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A HOUSE OF RISK-BASED FRAMEWORK FOR MANAGING RISKS IN IOT-ENABLED SOCIAL MANUFACTURING SYSTEMS

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Abstract:
This study proposes a risk management framework for an IoT-based Social Manufacturing system using the House of Risk (HOR) method. In a social manufacturing system, all distributed and collaborative production activities are highly dependent on real-time internet connectivity. In this study, 27 risk events and 22 risk agents were identified through observation and interviews, as well as SCOR-based process mapping. The method used is HOR Phase 1 and HOR Phase 2 analysis. In HOR Phase 1, which calculates the Aggregate Risk Potential (ARP), it was found that 12 risk agents predominantly contributed 78.52% of the total system risk, with the highest ARP values related to production planning errors (1872), production delays (1813), and inaccurate customer order identification (1148). In HOR Phase 2, 21 preventive actions were evaluated using the Effectiveness-to-Difficulty Ratio (ETD), yielding a priority-based mitigation sequence. The most effective actions include more careful production planning, improved coordination with SMRs, early identification of production bottlenecks, comprehensive recording of customer requests, and selective SMR qualification. This research contributes to the risk management literature by applying HOR to Industry 4.0 and provides practical guidance for risk mitigation in IoT-based social manufacturing systems.

Key words: house of risk, social manufacturing, internet of things, framework, integrated production system

INTRODUCTION

Industry 4.0 has transformed manufacturing by integrating cyber-physical systems, the Internet of Things (IoT), cloud computing, and advanced data analytics. These technologies enable greater automation, improved connectivity, and greater flexibility [1, 2]. Within this transformation, manufacturing systems are no longer confined to centralized factories but increasingly operate as distributed and collaborative networks. One paradigm that explicitly reflects this shift is Social Manufacturing, which emphasizes open participation, collaboration among heterogeneous actors, and the integration of social interaction with digital manufacturing platforms [3, 4]. In social manufacturing, production activities are distributed across multiple Social Manufacturing Resources (SMRs), such as small manufacturers, suppliers, and individual producers, who collaborate dynamically to fulfill customized customer demands. The adoption of IoT technologies plays a critical role in enabling social manufacturing systems. IoT facilitates real-time monitoring of machines, production status, and logistics, supports data-driven coordination among SMRs, and enhances responsiveness to changing customer requirements [5]. However, the same characteristics that provide flexibility and scalability, namely distributed decision-making, intensive data exchange, and reliance on digital connectivity, also introduce unique and amplified risks. These risks extend beyond traditional operational disruptions and include coordination failures among SMRs, inaccurate interpretation of customer requirements, data integrity and cybersecurity issues, unstable network connectivity, and organizational challenges related to trust and capability alignment [6]. IoT-based and social manufacturing systems are susceptible to specific cybersecurity threats such as unauthorized data access and ransomware attacks, data privacy concerns, including user data leaks and unauthorized sharing, operational disruptions like system downtimes and process interruptions, integration failures such as software incompatibilities, and organizational resistance to change, for example, reluctance to adopt new workflows [7, 8]. These risks extend beyond technical issues to encompass social, organizational, and economic dimensions, such as value chain management, system interoperability, and data governance [9]. Although recent studies indicate that IoT adoption in supply chain risk management can enhance collaboration among businesses, communities, and governments, there remains a lack of frameworks specifically tailored to IoT-based social manufacturing [10].

At the same time, the literature shows that supply chains and smart manufacturing systems face several fundamental risks, including customer information leakage, an inaccurate understanding of customer core needs, and limited risk identification in smart supply chains [11]. In addition, approaches to assess and mitigate IoT risks in supply chains using multi-criteria decision frameworks such as SWARA (Step-Wise Weight Assessment Ratio Analysis) to determine the relative weight of risk criteria, ARAS (Additive Ratio Assessment) to evaluate and rank organizational alternatives based on weighted risk criteria, with q-rung orthopair fuzzy sets, were found to indicate that the main risks are data security and privacy in the context of IoT for supply chain management [12]. In the context of IoT-enabled social manufacturing, a comprehensive risk management framework that integrates identification, assessment, and mitigation is essential to ensure that production flexibility does not compromise operational reliability and resilience [12, 13].

The House of Risk (HOR) method is a widely used approach for managing risks in supply chains and manufacturing processes [14]. This approach identifies risk events and agents, then ranks mitigation actions by Aggregate Risk Potential (ARP) [15]. However, applying HOR to IoT-based social manufacturing is rare. Most studies focus on traditional manufacturing or basic supply chains [16]. Therefore, there is a need for an HOR framework designed for IoT-based social manufacturing. This research introduces a HOR-based risk management framework for IoT-enabled social manufacturing. The framework identifies and groups key risks, ranks risk agents using the HOR method, and outlines mitigation steps to improve the reliability, flexibility, and resilience of social manufacturing systems. In theory, this work adds to the literature on Industry 4.0 and social manufacturing risk management. In practice, it offers organizations and networks ways to systematically identify, analyze, and address risks in highly connected environments. Since IoT-based social manufacturing involves complex interactions, real-time data sharing, and distributed production, this framework shows how to manage these challenges. For instance, IoT can speed up decisions and responses to disruptions, but without structured risk management, disruptions can have a greater technical and organizational impact [17]. Therefore, a systematic framework that connects risk identification, analysis, and mitigation is essential.

To fill this gap, this study introduces a House of Risk (HOR)-based framework for managing risks in IoT-enabled social manufacturing systems. The HOR method works well because it connects risk events to their causes and helps prioritize actions using quantitative analysis. By adapting HOR for social manufacturing, this research offers a framework that covers both technical and organizational risks in collaborative, distributed production settings.

This study has three main goals: (1) to identify and group key risk events and agents in IoT-enabled social manufacturing systems, (2) to rank these risks using the HOR method with Aggregate Risk Potential (ARP) and Pareto analysis, and (3) to create and rank preventive actions using the Effectiveness-to-Difficulty (ETD) ratio. The main contribution is a risk management framework that is both theoretically sound and practical, helping social manufacturing systems become more reliable, flexible, and resilient in Industry 4.0.

RELATED WORKS AND RESEARCH GAP

Risk Management in Industry 4.0 and IoT-Enabled Manufacturing

The House of Risk method is frequently integrated with other analytical tools and frameworks to enhance its scope and precision in risk assessment and mitigation [18, 19]. One common integration is with the Supply Chain Operation Reference (SCOR) model, which helps in systematically mapping supply chain activities and identifying risk events and agents across different process stages, such as Plan, Source, Make, and Deliver [20, 21]. This combined approach allows for a more structured and comprehensive identification of risks within complex supply chain networks. Additionally, HOR can be combined with the Analytic Hierarchy Process (AHP) for more nuanced prioritization, especially in selecting preventive actions where multiple criteria are involved [22].

The advantages of employing the House of Risk method are multifaceted, contributing significantly to improved organizational resilience and operational effectiveness. By offering a systematic framework for risk management, HOR enables companies to move beyond reactive responses to proactive prevention, minimizing potential losses and disruptions [23]. The method's ability to prioritize both risk agents and mitigation strategies ensures that resources are directed towards the most impactful areas, leading to more efficient and effective risk control [24]. This structured approach helps in building a comprehensive understanding of potential vulnerabilities, from supply chain disruptions to production defects and project delays, and provides actionable recommendations for addressing them [25]. Ultimately, the implementation of HOR can lead to enhanced product quality, increased customer satisfaction, and overall improved business sustainability by systematically embedding risk-aware practices into daily operations [26].

While the House of Risk method offers substantial benefits, it is important to acknowledge specific considerations when applying it. The effectiveness of HOR heavily relies on the quality and objectivity of the data collected, particularly during the initial phase, where severity, occurrence, and correlation values are assigned, often through interviews and expert judgment [27]. This qualitative aspect can introduce subjectivity, which some researchers have sought to address through advanced techniques like fuzzy logic to model qualitative decisions more precisely [28, 29]. Furthermore, the successful implementation of HOR-derived mitigation strategies often necessitates strong coordination among various departments and stakeholders, as well as a commitment to continuous monitoring and adaptation [30]. Despite these considerations, the HOR method remains a highly valued and adaptable tool for risk management, capable of providing a clear, prioritized pathway for organizations to navigate complexity and achieve their strategic objectives [31, 32].

Social Manufacturing and Its Risk Characteristics

Social manufacturing builds on smart manufacturing by adding social interaction, collaborative networks, and open innovation to production systems [3, 15]. Unlike traditional manufacturing, it relies on distributed SMRs that differ in size, skill levels, and technology. Production tasks are assigned as needed, and coordination happens through digital platforms and IoT-based information sharing. This setup brings unique risks. For instance, if customer needs are misunderstood, the problem can spread across many SMRs. Mistakes in planning at one point can affect the whole network, and poor coordination can cause delays and quality issues. Social manufacturing also relies heavily on constant connectivity and accurate data, making it vulnerable to network outages and data gaps. Even with these challenges, a few studies still focus on risk management in social manufacturing.

House of Risk (HOR) Method and Research Gap

The House of Risk (HOR) method, developed by Pujawan and Geraldin, is commonly used in supply chain and manufacturing risk management because it connects risk events to their root causes and helps set priorities for reducing them [16, 17]. HOR has also been combined with frameworks such as the Supply Chain Operations Reference (SCOR) model and decision-support tools such as AHP and fuzzy logic to improve risk ranking [18, 19]. However, most uses of HOR focus on traditional supply chains, logistics networks, or centralized production systems. There is limited research on applying HOR to distributed, collaborative manufacturing, especially in environments that use IoT and social manufacturing. The absence of a specific HOR-based framework for social manufacturing highlights a clear research gap. Table 1 summarizes key studies on risk management in Industry 4.0, IoT-enabled manufacturing, and social manufacturing, and highlights their main focus and limitations.

Table 1

The Summary of Key Studies on Risk Management in Industry 4.0

Author(s)	Context/Domain	Method Used	Main Contribution	Limitations Related to Social Manufacturing
Birkel et al. (2019)	Industry 4.0 manufacturing	Conceptual risk framework	Identification of sustainability-oriented Industry 4.0 risks	Focuses on firm-level manufacturing; no collaborative SMR perspective
Jinil Persis et al. (2021)	IoT-enabled supply chains	SEM-based modeling	Analysis of IoT impact on circular supply chains	Treats supply chain actors as homogeneous entities
Nagy (2023)	Industry 4.0 environment	Risk management framework	Categorization of digital manufacturing risks	Lacks focus on distributed social manufacturing systems
Ramadhan et al. (2025)	Manufacturing supply chains	Fuzzy HOR	Advanced HOR-based mitigation prioritization	Applied to conventional supply chains, not collaborative SMRs
Sari et al. (2023)	Social manufacturing (review)	Systematic literature review	Identification of social manufacturing characteristics	Does not propose a quantitative risk management framework

METHODS

Risk Management Using the House of Risk (HOR) Approach

This research adopts the House of Risk (HOR) framework developed by Pujawan and Geraldin as its risk management approach. HOR provides a structured, quantitative process for identifying, analyzing, and prioritizing risks, enabling organizations to allocate resources to address the most critical threats. In this study, the HOR framework manages risks in an IoT-enabled Social Manufacturing system, supporting informed decision-making within the dynamic, distributed, and interdependent Industry 4.0 ecosystem.

Risk Identification (HOR Phase 1)

The first phase, known as HOR 1, identifies risks that may affect the reliability and effectiveness of the Social Manufacturing system. By identifying these risks early, organizations can solve problems more quickly, reduce disruptions, and improve system performance. This phase has two main parts:

- Risk Events (E_i) are incidents that can disrupt the system's operation. For example, these might include IoT connection issues, data integration errors, human errors, or cyberattacks.
- Risk Agents (A_j) are the reasons these risk events happen. They can include insufficient digital infrastructure, poorly trained operators, new or untested technology, or weak data security rules. Experts identify these risks through interviews and research.

This method helps identify both practical and technical risks for Industry 4.0. The HOR 1 matrix shows each risk and connects risk events to their causes.

Risk Assessment

After identifying risks, each is rated for severity (S_i) and occurrence (O_j) using a 1-5 Likert scale. These ratings rely on expert judgment.

Severity reflects the impact of a risk event on production performance, while occurrence indicates the likelihood that a risk agent will trigger the event.

Occurrence indicates the likelihood that a risk agent will trigger the event.

A correlation score (R_{ij}) from 0 to 3 indicates the strength of the link between each risk event and risk agent. A score of 0 shows no relationship; 3 means a strong relationship.

Calculation of Aggregate Risk Potential (ARP)

The Aggregate Risk Potential (ARP) value is then calculated to prioritize the most critical risk agents. The ARP for each agent is computed using the following equation as presented in Equation 1.

$$ARP_j = O_j \times \sum_{i=1}^{n} \left(S_i \times R_{ij}\right), \quad (1)$$

where:

ARP_j = Aggregate Risk Potential for risk agent j,

O_j = Occurrence level of risk agent j,

S_i = Severity level of risk event I,

R_{ij} = Relationship score between event i and agent j.

Higher ARP values indicate higher aggregate potential risk, meaning that the corresponding agent significantly contributes to overall system vulnerability. These values are ranked in descending order to produce a priority list of key risk agents.

Pareto Analysis and Risk Prioritization

The Pareto principle (80/20 rule) is applied to identify a small subset of high-impact risk agents, typically around 20% of all agents that account for approximately 80% of total risk potential. Only the prioritized agents are carried forward into the second phase of HOR for mitigation planning, ensuring efficient and focused risk management efforts.

Development of Risk Mitigation Strategies (HOR Phase 2)

HOR 2 focuses on developing mitigation strategies for the prioritized risk agents identified in HOR 1. The steps include:

- Identifying preventive actions (P_k) to reduce the likelihood of each risk agent's occurrence.
- Assessing the effectiveness (E_{kj}) of each preventive action in addressing the corresponding risk agents.
- Evaluating the difficulty level (D_k) of implementing each action, considering cost, time, and resource constraints.

Each preventive action is then evaluated using the Effectiveness-to-Difficulty (ETD) ratio, as presented in Equation 2.

$$ETD_k = \frac{\sum_{j=1}^{m} \left(E_{kj} \times ARP_j\right)}{D_k} \quad (2)$$

A higher ETD value indicates a more efficient and effective mitigation action. The output of HOR 2 is therefore a prioritized list of mitigation strategies that balance potential impact reduction with implementation feasibility.

RESULTS AND DISCUSSION

Social Manufacturing System Design

This study explains the design of the social manufacturing system in Fig. 1.

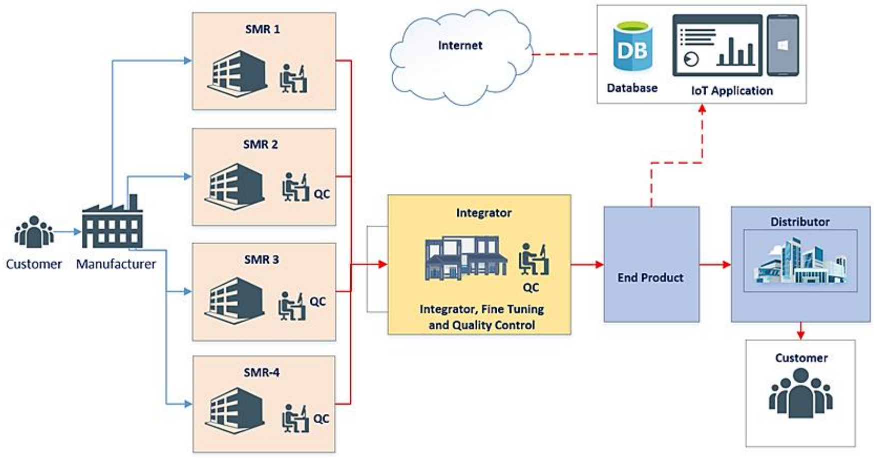

Fig. 1 Social Manufacturing system design

Alt-Text*: Workflow diagram showing customer requests distributed to multiple SMRs, integrated through IoT monitoring, assembled by an integrator, and delivered to customers.*

The process begins when the customer submits requirements. The manufacturer then breaks these down into tasks and assigns them to SMR 1, SMR 2, SMR 3, and SMR 4. An IoT-enabled setup distributes production among the SMRs. Each SMR completes its tasks, performs initial Quality Control (QC) to ensure standards are met, and sends its results for combination into the final product.

Once the components are made, they go to a central Integrator for assembly, fine-tuning, and quality checks. During this stage, SMRs and the integrator stay connected online through a central database and an IoT app. This setup enables real-time monitoring, production tracking, and data collection, and helps the team work together more easily. After assembly and validation, the Integrator finishes the product and sends it to a Distributor, who delivers it to the customer. This process demonstrates how digital tools and IoT technologies improve coordination, monitoring, and quality in distributed manufacturing, in line with Industry 4.0 principles.

Social Manufacturing System Risk Management

We collected data by observing and interviewing people who built or used the Disinfectant Chamber. Then, we mapped the supply chain using the SCOR steps: Plan, Source, Make, Deliver, and Return. This helped us identify possible risks and events. For each risk, we examined its causes and effects and rated its severity, likelihood, and frequency. Next, we calculated the Aggregate Risk Potential (ARP) to rank the risks. This helped us decide which risk agents to address first. Using a Pareto Diagram, we showed that most problems stem from only a few agents, so they should be managed first. This completed the first stage, HOR 1, in which we found the ARP value. In the second stage, HOR 2, we planned ways to reduce the risks. We chose which agents to focus on by looking at how effective and practical the solutions would be. Mitigation refers to the Effectiveness-to-Difficulty (ETD) ratio, which is assigned a weighted value. Before starting the calculation, it is necessary to identify preventive actions (PA) that can be taken to address the risk agents. The HOR method determines the sequence of mitigation strategies to implement in this social manufacturing-based production system.

Determining the Impact of Risk Events: Severity and Occurrence

Based on the interview results, the data obtained was used to determine the risk event's Severity and Occurrence. Then combine the Severity and Occurrence values into a single value to simplify the subsequent risk analysis, as shown in Table 2.

Table 2
Severity dan Occurrence

Risk Event	**Kode (E_i)**	***Severity***	***Risk Agent***	**Kode (A_i)**	***Occurrence***
Incorrect determination of customer demand	E1	5	Errors in recording customer demand	A1	5
Production processes at each SMR are not on schedule	E2	5	Production planning errors	A2	6
Sudden changes in the production process plan	E3	6	The production process is disrupted	A3	7
Product design does not meet requirements	E4	7	Incorrect identification of customer orders	A4	7
Product design changes require a long time	E5	7	Frequent changes in customer design requests	A5	6
Production schedule delays	E6	7	Inaccurate determination of the production schedule	A6	7
Inaccurate planning of additional materials	E7	5	Errors in additional material planning at the integrator	A7	5
Preparation of the integration process	E8	6	Errors in the integration process	A8	6
Planning for machine maintenance at the integrator	E9	5	Errors in planning machine maintenance at the integrator	A9	5
Quality control process after integration	E10	8	Quality control was not performed	A10	7
Inaccurate selection of SMRs	E11	7	Errors in SMR selection	A11	7
SMR is unable to fulfil the order	E12	7	SMR experiences difficulty in producing the product	A12	6
SMR cannot fulfill agreements/contracts	E13	6	SMR does not understand the contract/agreement	A13	6
Poor relationship among SMRs	E14	7	Improper distribution of tasks among SMRs	A14	6
Unstable or disconnected internet connection at SMR	E15	7	Newly assigned operator in that section	A15	6
Admin has not updated the SMR data	E16	6	Technical issues with network connectivity	A16	7
Admin has not updated the SMR data	E17	6	Errors in using the delivery application	A17	6
Delay in delivering product designs to SMRs	E18	7	Courier experiences transportation issues	A18	6
SMR does not produce the product according to design	E19	5	Smartphone malfunction	A19	5
Sudden design changes	E20	6	Disruptions or natural disasters	A20	7
Incorrect courier selection	E21	6	Errors in installing the delivery application	A21	5
The courier cancels the delivery agreement	E22	5	The product is damaged	A22	6
Courier does not install the delivery application	E23	5			
Late delivery of products	E24	6			
Delivery application error	E25	6			
Courier data not detected in the SMMS monitoring system	E26	5			
Return of incorrect or damaged products	E27	5			

Furthermore, calculations are performed to determine the HOR 1 matrix, presented in Table 3.

Table 3
House of Risk (HOR) 1 matrix

Risk Agent

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	A21	A22	SEV
E1	9	9	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
E2	1	9	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
E3	3	9	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**6**
E4	9	3	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**7**
E5	3	1	3	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**7**
E6	0	9	9	0	0	9	0	0	1	0	0	0	0	1	0	3	0	0	0	0	0	0	**7**
E7	1	1	0	1	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
E8	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**6**
E9	0	0	0	0	0	0	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
E10	0	0	0	0	0	0	0	9	0	9	0	0	0	0	0	0	0	0	0	0	0	0	**8**
E11	0	1	0	0	0	0	0	0	0	0	9	1	3	0	0	0	0	0	0	0	0	0	**7**
E12	0	0	0	0	0	0	0	0	0	0	3	9	0	1	0	0	0	0	0	0	0	0	**7**
E13	0	0	0	0	0	0	0	0	0	0	1	0	9	3	0	0	0	0	0	0	0	0	**6**
E14	0	0	9	0	0	0	0	0	0	0	9	0	0	9	0	0	0	0	0	0	0	0	**7**
E15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
E16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
E17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	**6**
E18	0	0	1	0	9	3	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	**7**
E19	0	1	0	9	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	**5**
E20	0	9	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**6**
E21	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	**6**
E22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	0	0	0	**5**
E23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
E24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	0	0	**5**
E25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	3	3	9	0	**6**
E26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	**5**
E27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	**5**
OCC	**5**	**6**	**7**	**7**	**6**	**7**	**5**	**6**	**5**	**7**	**7**	**6**	**6**	**6**	**6**	**7**	**6**	**6**	**5**	**7**	**5**	**6**	
ARP	**785**	**1872**	**1813**	**1148**	**756**	**623**	**315**	**570**	**260**	**504**	**1071**	**690**	**450**	**528**	**108**	**483**	**354**	**414**	**165**	**336**	**295**	**270**	
Rank	**5**	**1**	**2**	**3**	**6**	**8**	**17**	**9**	**20**	**11**	**4**	**7**	**13**	**10**	**22**	**12**	**15**	**14**	**21**	**16**	**18**	**19**	

***Alt-Text**: Matrix linking 27 risk events and 22 risk agents with severity, occurrence, and aggregate risk potential values.*

The calculation of the HOR 1 matrix presented in Table 2 is for Risk Agents A1-A22 and E1-E27, and it outputs the Severity and Occurrence values. The Aggregate Risk Potential (ARP) is then calculated. ARP is the result of the possibility of the emergence of a risk agent and the aggregate consequences of the occurrence of risks caused by the risk agent. This ARP value is obtained by summing the products of the severity and occurrence levels. The results of this risk analysis stage are in the form of risk priorities and ranking classifications based on the Pareto 80:20, which are then used as a reference for preparing a risk management plan.

In the Risk Evaluation stage, two steps are taken: ranking risk agents by their ARP values and determining the priority of risk agents to be reduced using predetermined mitigation actions. This stage uses the House of Risk 2 Model. Each risk agent has a mitigation action that is strongly related (correlation value of 9), moderately related (correlation value of 3), or weakly related (correlation value of 1). The total effectiveness of a mitigation action is calculated by multiplying the correlation values between risk agents and mitigation actions by the ARP value obtained from HOR 1. Meanwhile, the ETD (Effectiveness-to-Difficulty Ratio) is calculated by dividing the total effectiveness of mitigation actions by their level of difficulty. The greater the D (difficulty) value, the lower the ETD value. This means the mitigation action is less effective at reducing the risk posed by the agent. And vice versa. Once the ETD value is known, mitigation actions can be ranked by it. The mitigation action ranking shows the priority of mitigation actions to prevent the emergence of risk agents that cause risk events.

This ARP value is obtained by summing the results of multiplying the severity level by the occurrence level, as shown in Table 4, from the highest to the lowest.

The results of this risk analysis stage are risk priorities and rankings based on the 80:20 Pareto principle, which are then used as a reference for preparing risk management plans.

Table 4
ARP value

Risk Agent Code	ARP	Percentage	Cumulative
A2	1872	13.56	13.56
A3	1813	13.13	26.68
A4	1148	8.31	35.00
A11	1071	7.76	42.75
A1	785	5.68	48.44
A5	756	5.47	53.91
A12	690	5.00	58.91
A6	623	4.51	63.42
A8	570	4.13	67.55
A14	528	3.82	71.37
A10	504	3.65	75.02
A16	483	3.50	78.52
A13	450	3.26	81.77
A18	414	3.00	84.77
A17	354	2.56	87.34
A20	336	2.43	89.77
A7	315	2.28	92.05
A21	295	2.14	94.19
A22	270	1.96	96.14
A9	260	1.88	98.02
A19	165	1.19	99.22
A15	108	0.78	100.00
Total	**13810**		

Alt-Text*: Ranked aggregate risk potential values showing the most critical risk agents in the social manufacturing system.*

Table 3 presents the ARP calculation sequence, sorted from the highest to the lowest ARP value. Then, using the Pareto 80:20, the cumulative value is the maximum of 80. The highest value in the table is 78.52, and the lowest is 13.56, so 12 risk agents will be used to determine risk mitigation.
Figure 2 displays the Pareto Diagram form from the results of the HOR 1 calculation.

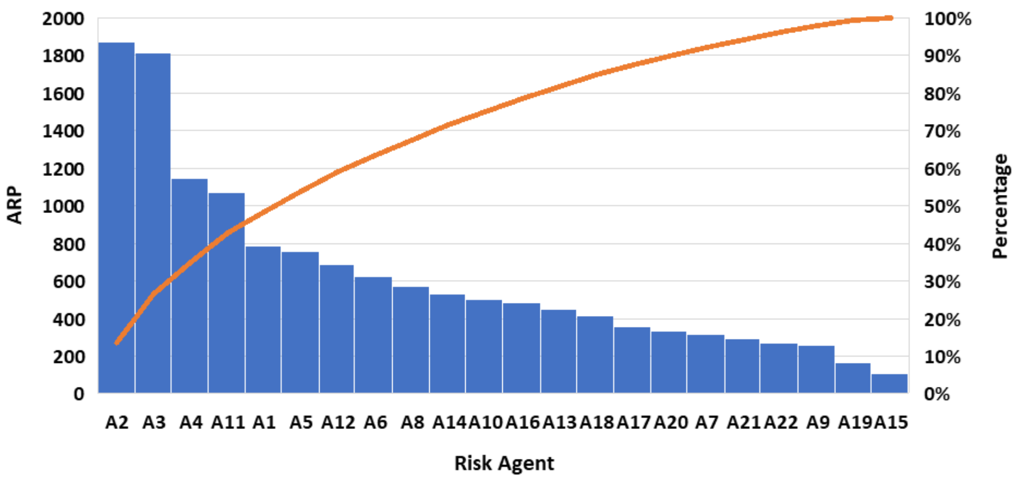

Fig. 2 Pareto Diagram of HOR 1
Alt-Text*: Pareto chart showing that 12 risk agents contribute approximately 78.5% of the total aggregate risk potential in the social manufacturing system.*

Next, after 12 risk agents have been identified, the next step is to determine the handling strategy or preventive action (PA), as presented in Table 5.

Table 5
Risk Mitigation with Preventive Action (PA)

Risk Agent Code	Risk Agent	Preventive Action (PA)	Code
A2	Production planning errors	Production planning must be carried out carefully	PA 1
A3	The production process is disrupted	Coordinate with the involved SMRs	PA 2
	The production process is disrupted	Identify factors that hinder the production process	PA 3
A4	Incorrect identification of customer orders	Record customer demand comprehensively	PA 4
	Incorrect identification of customer orders	Confirm customer product requirements	PA 5
A11	Errors in SMR selection	Select SMRs more selectively	PA 6
	Errors in SMR selection	Develop standards for SMRs to be involved	PA 7
	Errors in SMR selection	Create a database of SMRs to be involved in	PA 8
A1	Errors in recording customer demand	Identify customer requirements in detail	PA 9
	Errors in recording customer demand	Create customer demand records	PA 10
A5	Frequent changes in customer design requests	Provide various product design options	PA 11
A12	SMR experiences difficulty producing the product	Provide product information to the involved SMRs	PA 12
	SMR experiences difficulty producing the product	Clarify product manufacturing agreements	PA 13
A6	Inaccurate determination of the production schedule	Develop more detailed production plans	PA 14
	Inaccurate determination of the production schedule	Check the readiness of the involved SMRs	PA 15
A8	Errors in the integration process	Conduct training for integrator operators	PA 16
	Errors in the integration process	Provide detailed information on products to be integrated	PA 17
A14	Improper distribution of tasks among SMRs	Identify each SMR's capability before production	PA 18
A10	Quality control was not performed	Conduct quality control training at the integrator	PA 19
	Quality control was not performed	Develop quality control standards for each SMR	PA 20
A16	Technical issues with network connectivity	Inspect and maintain network infrastructure	PA 21

Each risk agent can have multiple PAs, depending on the risks it poses. The mapping results in this table yield 21 PAs. The next step is to determine the correlation between the Risk Agent (RA) and PA to prioritize risk-handling strategies.

Figure 3 presents the House of Risk (HOR) Phase 2 matrix, which illustrates the relationship between the identified *risk agents* and the proposed *preventive actions* intended to mitigate their occurrence within the IoT-enabled Social Manufacturing system.

Risk Agent	*Preventive Action*																				
	PA 1	PA 2	PA 3	PA 4	PA 5	PA 6	PA 7	PA 8	PA 9	PA 10	PA 11	PA 12	PA 13	PA 14	PA 15	PA 16	PA 17	PA 18	PA 19	PA 20	PA 21
A2	9																				
A3		9	9																		
A4				9	3																
A11						9	3	3													
A1									9	3											
A5											3										
A12												9	9								
A6														9	3						
A8																9	3				
A14																		3			
A10																			9	3	
A16																					9

Fig. 3 The correlation between Risk Agent and Preventive Action
Alt-Text: *Matrix showing the relationships between prioritized risk agents and preventive actions using HOR Phase 2 correlation scores.*

The matrix serves as a structured decision-support tool that enables prioritizing mitigation strategies by evaluating the extent to which each preventive action reduces the potential impact of specific risk agents.

In this matrix, each row corresponds to a risk agent (A1-A16), and each column corresponds to a preventive action (PA1-PA21). The numbers show how strongly each risk agent connects to a preventive action, using the standard HOR scoring scale. A score of 9 means the preventive action is highly effective at reducing the risk posed by that agent. A score of 3 means the action has a moderate but still significant effect. If a cell is blank, there is no direct link, so the preventive action has no significant impact on that risk agent.

When you look at the matrix scores, you can see that some risk agents are managed primarily by a single preventive action. This appears as a diagonal line of 9s. For example, PA1 has a strong effect on A2, and PA2 affects A3. Both PA3 and PA4 affect A4. These patterns show clear ways to reduce these risks. Other risk agents, such as A11, are linked to several preventive actions, including PA4, PA5, and PA6. These are more complex and need several approaches to manage. The matrix is also used to calculate the Effectiveness-to-Difficulty (ETD) ratio for each preventive action. The ETD ratio helps set priorities. Actions that are highly effective and not too difficult to implement receive higher ETD scores and are given priority in the risk mitigation plan.

The HOR Phase 2 matrix provides a clear, measurable way to match risk-reducing strategies with the primary sources of risk in manufacturing. By linking risk agents to the most effective preventive actions, the matrix helps decision-makers use resources wisely and build a focused risk mitigation plan. This method also improves system reliability and resilience in an Industry 4.0 environment. The results of the HOR 2 calculation are shown in Figure 4 below. Next, assign a Priority ranking (Rk) to each action, giving the highest ranking to the action with the highest ETD.

The Figure displays the HOR Phase 2 matrix, which helps prioritize preventive actions to lower key risks in the system. Each row corresponds to a risk agent, and each column corresponds to a preventive action (PA1-PA21). The numbers in the matrix, mostly 9 and 3, indicate how much each action addresses each risk. Higher numbers mean greater risk reduction.

Risk Agent	Preventive Action																					
	PA 1	PA 2	PA 3	PA 4	PA 5	PA 6	PA 7	PA 8	PA 9	PA 10	PA 11	PA 12	PA 13	PA 14	PA 15	PA 16	PA 17	PA 18	PA 19	PA 20	PA 21	ARP
A2	9																					1872
A3		9	9																			1813
A4				9	3																	1148
A11						9	3	3														1071
A1									9	3												785
A5											3											756
A12												9	9									690
A6														9	3							623
A8																9	3					570
A14																		3				528
A10																			9	3		504
A16																					9	483
Tek	16848	16317	16317	10332	3444	9639	3213	3213	7065	2355	2268	6210	6210	5607	1869	5130	1710	1584	4536	1512	4347	
Dk	3	3	3	3	4	3	3	4	3	3	4	3	3	3	4	3	3	4	3	4	4	
ETD	5616	5439	5439	3444	861	3213	1071	803.25	2355	785	567	2070	2070	1869	467.25	1710	570	396	1512	378	1086.8	
Ranking	1	2	3	4	14	5	13	15	6	16	18	7	8	9	19	10	17	20	11	21	12	

Fig. 4 The Calculation of HOR 2

***Alt-Text**: HOR Phase 2 matrix presenting total effectiveness, implementation difficulty, ETD ratios, and priority rankings for preventive actions*

On the right side of the table, the Aggregate Risk Potential (ARP) values indicate the importance of each risk agent, based on results from HOR Phase 1. At the bottom of the matrix, three main calculations are listed:

– Tek (Total Effectiveness) shows the overall impact each preventive action has on all risk agents.
– Dk (Difficulty) shows the effort, cost, or complexity needed to complete each action.
– The ETD (Effectiveness-to-Difficulty Ratio) is found by dividing Tek by Dk. This ratio shows the efficiency of each preventive action.

Actions with the highest ETD scores, such as PA1, PA2, PA3, and PA4, are considered the most effective and practical, so they are given priority in the risk mitigation strategy. The ETD ranking helps decide the order of mitigation measures to address risks in the developed social manufacturing, as shown in Table 6.

Table 6
Risk Mitigation Priority Order

Priority Order	Code	Preventive Action
1	PA 1	Production planning must be carried out carefully
2	PA 2	Coordinate with the involved Social Manufacturing Resources (SMRs)
3	PA 3	Identify factors that hinder the production process
4	PA 4	Record customer demand comprehensively
5	PA 6	Select SMRs more selectively
6	PA 9	Identify customer requirements in detail
7	PA 12	Provide product information to the SMRs involved
8	PA 13	Clarify the agreement regarding product manufacturing
9	PA 14	Develop more detailed production plans
10	PA 16	Conduct training for integrator operators
11	PA 19	Conduct quality control training at the integrator
12	PA 21	Perform inspection and maintenance of network infrastructure
13	PA 7	Develop standards for the SMRs to be involved
14	PA 5	Confirm the desired product specifications with the customer

This list shows the most effective and practical ways to reduce key risks in IoT-based Social Manufacturing, organized by focus area.

1) Planning and Communication: Careful production planning (PA1), working closely with all SMRs (PA2), and identifying production constraints early (PA3) help prevent disruptions.

2) Customer and Partner Alignment: Documenting customer requirements clearly (PA4), carefully selecting SMRs (PA6), and fully understanding customer needs (PA9) help ensure accurate information and the right partners.
3) Collaboration and Clarity: Sharing product details with SMRs (PA12), clarifying production agreements (PA13), and making detailed production plans (PA14) reduces confusion during collaboration.
4) Skills and Reliability: Training (PA16 and PA19) helps operators and quality control staff build needed skills, and regular maintenance (PA21) keeps the network reliable.
5) Additional Supporting Actions: Lower-ranked actions, such as setting clear SMR criteria (PA7) and confirming customer specifications (PA5), also help keep everyone aligned.

Taken together, these actions create a strong strategy to improve coordination, information accuracy, reliability, and resilience in Industry 4.0 Social Manufacturing.

CONCLUSIONS

This study applied the House of Risk (HOR) framework to find and rank ways to reduce risks in an IoT-enabled Social Manufacturing system. First, the team identified 22 risk agents and 27 risk events, scoring each on severity, frequency, and their interrelationships. The Aggregate Risk Potential (ARP) scores ranged from 1872 for production planning errors (A2) to 108 for new operator placement (A15), totaling 13,810. Using the 80/20 rule, the study found that 12 risk agents accounted for 78.52% of the total risk, making them the main focus. The top three agents, A2 (1872; 13.56%), A3 (1813; 13.13%), and A4 (1148; 8.31%) highlighted issues in production planning, production flow, and customer order identification. In the next phase, the team developed 21 preventive actions and linked them to the main risk agents using a correlation matrix. This matrix rated the strength of each action on a scale of 3 (moderate) to 9 (strong). These ratings were used to calculate Total Effectiveness (TEk), Difficulty (Dk), and the Effectiveness-to-Difficulty (ETD) ratio. Actions with the highest ETD were the most efficient and practical. The top actions were careful production planning (PA1), working with SMRs (PA2), finding production barriers (PA3), and keeping detailed records of customer demand (PA4). These four actions were most effective for the main risk agents, as shown by strong scores in the HOR matrix. The final list includes 14 key steps, such as better production planning, improved information sharing, standardizing SMR selection, operator training, quality control, and infrastructure maintenance. Together, these steps provide a clear, data-driven plan to make Social Manufacturing more reliable and resilient. This research is valuable in two ways: it shows that the HOR method works well in the complex setting of Social Manufacturing in Industry 4.0, and it provides organizations with a structured, quantitative way to manage risks arising from distributed production, IoT, and collaboration. Future research could build on this by using real-time IoT data, simulations, and predictive analytics to improve risk monitoring and response.

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