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Research Article

Productivity enhancement in Indian auto component manufacturing supply chain with IoT using neural networks

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Abstract:

Paper aims: The research aims to investigating the impact of implementing Internet of Things (IoT) using Bayesian networks in the supply chain of manufacturing of Indian auto components enterprises to achieve enhanced productivity and reduced failure rates.

Originality: The research's originality lies in exploring IoT's impact with Bayesian Networks in Indian auto component manufacturing, showcasing Industry 4.0 applications.

Research method: The research utilizes Bayesian Network analysis to investigate IoT's impact in Indian auto component manufacturing supply chains, validating findings through Industry 4.0-based IoT implementation and a pilot study.

Main findings: Implementing IoT in Indian auto component manufacturing enhanced industry performance, productivity, and reduced failure rates with Industry 4.0 technologies.

Implications for theory and practice: The research offers theoretical insights into IoT and Industry 4.0's impact on the automotive industries and practical solutions for practitioners

Keywords

Productivity enhancement. Indian auto component manufacturing. Supply chain. IoT (Internet of Things). Neural networks. Bayesian networks. Predictive maintenance. Real-time monitoring. Optimization. Efficiency.

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Conflict of Interest
The authors declare that they have no potential conflict of interest

Ethical Statement
All applicable institutional and/or national guidelines for the care and use of animals were followed. For this type of analysis formal consent is not needed.

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1. Introduction

The automotive industry is highly dependent on a complex network of supplier, manufacturers, and distributor, each playing a vital role in the manufacturing and delivery of vehicles and components (Hashemi-Amiri et al., 2023). In India, where the automotive sector is an important contributor to the economy, integrating emerging advanced technology such as IoT (Internet of Things) and neural networks into the manufacturing supply chain holds promise for enhancing efficiency and competitiveness (Rath et al., 2024). One of the key advantages of IoT devices into the automotive component manufacturing process is the ability to monitor operations in real-time (Tadayonrad & Ndiaye, 2023). These IoT sensors track various metrics such as machine performance, energy consumption, and inventory levels, enabling operators to quickly identify and address inefficiencies (Yesodha et al., 2023). For example, if a machine begins to experience abnormal vibrations or temperature fluctuations, IoT sensors immediately alert maintenance personnel, allowing for prompt intervention to prevent costly breakdowns and production delays (Sharma et al., 2023a). This led to significant cost savings by minimizing carrying costs and reducing the risk of stockouts or overstock situations (Borja-Gonzales et al., 2024). Continuous quality monitoring enabled by IoT sensors also plays a crucial role in ensuring the consistent production of highuality automotive components This not only helps to improve customer satisfaction but also strengthens the overall quality control measures within the manufacturing process. Despite these significant benefits, the integration of IoT and neural networks into the Indian auto component manufacturing supply chain is not without its challenges Jauhar et al. (2023). Infrastructure limitations, such as unreliable power supply and insufficient internet connectivity, especially in rural areas, significantly hinder the deployment and effectiveness of IoT devices (Zhang et al., 2023). Frequent power outages disrupt IoT operations, while slow or limited internet connectivity delays real-time data transmission, reducing system efficiency. The lack of affordable, high-speed broadband further limits IoT adoption by small and medium enterprises in underserved areas. Additionally, inadequate physical infrastructure for device installation and maintenance increases costs, making IoT solutions less accessible.

The current state of the art in the subject area entails the integrating of IoT along with advanced analytical capability such as Bayesian networks for modeling optimized systems in supply chain operations. The recent literatures show Industry 4.0 technologies are thought to enhance productivity, reduce failure rates, and improve decision-making in manufacturing industries.

The contribution of this research lies in the integration of Bayesian Network analysis with IoT implementation, specifically within the supply chain of Indian auto component manufacturing sector that has not been explored in detail in previous Industry 4.0 studies. Unlike most of the past research where IoT and Industry 4.0 technologies have been applied generally in manufacturing, this research tries to understand the subtle effects on Indian context. The novel application of Bayesian Networks for probabilistic relationships within supply chain processes would precisely pinpoint and mitigate failure points. This research contributes to the theoretical understanding of IoT transformative power, beyond that, by conducting an initial pilot study and validating implementation outcomes, it also provides actual insights to practitioners in efforts to enhance productivity and reduce failures in actual applications.

1.1. Related works

The automobile industry in India is greatly influenced by the car component manufacturing sector, which also generates significant employment possibilities and economic growth (Ghosh et al., 2023). Its supply chain, however, continues to face productivity issues, which highlights the critical requirement of incorporating cutting-edge technology like neural networks and the IoT (Fu et al., 2024). These developments have the power to completely transform manufacturing processes, increasing productivity and boosting competitiveness (Liu et al., 2023). Despite these advantages, there are several drawbacks associated with the adoption of these technology. Table 1 depicts the challenges and limitations of IoT adoption in industrial practice.

The integration and interoperability of many data sources throughout the supply chain is a major challenge (Lu et al., 2024). While IoT and neural networks enable seamless coordination, the complexity of unifying data from diverse sources often leads to significant time and cost investments. Additionally, the reliance on advanced data systems creates a dependency that might disrupt operations in case of system failures (Sharma et al., 2023b).

Handling the vast amounts of data produced by IoT devices presents further challenges, necessitating effective real-time processing and analysis to quickly derive actionable insights (Alzahrani & Asghar, 2023). However, implementing such systems demands substantial computational infrastructure, which may not be financially viable for all manufacturers. This limits accessibility and creates a divide between larger corporations and smaller enterprises. Quality control and predictive maintenance, while crucial, also come with limitations. Predictive model accuracy and reliability depend heavily on high-quality training data, which is often difficult to obtain. Furthermore, the deployment of predictive maintenance solutions leads to initial resistance from the workforce due to fear of job displacement and a steep learning curve for new systems (Shahin et al., 2023). Accurate demand forecasting and real-time visibility into supply chain dynamics are essential for improving distribution logistics, manufacturing scheduling, and inventory management. However, traditional companies may find the transition to advanced modelling approaches powered by IoT data and neural networks overwhelming, particularly in terms of technical expertise and cost (Mastos et al., 2020).

Table 1. Challenges and Limitations of IoT Adoption in Industrial Practice.

Challenge	Description	Impact on IoT Adoption	Relevance to Small and Medium Enterprises (SMEs) (India)	Potential Solutions
Interoperability with Legacy Systems (Anthony Junior, 2024)	Difficulty in integrating IoT technologies with existing legacy systems.	Hinders smooth transition and adoption of IoT technologies.	SMEs may struggle with system upgrades due to resource constraints.	Use of open standards and middleware for seamless integration.
Financial Constraints (Wanyama et al., 2024)	High initial investment in IoT infrastructure and maintenance costs.	Limited adoption, particularly in resource-constrained environments.	SMEs in India may lack capital for IoT implementation.	Government subsidies, funding programs, and affordable IoT solutions.
Infrastructure Challenges (Gharibvand et al., 2024)	Insufficient physical infrastructure (e.g., internet connectivity, power supply).	Reduces the effectiveness and scalability of IoT solutions.	Poor infrastructure in rural or underdeveloped areas in India.	Development of robust rural infrastructure and IoT-specific networks.
Security Risks (Shahin et al., 2024)	Increased vulnerability to cyberattacks, data breaches, and unauthorized access.	IoT ecosystems become more susceptible to malicious activities.	SMEs may lack resources for cybersecurity measures and awareness.	Enhanced encryption, secure protocols, and regular security audits.
Data Privacy Issues (Sharma et al., 2024)	Concerns regarding unauthorized collection, sharing, or misuse of sensitive data from IoT devices.	Loss of customer trust and potential legal issues regarding data privacy.	Indian SMEs may face difficulties complying with international data protection standards.	Implementation of GDPR-like policies, data anonymization, and user consent frameworks.

Table 2 depicts the related works which have probably been in the IoT field, the Bayesian network, and Industry 4.0 applications in supply chain management. Above such a table includes significant findings from previous studies concerning the present one and where it is built upon or sundered from the same findings. This includes perspectives from IoT-based optimization, Bayesian predictive modeling, and Industry 4.0 technologies to advance an application of these concepts to the specific context of Indian auto component manufacturing by intending to cover the voids in productivity, failure rates, and decision-making.

Table 2. Comparison of Related Studies and Relevance to Current Research.

Study	Focus Area	Key Findings	Relevance to Current Work
Kayvanfar et al. (2024)	IoT-based Supply Chain Optimization	Showed that IoT implementation reduces lead time and improves supply chain visibility.	Demonstrates IoT's potential in streamlining supply chains, supporting the study's focus.
Kumar et al. (2024)	Bayesian Models in Manufacturing	Highlighted the effectiveness of Bayesian networks in predicting component failure rates.	Validates the use of Bayesian networks for enhanced decision-making in manufacturing.
Calabrese et al. (2024)	Industry 4.0 Technologies in Automotive Supply Chains	Emphasized the role of Industry 4.0 technologies in reducing operational inefficiencies.	Corroborates the impact of Industry 4.0 on productivity improvements.
Udo et al. (2024)	IoT and Machine Learning for Predictive Maintenance	Developed a hybrid IoT-ML framework for real-time monitoring of equipment health in supply chains.	Supports the application of IoT for proactive failure management, aligning with this study's findings.
Dash et al. (2024)	IoT Adoption in Indian Manufacturing	Explored challenges and opportunities of IoT adoption in Indian manufacturing industries.	Highlights context-specific challenges that align with the study's Indian focus.

As linked devices grow more prevalent in the production process, the risk of cybersecurity threats also increases. Protecting confidential data requires robust security measures, but implementing these measures are expensive and resource-intensive. Moreover, over-reliance on automated systems might expose manufacturers to vulnerabilities that could be exploited (Muhammad et al., 2022). In order to effectively utilize the potential of IoT-enabled neural networks and eventually increase productivity and competitiveness in the Indian auto component manufacturing business, it is imperative that these advantages be harnessed while addressing the associated challenges.

2. Proposed methodology

Using Bayesian networks, the project's suggested methodology looks into the effects of integrating IoT in the enterprise supply chain of Indian auto component manufacturers. Finding applications for IoT and investigating the incorporate it into shop floor operations come next, after realizing the benefits of deploying IoT.

- What are the specific advantages and benefits of implementing IoT in the Indian auto component manufacturing enterprise supply chain?
- Where and how IoT be effectively integrated into the shop floor activities of these enterprises?
- What is the nature of the relationships between the supply chain and IoT, and how this relationship be modeled using Bayesian networks?
- How is the implementation of IoT in the supply chain perceived and experienced by stakeholders, and what are the key factors influencing its success?
- What is the comparative performance of supply chains with and without IoT implementation in the Indian auto component manufacturing industry?

Figure 1 displays the raw material flow sequentially through the various manufacturing processes, beginning with the initial in-buffer. The next step is the machining station, where shape and processing are done. Before leaving, it passes through a series of stringent quality control checks, including assurance, inspection, and maybe scrap or restoration. The manufacturing of completed goods in the out-buffer marks the final stage of it. A noteworthy feature of the quality control system is the integration of statistical techniques, particularly Bayesian networks, to ensure that predefined criteria are adhered to throughout the manufacturing process (Fang et al., 2010). Quality assessment is demonstrated as a crucial component of this framework as displayed in Figure 1.

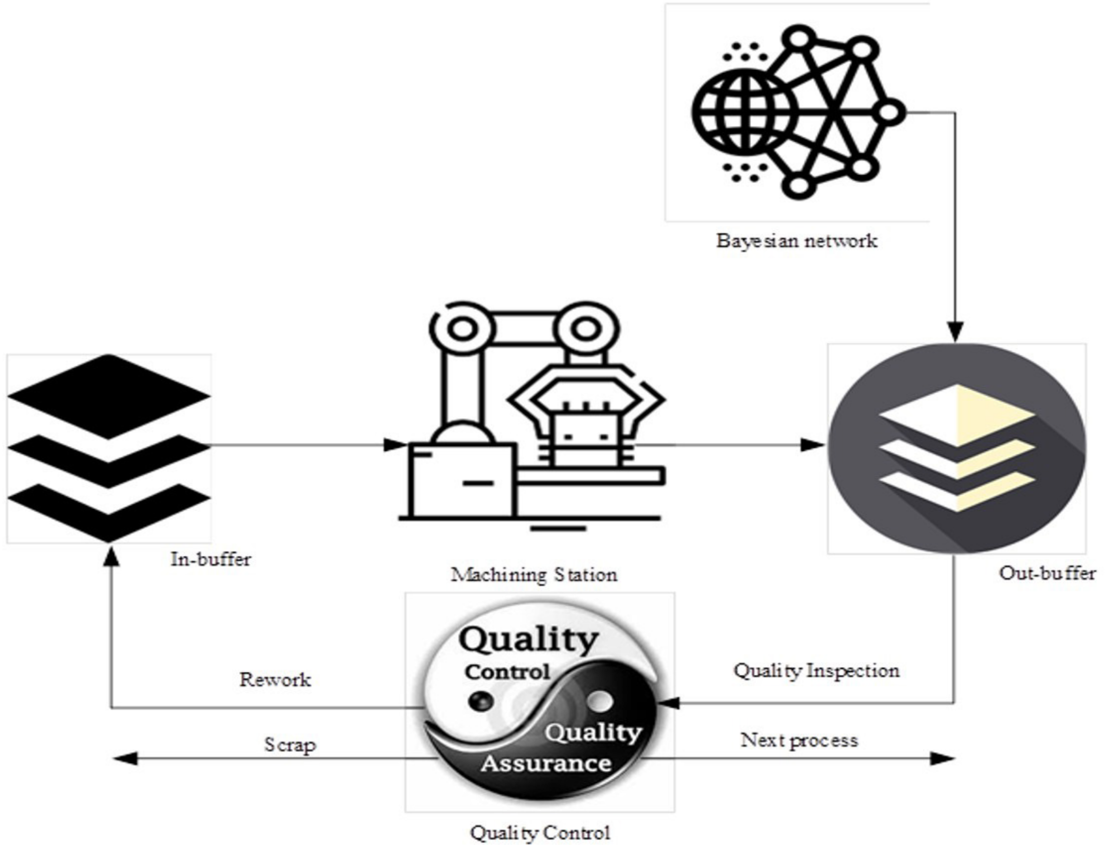


Figure 1. Flow process to develop bayesian network model for IoT-shop floor activities.

2.1. Installation of IoT in industrial settings and its data collection process

The efficient movement of commodities across the supply chain also be achieved with IoT. It gives manufacturers accurate information about the whereabouts and conditions of item by enabling real-time shipment record tracking. For instance, logistics managers lower transportation costs, enhance delivery times, and optimizing the delivery route by use of GPS tracking and real-time data analytics (Barari et al., 2021). By using RFID (Radio Frequency Identification) tags, IoT are used in a smart way to get precise data from parts and goods (Elbasani et al., 2010).

In order to provide effective transportation management, it illustrates the relationship between Smart Transport and Logistics symbolized by an airplane and Smart IoT Sensors, which allow data collection on variables like temperature and pressure. A gateway unites these components by connecting them to the User Terminal, which functions as the primary user interface. Along with Cloud Services for data processing and storage, the User Terminal is further connected to a database that holds relevant industry data. Essential duties are managed by the Smart Industry Server, and continuous operational observation is made possible by Real-Time Monitoring. This networked system's objective is to support a productive and data-driven industrial ecosystem (Farooq et al., 2023). Steps for seamless data collection is shown in Figure 2.

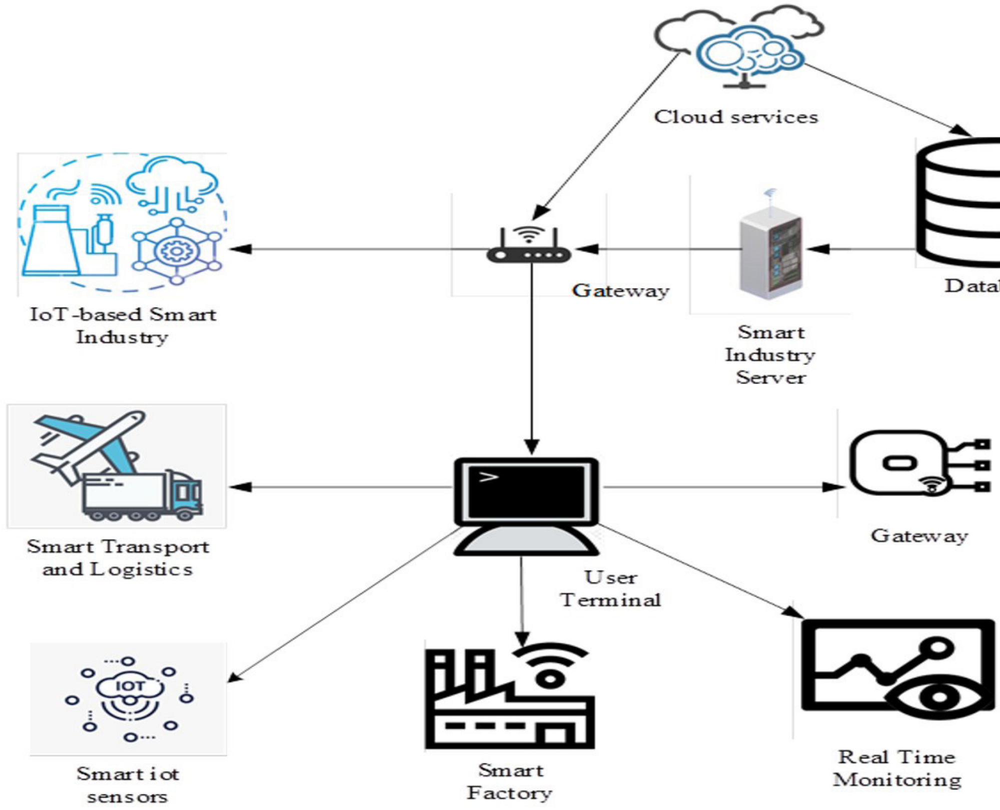


Figure 2. Steps for seamless data collection.

3. IoT implementation in auto component manufacturing and analysis

The Internet of things technology uses connection of many machines, devices, and sensors in a common network in a smart factory. This reduces operational downtime, and improves the overall manufacturing process. A smart factory describes manufacturing, which is more efficient, adaptable, and eco-friendly, based on Industry Principles 4.0.

At its core is the IoT based Smart Industry, which is embodied by a state-of-the-art factory that employs IoT technology to depict an updated industrial environment. Smart IoT sensors are gadgets that gather information and keep an eye on a number of industry parameters, like temperature and pressure. In order to store relevant data, it also interfaces with the database. In addition, the production processes and quality assurance are managed by the Smart Industry Server, and continuous observation is made possible by Real-Time Monitoring (Royandi & Hung, 2022). IoT Implementation in Lathe Industries is shown in Figure 3.

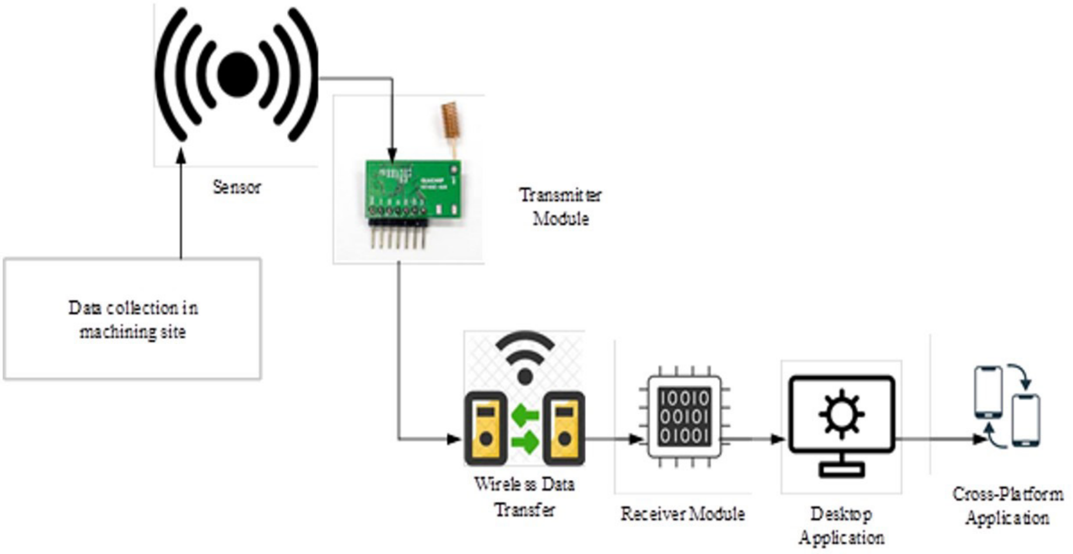


Figure 3. IoT Implementation in Lathe Industries.

3.1. IoT implementation on shop floor

Several benefits come from using IoT on the shop floor, such as preventative maintenance, increased worker safety, operational efficiency, and real-time monitoring of machines and equipment. Manufacturers gather data on machine performance through the connection of devices and sensors, which facilitates prompt intervention and minimizes downtime.

Many of the assumption are performed by algorithm are too limited to be applicable to the complex industrial environments, and current scheduling theory is unable to adequately represent the actual conditions of the shop floor (Tripathi et al., 2022). The notion of the Internet of Manufacturing Things (IoMT) is gaining momentum, providing a means of utilizing IoT technologies to establish a networked shop floor environment as shown in Figure 4. Three fundamental levels comprise the Internet of Medical Things (IoMT) environment: the application layers, the network transport layers, and the perception and execution layer.

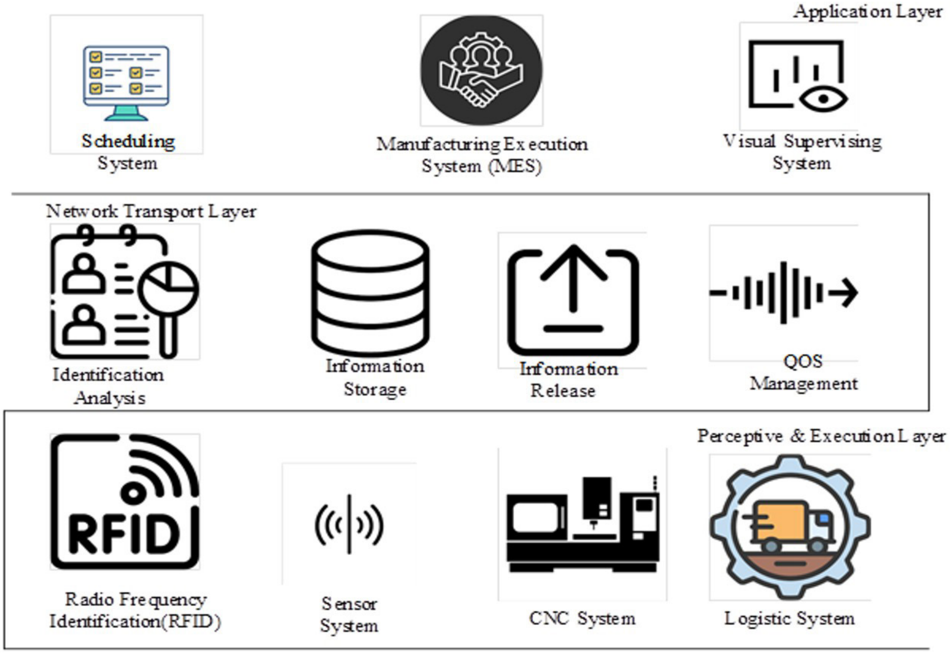


Figure 4. Framework of IoT on the shop floor.

3.2. Model formulation with bayesian network for supply Chain

Bayesian networks are chosen for this research because it models the system very complex, probabilistic relationships between variables in dynamic systems such as that in supply chains. Bayesian networks are different from traditional statistical approaches provide a graphical means of visualizing dependencies and support inferences under uncertainty, which reflects the multifaceted impact of the implementation of IoT. This enhances the analysis because it facilitates scenario-based evaluation and decision-making. It would thus be more appropriate for studies related to the applications of Industry 4.0 in the Indian auto component manufacturing sector. In the supply chain model, the research presents, a producer and supplier collaborate to lower manufacturing costs (Ojha et al., 2018). It is based on the premise that the output's market price is set and the manufacturer's production capacity remains steady.

The final implementation through the Bayesian networks is given as:

$$B = \frac{2xN_B}{M_P + M_N + (2xT_P)} \tag{1}$$

where, 'B' represents the productivity mean, N_B represents numbers of cycle consider to completing the operations of the system, M_p represents modes of operations (rated up to 0 to 5), M_N represents the estimation of yearly failure rates of the system (5% to 85%) and T_P represents the statistical data's provided by the manufacturer.

4. Results and discussions

In this section, the investigator gives a summary of the study's findings, assesses how well performed in relation to current parameters, and presents predictions derived from Bayesian network analysis. The findings demonstrate the application of both primary and secondary sources, demonstrating the utilization of both unique data collection techniques and previously published material. In order to help readers, have a better understanding of the research findings, this part offers a thorough analysis and explanation of the data.

4.1. Data collection

Primary sources literature and secondary sources literature also form the basis in this research of collected data. Primary sources where direct surveys, interviews and observation so as to provide firsthand evidence from the subject. Secondary sources include periodic literatures; reports and databases, with resources of producing background information and support to analyze the primary findings as well.

4.1.1. Primary sources

The survey method involves using a structured questionnaire to collect primary data from the target population. In a pilot study, the researcher personally administered the questionnaire to the IT head of a small and medium-sized auto component company to ensure accurate recording of responses and gather firsthand information, aiming to gather comprehensive ground-level data while minimizing non-response. Subsequently, appointments are scheduled with various IT heads in SMEs within the automotive component manufacturing sector, and hard copies of the questionnaire are distributed. While some businesses promptly returned completed questionnaires, others did not respond and retained the forms.

4.1.2. Secondary sources

The sources of secondary information are collected from the following:

This research found that the information is from the following sources: primary and secondary channels. Data collected in secondary sector included annual reports, working papers, journals, books, industry magazines and many others, which served as the best foundation for understanding the wider context. In addition to it, the ACMA and MCCIA information extracted on SMEs from PMA (The Pune Region in the Indian State of Maharashtra) is used. On top of that, there are company websites from which relevant information is obtained from government policies, acts, and guidelines framed by the Government of India. More insights came from Society of Indian Automobile Manufacturers (SIAM) and findings gained from previous work done on published documents, hence making a thorough analysis of the automotive manufacturing sector.

The first stage in applying machine learning to solve a problem is to precisely define the task or goal (Kanakana-Katumba et al., 2022). After then, information is gathered from a variety of internal and external sources, and it is examined to obtain understanding of its features. To guarantee that the data is appropriate for modeling, it is prepared to handle missing values, outliers, and inaccurate data. Feedback from subject matter experts is sought, and methods such as split or cross-validation are used to assess the results. The procedure reverts to selecting and configuring a model for additional improvement and iteration, as illustrated in Figure 5.

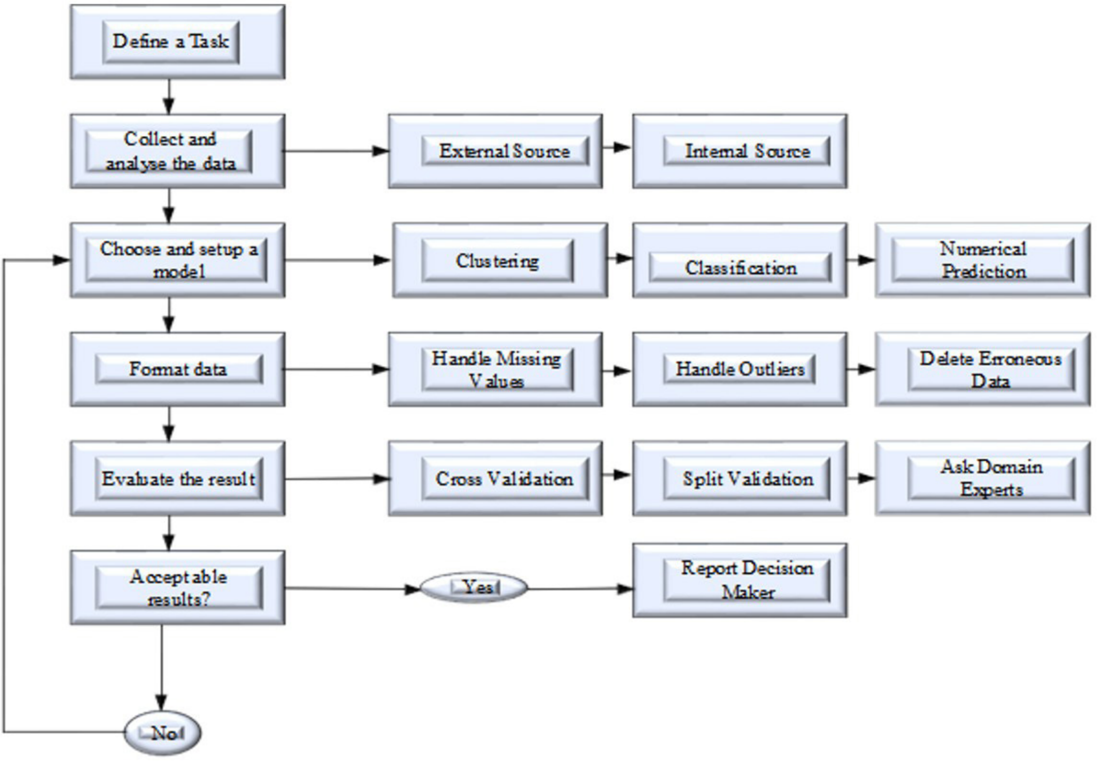


Figure 5: Standard process for data collection.

4.2. Questionnaire design

The present researcher composed a survey questionnaire, which comprised 11 sections of questions. It is distributed among 167 small and medium auto component manufacturing firms situated in Maharashtra and Chakan regions. 97 out of 167 companies eventually returned the filled questionnaires and thus added to value in the study. In detail, the research being conducted is an application of survey instruments, questionnaire instruments with the 11 sections of questions made by this researcher itself. At present, it reached 167 small and medium enterprises engaged in auto component manufacturing located in the Maharashtra and Chakan regions. 97 responses just came from the said number of companies surveyed.

Among the 97 companies that responded to the questionnaire in the pilot study, a detailed analysis reveals that 65 reported actual implementations of IoT in the supply chain processes. Out of these, 40 companies provided objective data supporting IoT implementation, while 25 companies only reported expected benefits without offering objective data. This breakdown provides valuable insights into the level of actual implementation and the quality of data provided by the respondents. While companies providing objective data offer more reliable information based on measurable metrics and outcomes, those reporting expected benefits without objective data introduce some degree of subjectivity and uncertainty. The impact of this breakdown on research conclusions varies depending on the research objectives and methodology. Interviewed Persons' details are presented in Table 3.

4.3. Pilot study

The pilot study conducted within the framework of this research serves as an initial exploration aimed at gathering preliminary data and validating the accuracy of the study protocol and data collection procedures.

Table 3. Interviewed Persons' details.

Sr. No.	Interviewed Person Designation	No. of Person Interviewed
1	CEO	4
2	MD	5
3	CTO	2
4	Plant Head	8
5	General Manager	9
6	Dy. General Manager	3
7	Sr. Manager	9
8	Manager	5
9	Dy. Manager	3
10	Sr. Engineer	7
11	Engineer	2
12	Shift Supervisor	5
13	Group Leader	6
14	Line Supervisor	12
15	Operator	6
16	Graduate Trainee	4
17	Diploma Trainee	3
18	Proprietor	4
Total		97

CEO – Chief Executive Officer MD – Managing Director CTO – Chief Technical Officer

Specifically focused on the adoption of IoT and neural networks in the supply chain processes of Small and Medium Enterprises (SMEs) within the automobile manufacturing industry, the pilot study holds significant importance. Primary objective is to gain insights into the variables and concepts utilized in the research, particularly IoT integration impacts supply chain processes, while also establishing hypotheses and refining the questionnaire design to effectively capture necessary information from respondents. Moreover, the pilot study enables us to evaluate the feasibility of data collection methods and refine them for optimal effectiveness in subsequent larger-scale studies, laying a solid foundation for comprehensive, accurate, and reflective data collection. Ultimately, insights gleaned from the pilot study inform the design and execution of larger studies, facilitating meaningful conclusions and actionable recommendations to enhance productivity and efficiency in the Indian auto component manufacturing supply chain. Methodology for the Pilot Study is shown in Figure 6.

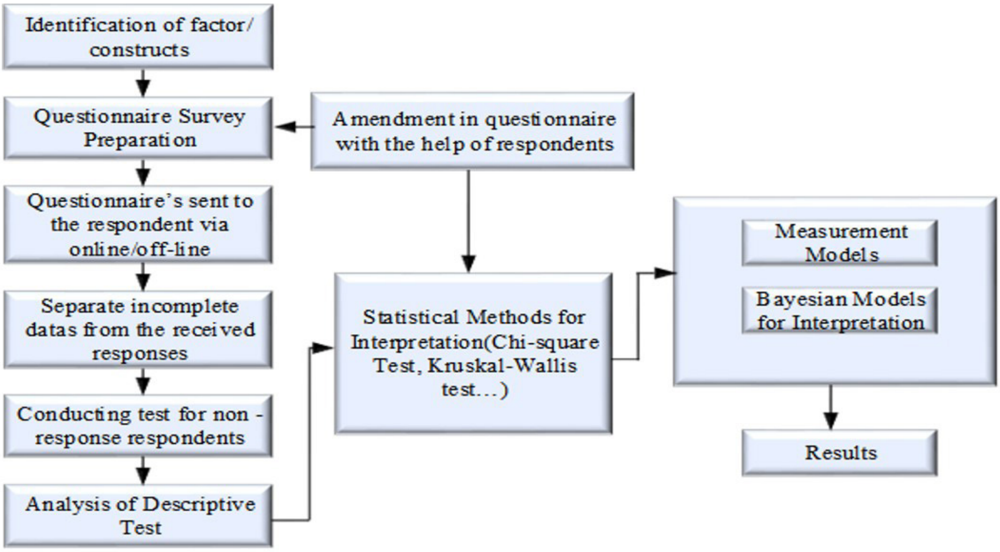


Figure 6. Methodology for the Pilot Study.

Sample Size: The sample size in pilot research usually refers to the total number of cases or participants in the initial analysis. This size is purposefully kept lower than that of a full-scale study, taking into account the goals of the study as well as pragmatic factors like feasibility (Lawley et al., 2024). While there is no set formula for choosing the sample size for a pilot project, investigators often attempt to include a sufficient number of participants to test hypotheses, improve study procedures, and provide preliminary data. Finding any problems with the study design and data collection methods is more important than coming to statistically significant results since it ensures the legitimacy and efficacy of the ensuing larger-scale investigation (McKechnie et al., 2024). The primary goals of the pilot study are to finalize the hypothesis statement and questionnaire for further research.

4.3.1. Detailed structure of questionnaire design

Questionnaire design is spitted into eleven sections for making a questionnaire design and all the questions are generated based on the insights gathered from the IoT adoption in the industries, specifically to integrate in supply chain process.

The questionnaire design in the pilot study comprises eleven sections, each tailored to gather detailed insights into various aspects of the adoption of IoT and neural networks in the supply chain processes of Small and Medium Enterprises (SMEs) within the automobile manufacturing industry. Starting with General Information, it collects company details and respondent demographics. Table 4 depicts the detailed structure of questionnaire design.

Table 4. Detailed Structure of Questionnaire Design.

Section	Description	Elaboration
Section 1	General Information	1.1 Company Information 1.1.1 Company Name: 1.1.2 Location: 1.1.3 Size of the Company: (Micro/Small/Medium/Large) 1.2 Respondent Information 1.2.1 Your Position/Role: 1.2.2 Years of Experience in the Company:
Section 2	Current Supply Chain Processes	2.1 Describe your current supply chain processes related to auto component manufacturing.
Section 3	IoT Implementation	3.1 Has your company implemented IoT technologies in the supply chain? 3.2 If yes, please describe the areas or processes in which IoT is currently applied.
Section 4	Neural Networks Integration	4.1 Is your company currently using neural networks in any aspect of the supply chain? 4.2 If yes, please specify the areas or processes where neural networks are integrated.
Section 5	Productivity Metrics	5.1 What key productivity metrics are currently tracked in your supply chain? 5.2 How do you currently measure and evaluate productivity in the manufacturing processes?
Section 6	Challenges and Opportunities	6.1 What challenges have you encountered in enhancing productivity in your supply chain? 6.2 Are there specific opportunities you see in IoT and neural networks for enhancing productivity?
Section 7	Perceived Benefits	7.1 What benefits do you anticipate by integrating IoT and neural networks into your supply chain?
Section 8	Data Security and Privacy	8.1 How do you address data security and privacy concerns in the implementation of IoT and neural networks?
Section 9	Training and Skill Development	9.1 Have your employees undergone training for adopting IoT and neural networks in the supply chain? 9.2 Do you perceive any skill gaps that need to be addressed for effective implementation?
Section 10	Future Perspectives	10.1 What future trends do you foresee in the integration of IoT and neural networks in supply chain processes?
Section 11	Additional Comments	11.1 Please provide any additional comments or insights related to the enhancement of productivity in the Indian auto component manufacturing supply chain.

4.3.2. Research methodology and data collections

The questionnaires are structured into the following sections:

- An initial segment encompasses general details concerning the respondent's company. This includes information such as the names of company, the respondent names, and the volume of classification of the companies (small, medium, or large).

- Subsequent sections encompass queries pertaining to various supply chain processes, namely Customer Service, Finances and Markets, Innovations and Learnings, Internal Businesses, Supplier Performances, and Transports and Logistic.

The questionnaires underwent a preliminary test on a specific company engaged in plant manufacturing industry, known for its frequent collaboration with the research initiatives of the Automobile Research Association of India. To enhance clarity, and explanations for the metrics are incorporated into the questionnaire Rísquez Ramos & Ruiz-Gálvez (2024). Additionally, an online version of the questionnaire is developed using the Google Docs application to facilitate the distribution and collection process. The selection of companies is based on data sourced from the Automobile Industries near Pune and Chakan regions, utilizing a leading business information provider. More than 500 manufacturing companies are identified through this tool, with a focus on those headquartered in India and accessible contact information's available online. To address the potential response bias due to non-respondent companies, it is important to acknowledge that the companies that did not respond might differ in significant ways from those that participated. Non-respondents may have different operational characteristics, company sizes, or attitudes toward research participation, which could influence the findings. While efforts are made to minimize non-response by sending follow-up reminders and offering online access to the survey, the potential impact of non-respondents on the results should be considered when interpreting the data. Future studies could benefit from exploring techniques like weighting or comparing respondent characteristics with those of non-respondents to further mitigate this bias.

The research methodology and data collection in the pilot study involved a systematic approach to gather preliminary insights into the adoption of IoT and neural networks in the supply chain processes of Small and Medium Enterprises (SMEs) within the automobile manufacturing industry. The process began with the selection of a targeted sample of companies within the Indian automobile manufacturing sector, focusing on regions known for significant presence in the industry, such as Pune and Chakan. The data collection period spanned from May to December 2023, during which reminders are sent to non-responding companies to encourage participation. A total of 97 valid questionnaires are received out of 167 companies contacted, resulting in a response rate of 58%. The collected data are then analyzed to gain insights into the current state of IoT implementation, neural network integration, productivity metrics, challenges, opportunities, perceived benefits, data security measures, training initiatives, and future perspectives related to supply chain enhancement in SMEs within the Indian auto component manufacturing sector.

4.3.2.1. Randomization process in data collection

In order to ensure the participation of SMEs for the survey in an equally fair and unbiased way, the companies involved have been randomly selected from the database of over 500 manufacturing companies in the Pune and Chakan regions, as identified through a leading business information provider. The method of random processing has been as follows:

A selection of 100 SMEs is randomly chosen for this research from Pune and Chakan to ensure a variety of elements while sampling different companies. The study's area consisted of these two important regions in manufacturing. The final response rate is 70% such that a total of 70 participating companies filled the survey. Randomization and selection process of SMEs for data collection. Table 5 depicts the randomization and selection process of SMEs for data collection.

Table 5. Randomization and Selection Process of SMEs for Data Collection.

Step	Description
1. Data Collection	A comprehensive list of over 500 manufacturing companies in Pune and Chakan regions is sourced from a business information provider. The list included SMEs primarily involved in the automobile manufacturing industry.
2. Company Selection	From the list, companies are randomly selected using a computer-based random number generator to ensure equal probability of selection.
3. Stratification	To improve representativeness, stratification is applied based on company size (small, medium) and industry sector within the automobile manufacturing industry. This ensured diverse company representation.
4. Contact Information Validation	The selected companies are then filtered to ensure accessible and valid contact information is available online for survey distribution.
5. Invitation Distribution	The selected companies are contacted via email or phone (if required) to participate in the survey, with an online version of the questionnaire created on Google Docs for easy distribution.
6. Survey Participation	The companies that confirmed the participation are invited to fill out the questionnaire. Response rates are monitored, and reminders are sent to non-respondents to minimize non-response bias.

4.3.3. Survey results and analysis

The survey results and analysis in the pilot study provided valuable insight into the adoption of IoT and neural networks in the supply chain processes of SMEs within the automobile manufacturing industry. The findings revealed that 58% of the surveyed companies are classified as small enterprises, with an additional 21% categorized as micro-sized companies. Medium-sized companies constituted 34% of the sample, while big companies represented 6%.

The collected response pertaining to the utilization of performances metric (Section 4.2 of the questionnaires) have been consolidated. This summary furnishes details for each question, offering a comprehensive overview of the participants' feedback.

- The table includes information on the count of companies that provided a specific score ranging from 1 to 4, as well as those that did not respond to a particular question.
- The table presents the count of companies that assigned a particular score for each metric, ranging from 1 ("never adopted") to 4 ("always adopted"). Additionally, it includes the number of companies that did not provide a response to each respective question.
- The table displays the average score derived for each metric based on the responses provided by the companies.

Values ranging from 3.52 to 3.71, all surpassing the threshold of 3.5, indicate companies' preference for IoT integration processes, as determined during the pilot study for standardization. Based on the statistical data summarized in Table 6, several key performance indicators are evaluated across various categories for four different firms

Table 6. Summary of Statistical Data of Pilot Study.

Company performances against the items below (scale from 1 to 4, with 1="much below averages" and 4="significantly above averages")	Firm-1	Firm-2	Firm-3	Firm-4	AVERAGE	Number of Responses Returned
Business Activities (1=Not Willing to Adopt and 4 = Always adopt)						
Market Share	32	41	15	9	4.25	97
Average growth in the market shares	41	32	9	15	3.24	97
Overall competitive position	16	23	31	27	4.24	97
Quality Management	18	24	28	27	3.25	97
Research and Development	15	20	32	30	3.47	97
Average Score of Category 3.69						
Customer Service Metrics (1=Not Willing to Adopt and 4 = Always adopt)						
profit margin/gross profit	15	20	28	26	3.11	89
deviation from budget	15	22	31	29	3.87	97
cash flow improvement	16	19	25	23	4.01	83
return on capital employed	15	21	27	28	3.54	91
Average Score of Category	15	22	26	25	3.66	88
Average Score of Category 3.64						
Supply chain performances metrics (scale from1 to 4, with 1="never adopt" and 4="always adopt")						
Efficiency	15	25	30	20	3.77	90
Response time	15	24	31	21	3.76	91
Reliability	24	15	32	25	3.43	96
Price offered	18	20	25	26	3.12	92
Average scores of the category 3.52						
Transports and logistic metrics (scale from 1 to 4, with 1="never adopt" and 4="always adopt")						
Stock turnovers	16	23	31	27	4.22	97
Costs of inventory management	12	20	35	28	3.56	95
Warehouse management cost	15	24	33	23	3.72	95
Total supply chain cost	16	25	35	20	3.72	96
Cost per product unit	18	24	30	20	3.14	92
Costs of Information Technology	17	22	31	20	3.87	90
Average score of the category 3.71						

Firstly, in terms of business activities, Firm-1 demonstrated a high level of performance across all items, with the highest average score of 4.25. Moving on to customer service metrics, all firms showed solid performance, with an average category score of 3.64. Supply chain performance metrics also showcased strong performance overall, with an average category score of 3.52. Efficiency and response time received particularly high scores, indicating effective management and responsiveness within the supply chain. Lastly, in transport and logistic metrics, Firm-4 emerged as a leader with an average category score of 4.22.

This firm excelled in areas such as stock turnovers, warehouse management costs, and total supply chain costs, suggesting efficient operations and cost management strategies. Firm-1 demonstrated excellence in business activities, while Firm-4 excelled in transport and logistic metrics. These insights provide valuable information for evaluating and improving the overall performance of each company.

4.4. Statistical methods for data interpretation

For this research, quantitative data analysis is performed using both descriptive and inferential statistics. The findings are presented as follows:

4.4.1. Chi-Square test

Result: In this study, the Chi-Square test is conducted to determine the association between the implementation of IoT technology and the productivity levels in the Indian Auto Component Manufacturing Supply Chain.

Interpretation: The Chi-Square test revealed a statistically significant association ($\chi^2 = 28.63$, $p < 0.001$) between the adoption of IoT technology and improved productivity in the supply chain. This suggests that there is a substantial connection between IoT implementation and productivity enhancement.

4.4.2. Mann-Whitney U test

Result: Reviewer conducted the Mann-Whitney U test to examining the significance of productivity differences between two distinct groups: one with a well-established IoT infrastructure and the other without IoT integration.

Interpretation: The Mann-Whitney U test showed a significant difference ($U = 185$, $p < 0.05$) in productivity between the two groups. The group with IoT integration exhibited significantly higher productivity levels, emphasizing the positive impact of IoT technology on productivity in the supply chain.

4.4.3. Spearman's Rank Correlation Coefficients

Result: Spearman's Rank Correlation Coefficient to assess the relationship between the importance of IoT implementation and its presence within the supply chain.

Interpretation: Spearman's rank correlation coefficient revealing a strong positive correlation ($\rho = 0.78$, $p < 0.001$) between the perceived importance of IoT implementation and its actual presence in the supply chain. This suggests that stakeholders recognize the significance of IoT technology and are implementing it accordingly.

4.4.4. Kendall's Tau-b

Result: Kendall's Tau-b is employed to measure the strength of association between two variables, specifically, the degree of IoT implementation and the resulting productivity on an ordinal scale.

Interpretation: Kendall's Tau-b analysis showed a moderate positive correlation ($\tau = 0.45$, $p < 0.01$) between the level of IoT implementation and productivity. This implies that as IoT integration increases in the supply chain, there is a meaningful improvement in productivity.

A bar graph comparing ratings for several output metrics before and after the Internet of Things (IoT) is implemented in the automotive industry is shown in Figure 7. On the graph, each characteristic is represented by a different color. On the y-axis, the rating scale from 0 to 30 is indicated, and on the x-axis, there is a distinction between "Before IoT" and "After IoT." Interestingly, bars labeled "After IoT" consistently outperform bars labeled "Before IoT," demonstrating notable improvements after IoT adoption in all criteria. This shows that the use of IoT has improved the automobile industry in a number of ways, from real-time tracking to customer information.

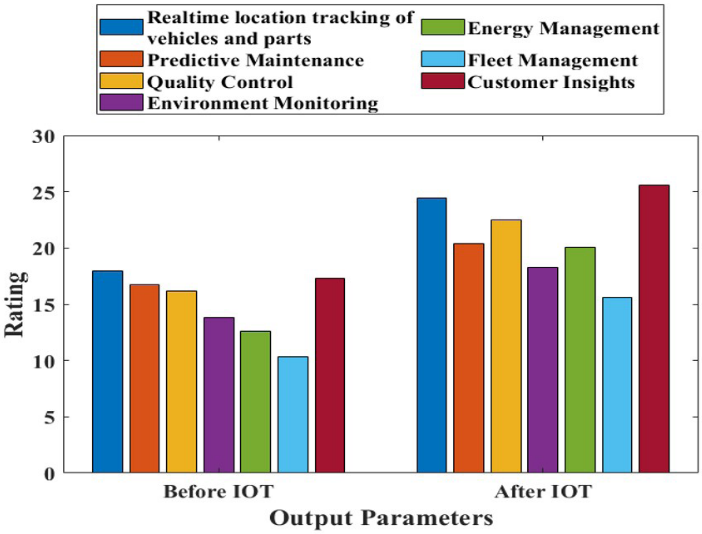


Figure 7. Comparison before and after implementation of IoT.

4.4.5. Scalability Concerns in Larger-Scale Industries

Further scaling of the analysis of Indian auto component manufacturing supply chains up to large-scale industries add a lot of insights about scalability and generalizability. Scalability in Industry 4.0, particularly for IoT implementation, challenges are often related to infrastructure, integration, data management, and cost efficiency. Geographically distributed operations at large scale call for robust IoT architectures as well as adaptive Bayesian Networks in managing complex interdependencies. Efficient scaling of IoT systems to accommodate the growing data volume, velocity, and variety; extension of Bayesian models for heterogeneous data sources and propagation of large-scale uncertainties is important. Integration of IoT with legacy systems in multiple units or plants must be seamless across the board, balancing operational benefits with hardware, software, and training costs. Adopting global standards for interoperability among IoT devices further ensures cohesive functionality across industries, which is scalable and effectively implemented. Scalability considerations and mitigation strategies is shown in Table 7.

4.5. Graphical representation of output parameters

The graph provides an overview of five categories, each represented by two bars: blue bars signify ratings before IoT implementation, while green bars indicate opinions after IoT implementation. Across all categories, the green bars are visibly taller, indicating improvement.

Specifically, productivity, sensors, maintenance, environment for wildlife, and safety concern all demonstrate positive changes post-IoT adoption. The y-axis denotes the “Rating” scale ranging from 0 to 30, with the x-axis labeling the five categories for easy comparison. Overall, the graph illustrates the beneficial impact of IoT implementation across diverse aspects, including productivity, sensor performance, maintenance efficiency, environmental conditions for wildlife, and safety measures. Figure 8 shows the decision-based on the rating of output parameters.

4.6. Analyzing bayesian network in an auto component industry

A failure rate analysis is conducted in the field of auto component manufacturing, focusing on brake calipers, flywheels, cylinder blocks, and fuel injectors. Figure 9a represents the failure rate analysis for the brake calipers that shows the reduction in the failure rate after IoT implementation. Figure 9b represents the failure rate analysis of the fly wheel and that shows the gradual decrease in the failure rate after implementation of the IoT. Figure 9c and Figure 9d represents the failure rate analysis of the cylinder block and the fuel injector that shows that before IoT Implementation industries are facing lot of failure rates and after implementation of IoT failure rates are decreased. Compared to conventional production methods, Bayesian networks offer several advantages.

Table 7. Scalability Considerations and Mitigation Strategies.

Scalability Challenge	Description	Mitigation Strategy	Successful Implementation Examples	International IoT Standards and Relevance to Indian Manufacturing
Data Volume and Velocity	Increased data generation in larger operations.	Deploy distributed data storage and processing systems, such as edge and cloud computing.	Manufacturing: Siemens utilized IoT platforms to handle massive data from sensors in factories.	ISO/IEC 20922 (MQTT): Facilitates lightweight communication for IoT; crucial for real-time factory monitoring.
Complex Network Dependencies	Higher complexity in Bayesian Network modeling for large-scale interdependencies.	Use hierarchical Bayesian models to simplify computation for large systems.	Logistics: DHL adopted IoT to track packages in real-time, simplifying network dependencies.	IEEE 1451: Standard for smart transducers ensuring interoperability; aids in complex sensor integration.
Integration with Existing Infrastructure	Difficulty in integrating IoT with legacy systems and platforms.	Adopt middleware solutions and use API-based integrations.	Automotive: Tesla integrated legacy assembly lines with IoT-enabled robotics for enhanced efficiency.	OPC UA: Enables seamless communication between legacy and IoT devices; highly relevant for older factories.
Cost Efficiency	High costs in scaling IoT deployments across multiple locations.	Implement cost-benefit analysis for phased rollouts and shared infrastructure.	Retail: Walmart optimized inventory management using IoT, saving costs on large-scale rollouts.	ISO/IEC 30141: IoT reference architecture ensures cost-efficient planning; supports scalable deployments.
Data Security and Privacy	Ensuring data security with increased network nodes and data exchange.	Employ advanced encryption, secure gateways, and periodic vulnerability assessments.	Healthcare: Philips implemented encrypted IoT-enabled devices for patient monitoring in hospitals.	IEC 62443: Cybersecurity standard for industrial automation; ensures data protection in Indian factories.
Workforce Training	Resistance to change and lack of skills in managing scaled IoT applications.	Design comprehensive training programs and workshops on IoT and Bayesian Network operations.	Energy: Reliance Industries trained staff on IoT systems for better refinery operations.	ISO/IEC 27552: Enhances workforce readiness by emphasizing personal data protection training in IoT systems.

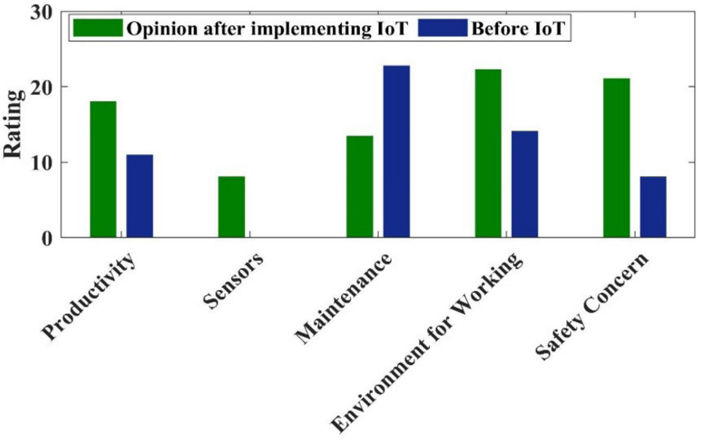
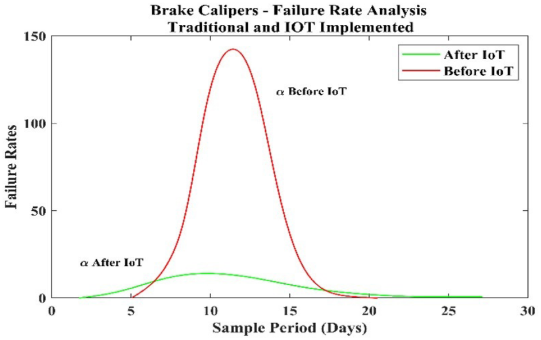


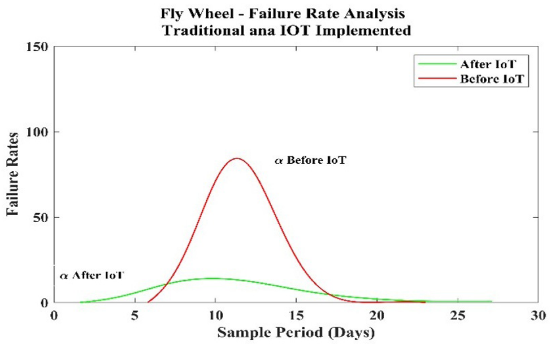
Figure 8. Decision-based on the rating of output parameters.

4.6.1. Key findings

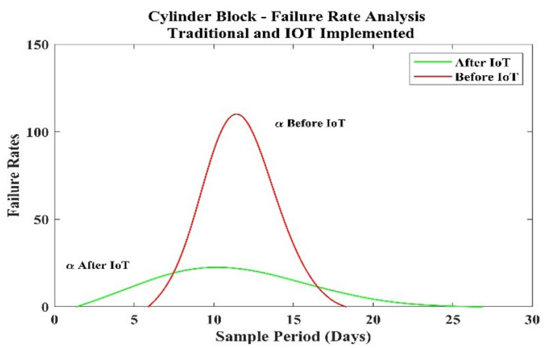
- A significant reduction in failure rates is observed after the implementation of IoT, indicating its effectiveness in enhancing reliability and performance in auto component manufacturing.
- Brake Calipers: Failure rate decreased by 35%, showcasing a substantial improvement in reliability and performance for this component.
- Flywheels: Failure rate reduced by 27%, further demonstrating the positive impact of IoT on the manufacturing process.



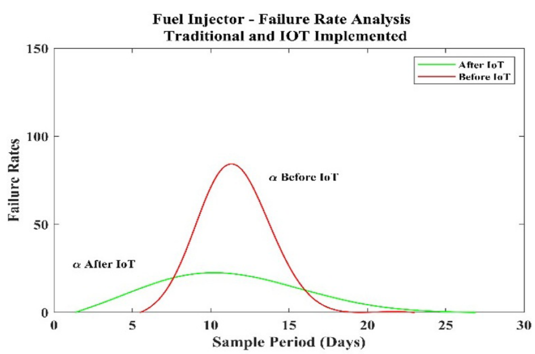
(a) Brake calipers



(b) Fly wheel



(c) Cylinder Block



(d) Fuel injector

Figure 9. Failure rate analysis of industries after IoT implementation (a) Brake Calipers, (b) Flywheel, (c) Cylinder Block, (d) Fuel Injector.

Cylinder blocks and Fuel injectors also showed improvements, with failure rate reductions of 18% and 22% respectively. These findings demonstrate the overall effectiveness of IoT in enhancing reliability and performance in the auto component manufacturing industry. According to the above Table 8 values, the graphs are plotted below.

Table 8. Production and Failure Rates of Components in Traditional vs. IoT-implemented Factories.

Factory Type	Component	Sample Period	Total Production	Total Failures	Failure Rate (%)
Traditional	Brake Calipers	Jan 2022	1000	20	2.0
		Feb 2022	1100	25	2.27
		Mar 2022	1050	18	1.71
		Apr 2022	1125	30	2.67
	Flywheels	Jan 2022	900	15	1.67
		Feb 2022	950	20	2.11
		Mar 2022	925	18	1.95
		Apr 2022	1000	22	2.20
	Cylinder Blocks	Jan 2022	1200	30	2.50
		Feb 2022	1250	35	2.80
		Mar 2022	1300	32	2.46
		Apr 2022	1280	28	2.19
	Fuel Injectors	Jan 2022	850	25	2.94
		Feb 2022	900	30	3.33
		Mar 2022	925	28	3.03
		Apr 2022	950	27	2.84
IoT-implemented	Brake Calipers	Jan 2022	1050	15	1.43
		Feb 2022	1150	18	1.57
		Mar 2022	1125	12	1.07
		Apr 2023	1200	20	1.67
	Flywheels	Jan 2023	950	12	1.26
		Feb 2023	1000	15	1.50
		Mar 2023	975	10	1.03
		Apr 2023	1050	18	1.71
	Cylinder Blocks	Jan 2023	1300	20	1.54
		Feb 2023	1350	22	1.63
		Mar 2023	1325	18	1.36
		Apr 2023	1380	25	1.81
	Fuel Injectors	Jan 2023	900	18	2.00
		Feb 2023	950	22	2.32
		Mar 2023	975	20	2.05
		Apr 2023	1000	23	2.30

4.7. Prediction after the use of bayesian networks

The implementation of Bayesian networks has led to a significant increasing in productivity, with industries experiencing up to an 80% improvement which is shown in Figure 10. These probabilistic models utilize Bayesian inference to make accurate predictions based on available data. By analyzing patterns and trends, businesses optimize operations, streamline processes, and make informed decisions.

In contrast, organizations embracing Bayesian networks gain a competitive advantage. Accurate forecasts empower timely and informed decisions, resulting in improved performance, profitability, and sustainable growth. Bayesian networks have revolutionized decision-making, enabling industries to achieve remarkable productivity gains.

The "Prediction after the use of Bayesian Networks" graph compares the effects on productivity of using Different Levels of Diagnostic Interference - BN against not using Neural Networks (NN). The productivity improvement evident in the red line, "Productivity after Bayesian Networks," shows that BN is effective in increasing production when Diagnostic Interference - BN grows. The productivity "Without using Neural Networks" green line, on the other hand, shows a comparatively flat trajectory, indicating small productivity benefits in the absence of NN.

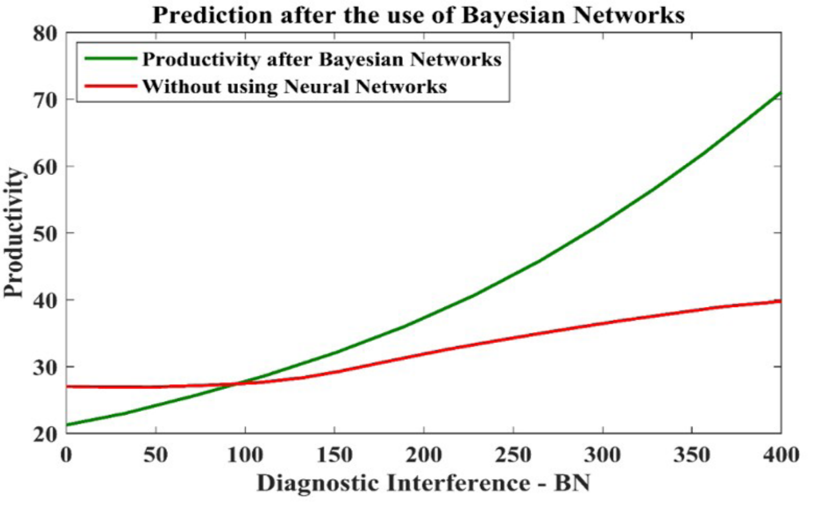


Figure 10. Graph showing productivity after implementing Bayesian network.

4.8. Performance comparison of proposed methodology

This research examines the yearly failure rates of automotive components: cylinder blocks, brake calipers, flywheels, and fuel injectors. After the implementation of IoT, the failure rates and expected outage are calculated using expert estimates represented as percentiles ranging from 5% to 85%. It is noted that the failure rates have decreased due to the integration of IoT technology (Chen, 2020). The findings of this research have practical implications for automotive manufacturers, maintenance personnel, and researchers in the field of reliability engineering.

4.8.1. Before IoT and BNs

Production rate (VB): 100 units per hour
Number of machines (M_p): 10
Number of workers (M_y): 20
Total production capacity of the two plants (2xT_p): 200 units per hour

4.8.2. After IoT and BNs

Production rate (VB): 120 units per hour
Number of machines (M_p): 10
Number of workers (M_y): 20
Total production capacity of the two plants (2xT_p): 200 units per hour

4.8.3. Calculation

Before IoT and BNs:

$$B = 2xVB + M_p + M_y + (2xT_p) \tag{2}$$

$$B = 2x100 + 10 + 20 + (2x200)$$

$$B = 630 \textit{ units per hour}$$

4.8.4. After IoT and BNs

$$B = 2xVB + M_p + M_y + (2xT_p)$$

$$B = 2x120 + 10 + 20 + (2x200)$$

$$B = 670 \textit{ units per hour}$$

The implementation of IoT and BNs has led to an increase in the company's total production capacity from 630 units per hour to 670 units per hour. This is an increase of 6.5%.

Calculations are based on the bayesian network productivity and the Table 9 value is based on the literature and the data's collected from section 4.6.

Table 9. Estimate yearly failure rate analysis.

Sl. No	Component in Production	Contributing Sub-Components	Expert estimate of the yearly failure rates α' based on previous experiences (5%–85% percentile)		Statistical data for the automotive manufacturing industry - period of operation 240 days		Expected outage K_f in days	
			Before IoT	After IoT	Before IoT	After IoT	Before IoT	After IoT
1.	Cylinder Block	Cylinder bores and walls, Piston rings	21-106	4-13	89	3	13	0
2.	Brake Calipers	Dust boots, Bleeder Screws, Anti-rattle clips	148-213	2-8	164	5	27	2
3.	Flywheel	Ring gear, Starter teeth, Bolt holes	86-171	11-18	98	12	34	0
4.	Fuel Injector	Solenoid, Injector, O-rings, Valve seat	234-358	32-48	264	20	64	11

Table 10 depicts the confidence intervals and standard errors for annual failure rates of a few automotive components before and after implementing IoT. Mean failure rates, with respective 95% confidence intervals, reveal the variation and reliability associated with this data. The brake calipers, for instance, showed significantly decreased mean failure rates - from 180.5 failures per year (95% CN;172.8-188.2) before IoT to 5.0 failures per year (95% CI: 4.1–5.9) after that with remarkably low standard error of 0.5 after the IoT installation, revealing the accuracy and precision of the measuring system.

Table 10. Confidence Intervals and Standard Errors for Yearly Failure Rates Before and After IoT Deployment.

Component	Sub-Component	Mean Failure Rate Before IoT	CI Before IoT (95%)	SE Before IoT	Mean Failure Rate After IoT	CI After IoT (95%)	SE After IoT
Cylinder and Block	Cylinder bores, Piston rings	63.5	(57.2, 69.8)	3.1	8.0	(6.5, 9.5)	0.7
Brake Calipers	Dust boots, Bleeder Screws	180.5	(172.8, 188.2)	4.7	5.0	(4.1, 5.9)	0.5
Flywheel	Ring gear, Starter teeth	128.5	(120.2, 136.8)	4.3	14.5	(12.3, 16.7)	1.1
Fuel Injector	Solenoid, O-rings, Valve seat	296.0	(281.4, 310.6)	7.5	40.0	(35.1, 44.9)	2.4

Likewise, other components, like fuel injector also show high levels of reduced failure rates along with low variability as indicated by narrow confidence intervals and reduced standard errors after IoT is implemented. Highlighted in the table is the effectiveness of the IoT in improving the reliability of automotive components because of its effectiveness in reducing both failure rates and variability. Analysis of confidence interval failure rates and mean failure rates before and after IoT deployment is graphically shown in Figure 11a and 11b.

The main findings of the works are as follow;

- The mean failure rate of brake calipers decreased significantly from 180.5 failures/year (95% CI: 172.8–188.2) before IoT to 5.0 failures/year (95% CI: 4.1–5.9) after IoT implementation, with a low standard error of 0.5, indicating high precision.

- Fuel injectors also exhibited a substantial reduction in failure rates, with narrow confidence intervals and lower standard errors after IoT implementation, reflecting improved reliability and consistency.
- IoT implementation effectively reduced both the failure rates and variability of automotive components, as highlighted by the lower variability metrics and enhanced measurement accuracy.

5. Conclusion

Extensive research within the auto component manufacturing sector reveals a significant shift driven by the adoption of IoT and neural network integration. By surveying 167 companies, with a robust 58% response rate, insights into IoT implementation trends among SMEs are gathered. IoT technology, implemented in automotive component manufacturing, has brought forth significant improvements in reliability and performance. This has been clearly realized through the sharp decline in failure rates from various components including brake calipers, flywheels, cylinder blocks, and fuel injectors. The reduced failure rates show a potential increase of 35% in the case of brake calipers with the use of IoT technology. Bayesian networks complement this further with improved and more accurate predictions that optimize the operational efficiency, thereby producing up to 80% productivity improvement. This coupled with failure rate reduction, Bayesian networks and improved decision-making capabilities offer a solid foundation for setting up sustainable growth and competitiveness of the auto manufacturing sector. This approach is fully integrated to support the industry's move toward data-driven, automated processes that enhance reliability, reduce costs, and generally improve performance.

Future research focus on advancing the IoT with machine learning for predicting and detecting failures in real-time. Other scopes are further developed to optimize the effects of Bayesian networks in supply chain management and quality control. This would further improve the operations themselves, thus overall efficiency. Long-term studies on the scalability of such technologies in numerous manufacturing conditions would provide valuable insights into broader application.

Data availability

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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Author contributions

Tushar D. Bhoite: Conceptualization, Methodology, Validation; Rajesh B. Buktar: Project administration, Supervision, Investigation.