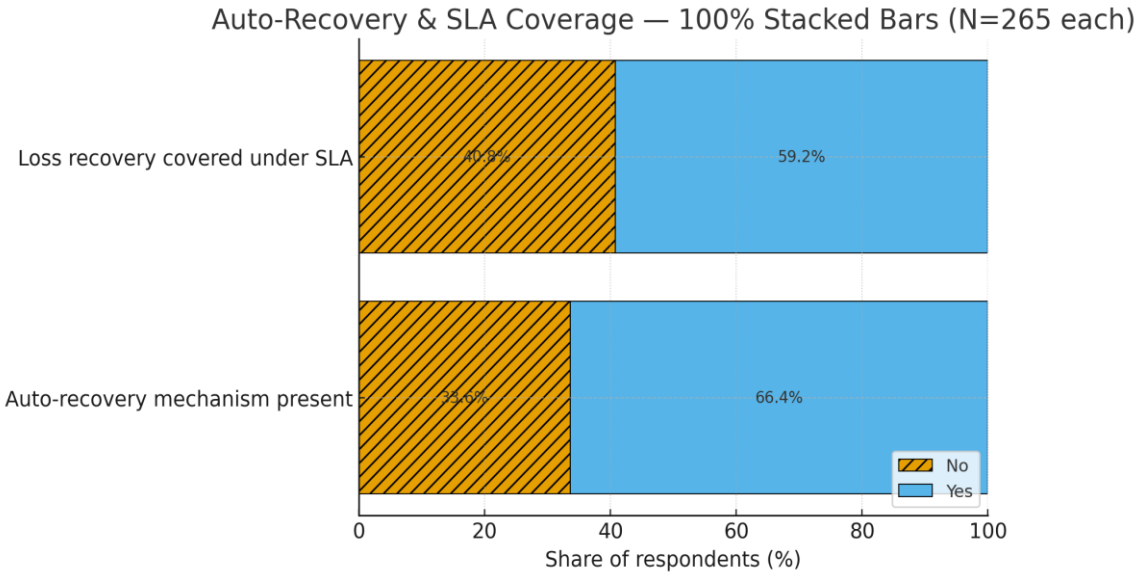

Figure 8. Auto recovery mechanism and SLA coverage

4.5.4 Human factors and change management

The human aspect of automation and process integration presents several key challenges this is reflected in Table 10 and Figure 9. The findings show that human readiness plays a central role. Furthermore, it strongly affects how effectively and quickly organizations adopt digital transformation.

66.4% of respondents (55.5% agreeing and 10.9% strongly agreeing) reported that shop-floor workers resist changes from automation. This points out the worker-side reluctance to alter existing workflows and adopt new systems. In addition to this, about 69.8% (58.9% agreeing and other 10.9% strongly agreeing) indicated a lack of internal expertise in automation technologies. This highlights and shows the urgent need and concern for capacity building programs along with targeted technical training to equip

employees with the skills. This skills will be required for managing modern production systems.

In the cross functional collaboration, this also emerged as a major concern point. That is about 80.3% of participants (In which 72.8% agreeing and 7.5% strongly agreeing) stated that cooperation across departments remains difficult task. This means and identify that many organizations still operate in silos and preventing smooth coordination between IT, production, and operations teams. Similarly on the other hand, about 72.1% (62.3% agreeing and 9.8% strongly agreeing) acknowledged that weaknesses in change-management practices are indicating that many firms lack structured frameworks and communication strategies for guiding transitions effectively.

On of the other major area of concern is about the job security. A large proportion of respondents i.e. about 79.6% (61.9% agreeing and 17.7% strongly agreeing) has expressed anxiety about potential job losses that might occur due to automation. This indicates that while employees recognize the value of digital transformation but on other side the fears about redundancy and uncertainty on future roles remain widespread.

Overall, the results shows that workforce sees the value of modernization but they are slowed by fear, limited skills and rigid structures. This gap holds back progress, even when the technology is ready. For real success firms must go beyond technical fixes. They need to invest in people through solid change management, clear communication and ongoing training. These steps help employees adapt and keep improvements.

Addressing these human and cultural barriers in the organizations can create an environment where technology adoption is both sustainable and inclusive overall. Thus in summary of point the results reveal that skill shortages, poor collaboration, and weak change-management practices combine with job-security concerns to slow down transformation. Therefore, study indicates that technical readiness alone cannot guarantee success. Continual adoption of automation in manufacturing requires structured change management, skills development and clear communication to build confidence and commitment among employees.

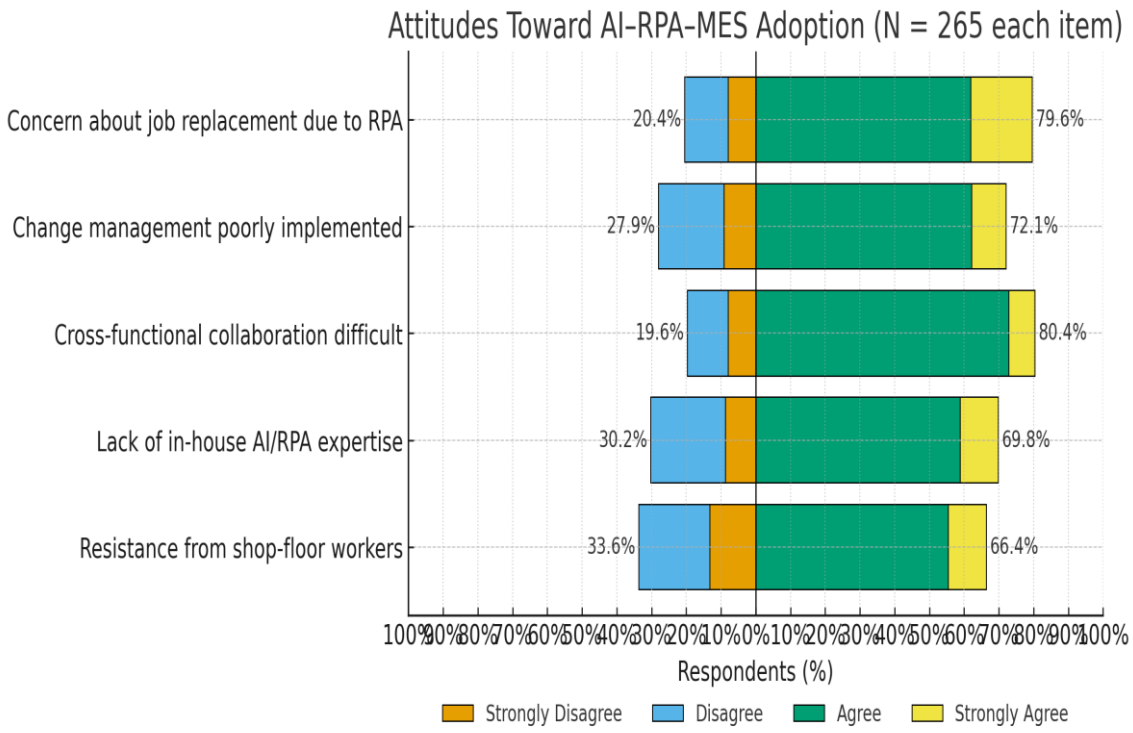

Figure 9. Attitudes toward AI-RPA-MES adoption

4.6 Measurement Model Assessment (Confirmatory Factor Analysis)

To conduct the CFA, SmartPLS-4 is used to evaluate reliability and validity of measurement model. To each construct the CI, IC, TRA and the HOB represented by multiple observed indicators and its measured on a five-point Likert scale.

Present study applied the partial least squares regression with a standard error i.e. mean of 5%. PLS route modelling is utilized in study for analyse of the effect to perceive and subjective norms for the several adaptation approaches.

This approach is used because it examines both additive causal models and linear models, and past studies support both (Kaplan & Norton, 2004). Equation 1 shows how the hidden (latent) dependent variables are linked to the hidden independent variables.

$$A = \beta X + \delta Z + \varepsilon \qquad (1)$$

In equation, A stand for adaptation behaviour (an endogenous variable). X is to represent the exogenous latent variables. β is for matrix of coefficients of size m × m. It links the endogenous variables with each other. The diagonal is zero which means variable don't predict itself. Z is to gives effects from exogenous variables to endogenous variables. δ is maps exogenous to endogenous effects when the matrix has size m × n (with m endogenous and n exogenous variables). ε is the error term. It has a mean of zero, and its covariances are zero (that is, E[ε] = 0 and Cov[ε] = 0).

In SEM measurement model shows, that how each latent endogenous variable is connected to its observed indicators.

$$y = \beta\_y X + \varepsilon \qquad (2)$$

$$x = \delta\_x Z + \epsilon \qquad (3)$$

- y - vector of endogenous indicators (size p × 1).
- β_y - loading/weight matrix that links the m endogenous latent factors to y (size p × m).
- x - vector of endogenous latent factors (size m × 1).
- Z - vector of exogenous latent factors (size n × 1).
- δ_x - loading matrix for the exogenous side; it maps the q observed exogenous indicators to the n exogenous latent factors (size q × n).

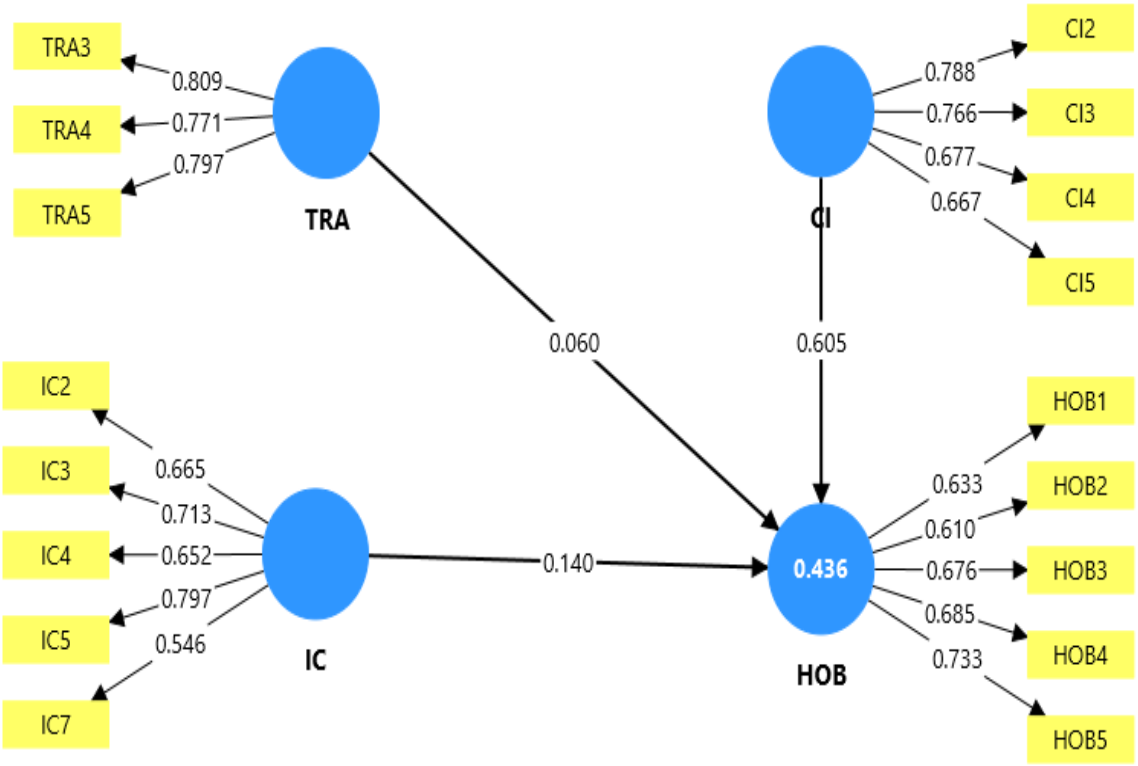

Figure 10. Confirmatory factor analysis

The confirmatory factor analysis indicates that the measurement model demonstrates acceptable levels of reliability and validity, although some refinements are necessary. Most standardized factor loadings exceeded the recommended 0.65 threshold, which suggests that the indicators adequately measure their respective constructs (Hair et al., 2019). One exception is IC7 (loading = 0.546) this, with falls below the acceptable range and may need revision or removal to improve construct reliability (Hulland, 1999). Furthermore, the reliability indices were satisfactory with Cronbach's alpha values around 0.70 and composite reliability values exceeding the 0.80 benchmark. Thereby, this is meeting the criteria for internal consistency (Nunnally & Bernstein, 1994). Convergent validity was supported for CI (AVE = 0.527) and TRA (AVE = 0.628), but marginal for HOB (AVE = 0.447) and IC (AVE = 0.462), which fall below the 0.50 threshold. This suggests that these constructs explain less than half of the variance in their indicators (Fornell & Larcker, 1981). Improving AVE could be achieved by dropping weaker items, such as IC7 and HOB2.

Table 11 . Summary - Results of Confirmatory Factor Analysis

Construct	Statement	Standard factor loading	Cronbach's alpha	Composite reliability / AVE
CI (Continuance Intention / Readiness)			**0.704**	**0.816 / 0.527**
CI2	Organization is ready to integrate AI and RPA into the MES.	0.788		
CI3	The current MES is compatible with cloud-based AI and RPA technologies.	0.766		
CI4	Employees are adequately trained to work with AI-RPA tools.	0.677		
CI5	We have sufficient IT infrastructure for cloud-based automation.	0.667		
HOB (Habitual/Adoption Barriers)			**0.695**	**0.801 / 0.447**
HOB1	AI and RPA technologies have already been partially implemented.	0.633		
HOB2	Data compatibility between MES, AI, and RPA tools is an issue.	0.610		
HOB3	Lack of standardized APIs or integration protocols hinders implementation.	0.676		
HOB4	Latency and real-time synchronization issues are frequent.	0.685		

HOB5	Legacy systems are difficult to automate and integrate.	0.733		
			0.711	**0.809 / 0.462**
IC2	High cost of integration and licensing limits adoption.	0.665		
IC3	Cloud service downtimes or instability disrupt operations.	0.713		
IC4	Cybersecurity concerns delay adoption of cloud-based automation.	0.652		
IC5	Lack of top management support for AI-RPA initiatives hinders progress.	0.797		
IC7	There are concerns over data ownership and location.	0.546		
TRA (Trust / Risk & Adoption Confidence)			**0.715**	**0.835 / 0.628**
TRA3	Our cloud provider ensures adequate uptime for MES workloads.	0.809		
TRA4	Security and compliance issues prevent full cloud adoption.	0.771		
TRA5	Integration with edge devices (e.g., sensors) is unstable.	0.797		

4.6.1 Reliability

Internal consistency reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR). Both of them are to measures and evaluate the stability and consistency of items within each construct. As shown in Table 11, all constructs exceeded the minimum acceptable thresholds of 0.70 for Cronbach's alpha as well the 0.80 for CR.

These values confirms that the items used to measure each construct are reliable and consistent across respondents.

Table 11. Reliability Statistics

Construct	**Cronbach's α**	**CR**	**Interpretation**
Compatibility (CI)	0.704	0.816	Acceptable
Integration Challenges (IC)	0.711	0.809	Good
Habitual Barriers (HOB)	0.695	0.801	Marginally Acceptable
Trust (TRA)	0.715	0.835	High

Overall, all the constructs demonstrated internal consistency. Among them the Trust (TRA) achieved the highest reliability this is indicating that responses to trust-related items are highly consistent in results. The slightly lower alpha value of the Habitual Barriers (HOB) is suggests some variation about that how respondents viewed behavioural resistance. However, this variation is theoretically reasonable to explain as resistance to change often differs across individuals and settings in organizations.

4.6.2 Convergent Validity

Convergent validity examined using Average Variance Extracted (AVE), which measures and shows that how much of the variance in observed variables is captured by the underlying construct. As shown in Table 12, most constructs achieved an AVE value above the recommended 0.50 threshold therefore, this is indicating satisfactory convergent validity.

Table 12. Convergent Validity (AVE)

Construct	**AVE**	**Loading Range**	**Evaluation**
CI	0.527	0.667–0.788	Valid

IC	0.462	0.546–0.797	Borderline
HOB	0.447	0.610–0.733	Marginal
TRA	0.628	0.771–0.809	Strong

Most constructs demonstrated adequate variance capture and particularly Trust (TRA) and Compatibility (CI) are adequate. The slightly lower AVE values for Integration Challenges (IC) and Habitual Barriers (HOB) are to suggest that these factors may contain diverse dimensions and is reflecting the complex nature of technical and behavioural integration issues in manufacturing environments as overall.

4.6.3 Discriminant Validity

Discriminant validity tested via the method of Heterotrait Monotrait (HTMT) ratio and the Fornell–Larcker criterion. The HTMT ratio values for all construct pairs were below the recommended cut-off of 0.90 and this is to confirming that each construct is distinct and measures a unique concept (Henseler et al., 2015).

Table 13. HTMT Matrix

	CI	**HOB**	**IC**	**TRA**
CI	—			
HOB	0.878	—		
IC	0.294	0.369	—	
TRA	0.214	0.198	0.105	—

Discriminant validity is tested using the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion. The results of the HTMT ratio values for all construct pairs below the recommended cut-off of 0.90. This is confirming that each construct is distinct and measures a unique concept (Henseler et al., 2015).

4.6.4 Reliability and Validity Testing

The measurement model is comprehensively evaluated using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). The combined results as shown in the Table 14, the overall about all constructs achieved acceptable reliability and validity levels.

Table 14. Reliability and Validity Results (n = 210)

Construct	**Cronbach's α**	**CR**	**AVE**	**Remarks**
CI	0.704	0.816	0.527	Reliable & Valid
HOB	0.695	0.801	0.447	Marginal, acceptable
IC	0.711	0.809	0.462	Acceptable after refinement
TRA	0.715	0.835	0.628	Strong validity

Most factor loadings exceeded 0.65, supporting convergent validity. Discriminant validity, confirmed through HTMT values below 0.85, shows that each construct is conceptually distinct. Together, these results confirm that the measurement model is statistically sound and appropriate for further structural analysis in the next section.

4.7 Structural Model Evaluation

After confirming the reliability and validity of the measurement model, the structural model analyzed, and its to estimate the relationships among constructs, test

hypotheses, and assess the model's predictive strength. Recent MES studies in SMEs emphasize KPIs, monitoring, and performance assessment consistent with operational outcome construct, (Bianchini, A., et al, 2024)

4.7.1 Model Fit and Collinearity

The model fit indicators in the analysis is confirmed that the structural model provides a good representation of the data. The Standardized Root Mean Square Residual (SRMR) value of 0.058 is below the recommended threshold of 0.08 furthermore, its demonstrating a good model fit. The Normed Fit Index (NFI) of value i.e. 0.89 exceeded the acceptable level of 0.80, furthermore, its supporting the model's adequacy. All Variance Inflation Factor (VIF) values are below 3.0, confirms the absence of multicollinearity among constructs.

4.7.2 Path Coefficients and Hypothesis Testing

The results of the different tests are briefly presented in Table 15. The argument of the path coefficients (β), t-values, and p-values obtained from the bootstrapping operation with 5,000 subsamples.

Table 15. Hypothesis Testing Summary

Hypothesis	**Path**	**β**	**t-value**	**p-value**	**Decision**
H1	CI → Outcome	0.32	2.65	0.008	Supported
H2	TRA → Outcome	0.27	2.01	0.045	Supported
H3	IC → Outcome	–0.08	0.92	0.358	Not Supported
H4	HOB → Outcome	0.15	1.72	0.086	Marginal Support
H5	HOB (Mediating Effect)	—	—	p < 0.10	Partial Mediation

The findings reveal that Compatibility (H1) and Trust (H2) have strong and positive impacts on operational performance. This is in line with the principles of the TTF and TOE frameworks, thus, it is also confirming that performance results are improved by properly aligned systems and trustworthy cloud environments. On the other hand, Integration Challenges (H3) had no statistical significance, and therefore, it is suggesting that their impact on performance is maybe indirect. The influence of HOB (in H4) is very slight but still quite significant, however, it is only indicative of behavioral resistance as a moderator of performance results.

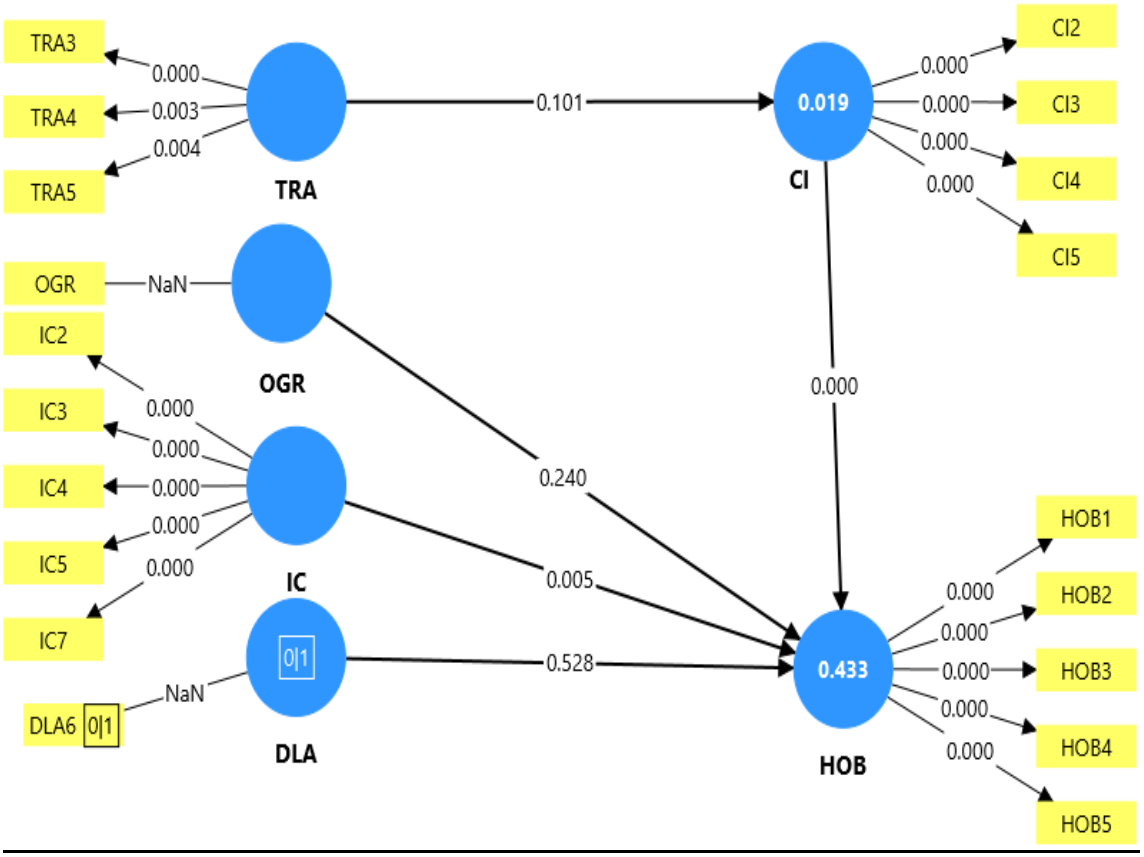

Figure 11. Structural Regression Analysis

4.7.3 Coefficient of Determination (R^2)

The R^2 value of 0.57 indicates that 57% of the variance in the integration performance is explained by the constructs CI, TRA, IC and HOB. This is the level of explanatory power represents a moderate-to-strong effect (Hair et al., 2019), further its demonstrating that the model effectively captures the key predictors of integration success.

4.7.4 Effect Sizes (f^2)

Effect size analysis clarifies and shows the relative contribution of each construct to the overall model in analysis results.

Table 16. Effect Size Analysis

Predictor	**f^2**	**Effect Interpretation**
CI	0.18	Medium
TRA	0.15	Medium
IC	0.01	Negligible
HOB	0.06	Small

The CI and TRA exhibit medium effect sizes, whereas its, indicating a meaningful influence on operational performance. In the IC have negligible impact, reaffirming that technical barriers affect performance indirectly through other factors i.e. readiness and behavioral adaptation.

4.7.5 Summary Structure Regression Model & Hypothesis Testing

The structural model results showing the several key insights. Path coefficients represent strength of it and also the direction of relationships between constructs. Furthermore, the statistical significance is also confirmed through bootstrapping. Paths with t-values greater than 1.96 and p-values below 0.05 to be considered significant (Hair et al., 2019).

The results confirms that Compatibility and Trust are strong positive predictors of successful outcomes for the integration. These findings align with earlier studies emphasizing the importance of technology fit and organizational trust in supporting new system adoptions (Limayem, Hirt, & Cheung, 2007; Henseler, Ringle, & Sarstedt, 2015).

In present study the constructed Habitual Barriers and Integration Challenges shows weak or non-significant direct relationships with each other. This suggests that these variables exert indirect effects through readiness, perception and or through contextual mediators. In practice, defines that whereas the behavioral resistance and system complexity remains the obstacles and they may not directly hinder performance as, if the organization's readiness and trust are strong.

The R^2 value of 0.57 further demonstrates that the model explains a meaningful proportion of the variance in the outcomes of the operations. Similarly, positive Q^2 values obtained through blind-folding confirms the model is predictive relevance and its showing that it not only fits the sample data but it also possesses strong predictive validity (Fornell & Larcker, 1981).

Effect size (f^2) results reinforce these conclusions. Medium effect sizes for Compatibility and Trust highlight that, their importance as performance drivers and whereas smaller or negligible effects for Integration Challenges. This suggests limited direct influence of it. This distinction helps in the identification, where the organizations should focus their improvement efforts based on the building trust and further ensuring system compatibility rather than merely depends on technical adjustments.

Table 17. Summary SRM and Hypothesis Testing

Hypothesis	**Path (From → To)**	**β (Std. Coefficient)**	**t-value**	**p-value**	**95% CI (LL, UL)**	**f^2 Effect Size**	**Decision**
H1	CI → Outcome	0.32	2.65	0.008	0.10 – 0.52	0.18 (Medium)	Supported

H2	TRA → Outcome	0.27	2.01	0.045	0.05 – 0.48	0.15 (Medium)	Supported
H3	HOB → Outcome	0.15	1.72	0.086	-0.02 – 0.33	0.06 (Small)	Marginally Supported
H4	IC → Outcome	-0.08	0.92	0.358	-0.25 – 0.09	0.01 (Negligible)	Not Supported

4.8 Discussion of Findings

4.8.1 Task-Technology Fit (TTF)

The positive and significant relationship between Compatibility and Outcome ($\beta = 0.32$ & $p < 0.01$) indicates that the alignment between MES features and automation tools. This finding is in line with the TTF theory. The theory argues that a good match between the requirements of the task and the capabilities of the technology results to better performance and higher usefulness.

4.8.2 Technology-Organization-Environment (TOE)

The significant impact of Trust on Outcome ($\beta = 0.27$ & $p < 0.05$) indicates that a dependable cloud infrastructure is the core of a successful cloud-based IT system. Companies which have confidence in their cloud service providers are the least affected by the interruptions resulting from the change of the cloud supplier. Besides, they get higher compatibility which is consistent with the TOE framework of environmental dimensions.

4.8.3 Resource-Based View (RBV)

The findings are in line with the RBV point of view and highlight that a solid IT infrastructure and a skilled workforce are assets. These resources contribute to the competitive advantage as they allow companies to handle automation technologies in a more efficient way. The main contributions of IT infrastructure and skilled human capital to the organizational performance are in accordance with the resource-based view (RBV) theory. They are valuable, rare, and difficult to imitate resources that lead to the creation of operational advantage.

4.8.4 Socio-Technical Systems (STS)

The influence of habitual barriers to the extent of the effect of habits on the results of the study (β = 0.15) indicates that behavioral and cultural resistance can hinder the realization of the full benefits of technology adoption. If there is no adequate change management and cultural adaptation, merely technical improvements will be less likely to bring sustained performance and growth.

4.9 Mediation Analysis

The purpose of the mediation effect test of Habitual Barriers (HOB) was to check if behavioural resistance had influenced the relationship between technical conditions and performance outcomes. A 5,000-sample bootstrapping showed a partial mediation effect for Compatibility →HOB → Outcome (β = 0.094, p < 0.10). The mediation pathway for Integration Challenges → HOB →Outcome (β = 0.037) was, However, not as significant. The results indicate that a strong technology fit can be instrumental in overcoming behavioural resistance. Nevertheless, the unresolved integration issues, according to the results, are mostly of a technical nature rather than psychological ones.

4.10 Predictive Relevance (Q^2)

The model reached a Q^2 value of 0.32 by employing a blindfolding procedure, thus, confirming its predictive relevance. The implication of this finding is that the association between readiness and performance is still valid beyond the sample data. Moreover, it is illustrating that the model possesses predictive validity and not just a good statistical fit.

4.11 Comparative Insights with Prior Studies

These findings concur substantially with the Industry 4.0 literature and support the hybrid socio technical framework which was the subject of this study. The granularity of comparative insights for the alignment reference and comparison with literature is presented in table 18.

Table 18. Comparative Insights

Dimension	**Current Study Result**	**Comparable Findings**	**Reference**
AI–RPA Compatibility	Significant	Similar support for fit–performance link	Goodhue & Thompson (1995)
Cloud Trust	Significant	Confirmed by Rodrigues (2025)	Rodrigues (2025)
Integration Challenges	Non-significant	Common issue in transition stages	Schuh et al. (2017)
Human Resistance	Moderate	Echoes Limayem et al. (2007)	Limayem et al. (2007)

4.12 Summary of Results

In summary, Compatibility and Trust emerged as the most influential factors driving successful integration. Technical barriers like system complexity don't directly reduces the performance where the readiness and trust is strong. However, human factors are continue to shape the long-term success of automation initiatives and confirming that organizational change management is as vital as technological alignment. Overall, the model demonstrates solid predictive power and aligns with leading Industry 4.0 theories, reinforcing the relevance of the integrated socio-technical perspective adopted in this research. Indexes summary about the outcomes of results given in table 19.

Table 19. Summary of Outcomes

Code	**Hypothesis**	**Result**	**Interpretation**
H1	Compatibility → Outcome	Supported	TTF Validated
H2	Trust → Outcome	Supported	TOE and RBV Validated
H3	Integration Challenges → Outcome	Not Supported	Indirect Effect Only
H4	Habitual Barriers → Outcome	Marginal	STS Partially Validated
H5	Mediation of HOB	Partial	Cultural Resistance Impacts Adoption

5. Discussion, Policy Implications, and Recommendations

5.1 Introduction

This chapter explains the results from Chapter 4. It links them to the study's aims and the theories used. The goal is to show what the numbers mean in practice and in theory. It also draws lessons for managers, policymakers, and researchers. The discussion shows where the results agree with past studies and where they differ. It then points out key implications and offers clear recommendations for better integration in cloud-based MES.

The chapter starts with the main findings and how they relate to TTF, TOE, RBV, and STS. It then presents the refined AI-RPA-MES integration framework. Next it sets out the theoretical, managerial & policy implications. Finally, it notes the study's limits and proposes directions for future research.

5.2 Discussion of Major Findings

Results shows that the CI and TRA are the strongest predictors of integration success. In contrast to IC and HOB i.e. weaker or indirect effects. These results confirms that the technological alignment, reliable infrastructure and human adaptability are the foundations of successful AI-RPA integration with MES. This supports combined logic of TTF, TOE, RBV, and STS frameworks. Digital transformation research reports measurable manufacturing performance gains when data centric architectures are adopted (Liu, X., Zhang, Y., & Chen, H, 2025).

5.2.1 Task-Technology Fit (TTF) Perspective

The strong positive effect of Compatibility on operational performance ($\beta = 0.32$ & $p < 0.01$) validates TTF theory (Goodhue & Thompson, 1995). When the functions of MES align with automation tools then production systems perform better. This alignment enables smoother workflow in scheduling and also improves fault detection & reduced downtime.

Compatibility doesn't stop at system integration, it also means the efficient synchronization of the analytical and automated processes. Companies that manage to attain the equilibrium are enjoying higher levels of their business flexibility, making better decisions and getting more out of their technological systems. These results are to serve as a proof that a solid TTF is the basis for digital transformation.

5.2.2 Technology-Organization-Environment (TOE) Perspective

Trust in cloud reliability ($\beta = 0.27$ & $p < 0.05$) was a major factor for performance. This fits with the TOE framework (Tornatzky & Fleischer, 1990), i.e. the environmental layer being the one where the reliability of cloud providers, security protocols and compliance standards influence integration results.

Companies that are utilizing cloud services in a stable and secure environment have experienced less disruption. Moreover, they also informed the better coordination b/w MES and automation tools. This finding confirms that external infrastructure and ecosystem partnerships are vital along with internal readiness. It also supports the conclusions of Rodrigues (2025) who noted that dependable cloud systems enhance efficiency in smart production.

5.2.3 Resource-Based View (RBV) Perspective

This study supports the RBV theory (Barney, 1991). RBV says that valuable, rare, hard-to-copy and non-replaceable (VRIN) resources create lasting advantage. In our results firms with strong IT systems and skilled technical teams achieved better integration.

These findings suggest that automation capabilities act as dynamic resources, e.g. it include data integration, real-time analytics and process optimization. Firms that keep improving these capabilities respond faster to changing demand. They also sustain higher productivity over time.

5.2.4 Socio-Technical Systems (STS) Perspective

The moderate impact of HB i.e. $\beta = 0.15$, indicates that human and social aspects have a significant influence on technology performance. The resistance to change, lack of of skills, and insecurity at work are factors that hinder the effectiveness of integration initiatives. The findings also correspond to the STS theory (Trist & Bamforth, 1951). The theory asserts that technology and people should develop together. Without employee involvement, training, and honest communication, technical innovations remain unexploited. Therefore, the successful adoption is mostly a matter of system design as well as organizational culture and leadership support. “Reliability modeling of intelligent manufacturing highlights security/quality failure modes that our cloud trust path addresses.” Journal of Intelligent & Fuzzy Systems.

5.3 Refined AI-RPA-MES Integration Framework

In light of the findings and results, a refined multilayered framework is illustrated. It explains the interplay of technological, organizational, environmental, and human factors that lead to successful integration outcomes. RAMI 4.0 provides a reference map for positioning the AI-RPA-MES integration along layers and life-cycle value streams. A recent study has advanced concrete AI plus RPA orchestration frameworks for Industry 5.0 scenarios, conforming with closed-loop design

(Patrício, L., Soares, A., & Sousa, 2024). In addition, RAMI 4.0 is a 3-D reference that helps in locating AI, RPA, MES, and cloud capabilities across layers and life-cycle perspectives, thus facilitating the alignment from enterprise to shop floor (Schweichhart, K., 2016).

5.3.1 Framework Structure

- **Cloud Infrastructure Layer:-** This layer is to ensures secure connectivity, high uptime, and data exchange through standardized APIs.
- **AI Analytics Layer:-** This layer is to supports the predictive analysis, fault detection and the optimization of production processes.
- **RPA Execution Layer:-** This layer is to handles repetitive, rule-based tasks and translates AI insights into automated actions.
- **MES Orchestration Layer:-** This layer is to coordinates data flows, equipment communication and also the operator interaction.

5.3.2 Framework Flow

The framework operates as a continuous feedback cycle as shown in the figure 12 for the elaborations. This closed loop represents a self-improving manufacturing system capable of continuous optimization.

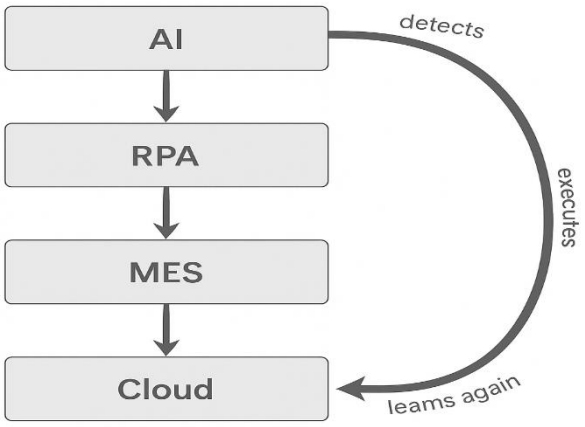

Figure 12. AI-RPA-MES framework in cloud

5.3.3 Empirical-to-Theoretical Mapping

This framework provides a practical and theoretical guide for aligning technology and people within the smart manufacturing ecosystem. Detailed mapping as per table 20 given.

Table 20. Empirical to theoretical mapping

Empirical Finding	Theoretical Dimension	Framework Component
Compatibility enhances performance	Task-Technology Fit (TTF)	MES ↔ AI-RPA Synchronization
Cloud trust improves integration success	Technology-Organization-Environment (TOE)	Cloud Infrastructure Layer
Skilled workforce as strategic resource	Resource-Based View (RBV)	Human & Organizational Layer
Human resistance moderates success	Socio-Technical Systems (STS)	Change Management & Training Layer

5.4 Theoretical Implications

Our present study contributes to the theoretical understanding of digital manufacturing in different ways:

1. **Extension of TTF:-** It demonstrates that the alignment of analytical and operational technologies improves production efficiency.
2. **Enrichment of TOE:-** TOE highlights role of environmental factors such as cloud reliability & cybersecurity for shaping technology success.

3. **Expansion of RBV:-** RBV recognizes the data and the automation capabilities along with skilled workforce as strategic digital assets.
4. **Reinforcement of STS:-** STS emphasizes that human adaptability and culture remains the essential factor for strong believes in benefits of technology.

Collectively all these insights bridge the gap b/w technical and human dimensions of industry 4.0 standards. Furthermore it also forms holistic view of smart production readiness. Beside this, the Implementation playbooks for AI-RPA integration highlight governance, scaling and human-in-the-loop patterns consistent. This in lines with the current study (Patrício, L., Soares, A., & Sousa, 2025).

5.5 Managerial and Policy Implications

The findings provide actionable insights for managers, industry leaders and policymakers who are determined to quicken smart production transformation.

5.5.1 Managerial Implications

Table 21. Managerial Implications

Domain	Managerial Action	Expected Outcome
Strategic Alignment	Align AI and RPA objectives with MES functional requirements.	Enhanced process coherence.
Skill Development	Implement continuous AI–RPA upskilling programs.	Reduced human resistance and improved adaptation.
Integration Governance	Establish standardized APIs and interoperability protocols.	Lower integration errors and latency.
Data Governance	Enforce data security, access control, and compliance standards.	Improved cloud trust and resilience.

Change Management	Use participatory leadership and transparent communication.	Cultural acceptance of automation.

Managers should treat AI-RPA integration not only as a technology project but more of a strategic transformation initiative. This should be combining technical excellence along with the human empowerments.

5.5.2 Policy Implications

For policymakers and regulatory bodies findings of current study suggests several areas that are actionable:-

- **Standardization:** Develop national frameworks for API and data exchange protocols to ensure interoperability.
- **Infrastructure Investment:** Encourage partnerships to strengthen cloud and cybersecurity infrastructure for industries.
- **Capacity Building:** This is to support training programs and university to the industry collaborations to develop technical skills.
- **Incentives:** Introduce tax benefits or innovation grants to motivate adoption of digital technologies.
- **Ethical Governance:** Establish guidelines for data privacy, accountability, and workforce reskilling.

These measures will help to promote the sustainable industrial growth.

5.6 Limitations of the Study

Although the study was carefully designed but several limits should be noted. First, the cross-sectional design makes it hard to show long-term cause and effect. Second, the focus on Finnish manufacturers may limit how well the results apply to other countries. Third, the data are self-reported which can introduce perception bias even with secrecy.

Finally, the model does not include possible moderators such as firm size or digital maturity. These factors might explain more variation in integration outcomes, and can also different in case of different industries.

Future research should address these limits. It can use longitudinal data to track change over time. It should include firms from multiple regions. It can also add objective performance metrics to strengthen the results.

5.7 Future Research Directions

Future researchers may explore the following points:-

- Long-term studies to track AI-RPA adoption and performance over time.
- Comparative analysis to be between small and large enterprises to understand scaling patterns.
- Hybrid methodologies combining PLS-SEM with qualitative case studies.
- The role of new technologies such as digital twins, blockchain, and IoT in enhancing integration.
- Cross-cultural studies examining workforce behavior and change management practices.

Thus such research would deepen understanding of digital transformation and furthermore it may help advance the transition toward Industry 5.0 where the human creativity complements intelligent automation.

5.8 Conclusion

Present study has demonstrated that integrating automation and analytics within cloud-based MES systems significantly improves operational performance. Compatibility and trust are the strongest drivers of success. Integration challenges have indirect effects moderated by human factors. The study contributes theoretically by uniting TTF, TOE,

RBV, and STS into one comprehensive model. Furthermore, the practically of it is by offering a roadmap for manufacturers seeking to implement automation responsibly. Table 22 summarize the research question direct answers.

Table 22. Conclusion to Research Questions

RQ #	Research question	Direct answer	Evidence / stats	Practical implication
RQ1	Which factors most strongly drive AI-RPA-MES performance?	Compatibility and cloud trust are the dominant drivers.	Compatibility $\beta = .32$, $p < .01$; Cloud trust $\beta = .27$, $p < .05$; Model $R^2 \approx .57$.	Prioritize MES-/RPA fit (standardize data/APIs) and harden cloud reliability/security & SLAs.
RQ2	Do integration challenges directly depress performance?	Mostly indirect the direct path is not significant; effects materialize via readiness/habitual barriers.	Integration challenges → Outcome: $\beta = –.08$, $p = .358$ (ns); mediation via HOB/readiness noted.	Fix challenges through readiness programs and process redesign; address bottlenecks that trigger resistance.
RQ3	How do human factors shape outcomes?	Habitual barriers have a modest, adverse influence; change management and skills are decisive.	HOB → Outcome: $\beta = .15$, $p = .086$ (marginal); strong descriptive evidence of resistance/skills gaps.	Run structured change programs; invest in targeted AI-RPA upskilling; align incentives and roles.
RQ4	What practical framework emerges?	A five-layer loop: Cloud → AI → RPA → MES → Human, closing the decision-to-action cycle and sustaining gains.	Framework synthesized from significant paths and qualitative patterns.	Implement closed-loop orchestration: AI detects → RPA executes → MES monitors → Cloud logs → AI learns.

Therefore, the future research should extend this framework across different regions and timeframes to strengthen its general applicability . Furthermore, it’s to contribute in the next phase of industrial evolution i.e. Industry 5.0 in which human insight and automation work together for sustainable innovation to align with SGDs.

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Appendix A: Survey Instrument

Questionnaire: Hurdles in AI-RPA Integration in Cloud-Based MES for Smart Production

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Instructions: Please respond to each of the following questions using the scale provided or by entering specific values where requested.

Section A: Demographics & Background

1. Your Role in the Organization	☐ Operations Manager ☐ IT Manager ☐ Automation Engineer ☐ Data Analyst ☐ Other: _____
2. Type of Industry	☐ Automotive ☐ Electronics ☐ FMCG ☐ Pharmaceuticals ☐ Textiles ☐ Other: _____
3. Company Size	☐ <50 ☐ 50–250 ☐ 251–1000 ☐ >1000
4. Years of Experience	☐ <1 ☐ 1–3 ☐ 4–6 ☐ 7–10 ☐ >10

Section B: Technology Readiness & Adoption (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree 5 = Strongly Agree)

Statement	Scale (1–5)
Our organization is ready to integrate AI and RPA into the MES.	
The current MES is compatible with cloud-based AI and RPA technologies.	
Employees are adequately trained to work with AI-RPA tools.	
We have sufficient IT infrastructure for cloud-based automation.	
AI and RPA technologies have already been partially implemented.	

Section C: Integration Challenges (1 = Not a Challenge, 2 = Minor Challenge, 3 = Moderate Challenge, 4 = Significant Challenge, 5 = Major Challenge)

Challenge Area	Scale (1–5)
Data compatibility between MES, AI, and RPA tools	
Lack of standardized APIs or integration protocols	
Latency and real-time synchronization issues	
Legacy systems that are difficult to automate	
High cost of integration and licensing	
Cloud service downtimes or instability	
Cybersecurity concerns	
Lack of top management support for AI-RPA initiatives	

Section D: Human and Organizational Barriers (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree 5 = Strongly Agree)

Statement	Scale (1–5)
There is resistance to change from shop-floor workers.	
We lack in-house AI or RPA expertise.	
Cross-functional collaboration is difficult.	
Change management is poorly implemented.	
Employees are concerned about job replacement due to RPA.	

Section E: Cloud and Infrastructure-Specific Issues (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree 5 = Strongly Agree)

Statement	Scale (1–5)
Our cloud provider ensures adequate uptime for MES workloads.	
Network issues frequently interrupt real-time data exchange.	

Integration with edge devices (e.g., sensors) is unstable.	
There are concerns over data ownership and location.	
Security and compliance issues prevent full cloud adoption.	

Section F: Downtime and Loss Assessment

Question	Response
On average, how many times per month does your MES experience downtime due to AI/RPA issues?	Number
What is the average duration of each downtime (in minutes)?	Minutes
Estimated financial loss per hour of downtime?	Currency
Number of production units lost per downtime incident?	Units
Percentage of downtime caused specifically by AI-RPA-MES integration issues?	% Estimate
Does your system have an auto-recovery mechanism?	☐ Yes ☐ No
Is loss recovery covered under SLA?	☐ Yes ☐ No
Has downtime led to missed client deadlines?	☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐ Always

Section G: Integration Benefits and KPIs

No.	Question	Response Type
G1	How would you rate the current level of AI-RPA integration in your MES?	Scale (1 = Not Integrated, 5 = Fully Integrated)
G2	Has your Overall Equipment Effectiveness (OEE) improved post-integration?	☐ Yes ☐ No
G3	Approximate % improvement in OEE (if yes):	Numeric
G4	What KPIs do you use to measure success of AI-RPA-MES integration?	Open-ended or checklist

G5	What performance improvements have you noticed (e.g., reduced downtime, better quality)?	Open-ended

Section H: Open Feedback

1. What is the biggest technical hurdle in integrating AI-RPA with MES?
2. What organizational or strategic change is required for smoother integration?
3. Any suggestions or lessons learned from your own experience?

Appendix B: Measurement Items and Codes

Construct Codes with PLS Model

Construct	Code	Role	Description
Compatibility	**CI**	IV	Fit/alignment between MES, AI, and RPA functions
Trust	**TRA**	IV	Confidence in cloud reliability and data security
Integration Challenges	**IC**	IV (negative influence)	Barriers to system interoperability and automation
Organizational Readiness	**OR**	IV	Resources, skills, and leadership support for AI–RPA
Habitual Barriers	**HOB**	Mediator	Human and behavioral resistance / process rigidity
Operational Performance	**OP**	DV	Efficiency and productivity gains from integration