IoT based Data-Driven Methodology for Real Time Production Optimization and Supply Chain Visibility in Smart Manufacturing and Logistics

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Abstract: - This research looks at how data methods and IoT technologies can be used effectively for planning and improving supply chain transparency. It seeks to explain the importance of measurements namely cycle time, lead time, on-time delivery, inventory turns, and fill rate. Analyzing the company objectives and requirements based on the identified ones, the study underscores the paramount importance of KPI visualization in helping the users comprehend organizational processes and seek improvement. The study also explores how the effectiveness of the IoT infrastructure is assessed and how the IoT devices are chosen and subsequently deployed for strategic purposes and the building of real-time data acquisition systems. In addition, the article also covers the approaches with regard to data acquisition and assimilation; more focus is given to the understanding of the performance of the machine, conditions of the environment, and the logistical aspects by means of data visualization of the IoT. The study also emphasizes data quality governance mechanisms to ensure the accuracy and comprehensiveness of IoT data, and thus make people more confident in data reliability.

Key-Words: - IoT infrastructure, Operational management, Data-driven decision-making, Supply chain visibility, Real-time analytics, Industry 4.0 technologies.

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1 Introduction

New advances in manufacturing cyber-physical systems have paved the way for great transformationist directions in industrial processes. This research based on information from recognized sources including Capgemini, Deloitte, IoT World Today, Management Events, McKinsey, PAC, PwC, and SME, is centered on using Internet of Things (IoT), big data analysis, and industrial artificial intelligence (AI) to enhance real-time production material flow and decision-making. It focuses on the application of I REC, A RS, P M, and S, in an effort to enhance industrial performance. Our work revolves around the concept of autonomous production collaboration for data-driven smart transformation alongside supplementation for industrial units. It highlights the enhancement of automation control and efficiency as well as varying manufacturing systems testing the use of smart linked devices through dispersed and reconfigurable manufacturing engineering systems. In addition, collaborative robots become regarded as an integral part of establishing decentralized and cooperative production systems. It is surprising that many manufacturing companies have not invested in predictive maintenance and manufacturing dynamic monitoring strategies, which combined with results from multiple industry reports and surveys, are analyzed in this article to ensure operational stability and flexibility. Additional descriptive statistics obtained from aggregated self-report survey data serve to strengthen the arguments presented, presenting empirical confirmation of the effectiveness of the presented technological interventions within SC-IPM and analogous cyber-physical manufacturing systems, [1].

Smart technologies have ushered in a pattern in production logistics that provides solutions to conventional issues perceived to have low visibility and high systematized bureaucracy. Although much discussion has been brought to the more generic use of smart technologies in manufacturing and logistics, literature still lacks studies focusing on these systems' implementation and effects on the level of production logistics. In response to this gap, this paper performs a systematic literature review involving 142 articles to examine the link between smart technologies and production logistics. This study identifies and defines ten technology groups relevant to production logistics and divides the production logistics operations into three main domains based on the applicability of each group to various production logistic activities. In general, the article is also based on a quantitative share evaluation, thus demonstrating the significance of these technologies for the overall range of production logistics processes. Furthermore, the research investigates the overriding goal of these technical implementations: concerning the creation of market-related worth. While the analysis illustrates the "production logistics data lifecycle" framework and underscores a need for a balanced and integrated approach to technology management, the major value of the study lies in its call for linking IT enhancement efforts with strategic organizational goals and objectives. Last but not least, the findings of this article lay down a simpler framework for moving from a literature study to a data-driven state in production logistics, thereby offering an understanding of the applications and use cases as captured in the literature for the chosen technologies, [2].

In the context of supply chain management (SCM), IoT, Ml, BD, and blockchain elements give a reasonable approach to the attempt to address existing research deficits and enhance the effectiveness of a manufacturing process. This research looks at the ability of Industry 4.0 technologies for decision-making and smart manufacturing within the SCM frameworks. There are several dilemmas inherent in current SCM systems that are: System major complexities; Scalability issues; Operating costs; and Volatility under dynamic demand situations. Despite these challenges, the article suggests that there is huge potential for new solutions in SCM processes in today's unpredictable markets. Also, the presented paper investigates how individual components of Industry 4.0 influence SCM practices, with specific emphasis given to the understanding of how IoT, machine learning, Big Data, and blockchain can address operational issues and enhance supply chain preparedness. Thus, in more detail, the paper presents how these technologies could dramatically transform the conventional SCM best practices, introducing greater transparency, identification, and, most importantly, forecasting. Furthermore, the paper introduces a new six-layer architecture of Industry 4.0 components that, in combination with theoretical and conceptual contributions to this paper, contributes to developing smart production planning and decision-making within SCM frameworks as a blueprint. The paper is therefore written to provide a roadmap through which the industry players and scholars themselves can unleash the change that Industry 4.0 brought forth in the supply chain management realm, [3].

The concept of production logistics, which has long been regarded as an organizationally marginal and technologically simple activity that does not create additional customer value as it has been conventionally executed with limited degrees of automation and digitalization, has been experiencing a standard shift because of the current technological developments. The steadily growing framework for real-time data collection now represents a critical enabler of smart production logistics and offers corporations the potential to implement more effective and accountable data-driven solutions supporting intrasite logistics systems. Nevertheless, this is a promising approach for the development of advanced control systems, but the experience that has been accumulated on the topic is still limited in terms of real industrial applications and the problems that arise when implementing changes of such type. This paper will therefore seek to fill this gap by presenting a critical analysis of the opportunities and challenges likely to be faced when implementing data allowanced production logistics, from an industrial survey conducted on a manufacturing firm in the international pharmaceutical industry. The study identifies technical enablers that are critical for data-driven solution deployment using existing frameworks for data-driven manufacturing. The projected benefits of the data-driven approach are measured through performance metrics comparing the future state with the SCOR framework's five essential performance criteria: dependability, responsiveness, agility, cost, and asset utilization. The results illustrate the aspects of change resulting from the adoption of a data-based approach and focus mainly on the lead time, resource and space management, the Arrangement of logistics operations, and integration of production logistics. Yet the analysis also reveals the great challenges faced in carrying out such schemes, including the deficit of requisite competencies; technological constraints; an absence of genuine strategic direction; and concerns regarding data custody. The major contribution of this research is the analysis of a case study from an actual industry in order to gain a valuable understanding of the potential benefits and disadvantages associated with the application of intelligent, data-based production logistics systems, [4].

Drawing on the notion of the Industrial Internet of Things (IIoT), digital sterilization (DS) has become an imperative conceptual platform for guaranteeing sustained manufacturing competitiveness. Substantial studies stress the need to have clear data models to facilitate the channels of many-to-many communication of IoT devices to achieve the general idea of DS. 'Such models are crucial when it comes to avoiding the development of isolated systems, supported solely by proprietary solutions and to encourage the data sharing between current and future DS applications.' In response to this critical need, this research offers a comprehensive data model particularly created for menggunakan komunikasi multichannel dalam IIoT DS dengan tumpuan smart production logistics (SPL). Three significant implications come out of this paper, which analyzes material handling at a manufacturing firm. First, there is a consideration of the paper containing, the conceptual model with four modeling profiles and IIoT devices, databases, and services for multichannel communication support. Second, it elaborates on the way these modeling profiles facilitate information flows for succeeding tasks, including monitoring, control, optimization, and auto-decision services. Lasting, the study focuses on the real effectiveness of the proposed data models to achieve improvement in the delivery efficiency, reduction in the manufacturing span, and optimization in energy to the material handling process of the IIoT-enabled DS for SPL; These findings signify the importance of the efficient collection, storage, and dissemination of information over goods, services, and software databases of the IIoT-enabled DS for SPL. Hence, they are of interest to both manufacturing managers and researchers to offer useful knowledge about the implementation of IIoT-based DS in production logistics. In addition, the present work contributes to advancing the knowledge base concerning the complex issues surrounding the deployment of IoT enabler for DS inside manufacturing systems, [5].

This global diversification of markets has called for companies to add more complex distribution networks hence the supply chain complications. That is, on the one hand, the Element outlines a number of ways to diversify supply chain operations to meet the requirements of Hoje's challenging temores, and on the other, it poses threats to the supply chain visibility and-generated organizations' fundamental business processes. However, these challenges call for research to establish how Digital Twins could be incorporated into logistics supply networks to improve visibility. In this paper, the author conducted SRR, which was followed by comprehensively reviewing 227 articles published between 2002 and 2021, using the ATLAS.ti 9 software. Among them, 104 were considered as essential to the extent of the study planned, for analysis and discourses. Surprisingly, this article is one of the first to tackle the supply chain visibility concerns based on the Digital Twins within the scope of logistics. The research outcomes affirm Digital Twins' utilization in creating logistics performance indicators, diagnostics, forecasts, and detailed physical asset descriptions for companies. In addition, the research provides recommendations on how to minimize deployment issues related to Digital Twins in the logistics sector. For researchers, this review lays a basic framework for integrating and enhancing the existing solutions and for discovering new avenues for their investigations. From the managerial side, the research highlights the directions of possible search for future strategies and technologies to mitigate logistics problems and outlook for new solutions to adapt to increasing future needs. Altogether, this paper helps to extend the knowledge of how Digital Twins can improve SC visibility and provides suggestions for researchers and managers who look for ways of facilitating LM within complex SC networks, [6].

This pursuit of competitiveness in manufacturing industries has placed the global supply chain in focus with organizations looking to harness great strides made in smart manufacturing in performance. The challenges that are operational within today's business environment include short and volatile product life cycles, outsourcing, intensification of product differentiation, outsourcing, and focusing on the customer and technology. All of the above make supplying chain management a little difficult to handle hence the reason why companies insist on seeking new ways to deal with the complexities of new manufacturing environments. Smart manufacturing has now become an innovation to the Industrial revolution with innovative technologies that are resource-oriented, flexible and possess high maneuverability due to the increased use of internet technologies and innovative engineering solutions. In this paper, the customers and business value processes have been explained to be the means through which smart manufacturing activities shape an improved manufacturing environment for better operation performance. In its initial phase, this research aims to perform a literature review within the scopes of smart and digital manufacturing. Fostering from previous literature review, it is the intention of this study to provide examples of best practices and methodologies to identify similarities and differences with an end view of coming up with detailed systematic findings that highlight key research studies in the field. This paper is a literature review prepared for a proposal aiming to uncover the advantages of the SM concept and the resulting improvement of performance in value chains. Through the review of the literature and examination of the examples identified within this study, an attempt is made to add to the knowledge of the ways in which smart manufacturing enables a supply chain of the future, [7].

The use of Industry 4.0 technologies has shown efficacy where performance changes and other efficiencies and non-delays within manufacturing plants. Of these plants, automotive manufacturing plants are set to benefit a lot from these technologies based on the fact that most of these technologies can be applied universally throughout the manufacturing process. Although it could be very rigorous to make an overall evaluation of all procedures that take place in the automotive industry this paper conveniently limits the evaluation of key areas, specifically the operations of; logistics and supply chain. The goal of this article is the identify the possibilities for the diffusion of Logistics 4.0 and Supply Chain 4.0 in the automotive industry plants in Bulgaria. To this end, a survey specific to the needs of the study was constructed and completed by 12 participants in the automotive logistics field with experience in six diverse logistics roles. These insights indicate that some Industry 4.0 technologies, including network connectivity of the assembly line and blockchain, can have valuable implications for the logistical improvement of supply chains. Nevertheless, the survey also reveals cybersecurity threats and related problems with improper data as major difficulties that prevent the attainment of such advantages. Thus, based on the understanding of the indicated views from the representatives of the manufacturing industry, this article contributes to the development of certain recommendations regarding the specific usage and prospects of Logistics 4.0 and Supply Chain 4.0 in the automotive industry of Bulgaria. Finally, this study adds knowledge to the identified directions in using Industry 4.0 technologies for enhancing logistics and supply chain management in the automotive industry perspective, [8].

Robotics connectivity with IoT is arguably one of the remarkable advancements in the Industry 4.0 world, decisive for the evolution of the smart manufacturing structure. This chapter examines the possibility of integrating these two technologies in order to shape the future developments of smart IoT technologies. Starting with the definitions of the concept of IoT and robots, the chapter defines their significance in promoting the Industry 4.0 model. It underlines the prospects of smart factories IoT-integrated and the necessity of collecting, processing, and executing decisions based on the data in production contexts. Altogether, the chapter stresses the importance of the use of robots and IoT systems in constructing smart manufacturing environments. On the positive side, it expects enhanced levels of automation, efficiency, and productivity from this integration. However, it also indicates the importance of removing similar challenges to completely unlock this synergy and escort in the emerging age of smart IoT technology, [9].

Many challenges present themselves to the manufacturing industry due to the rapid growth of ICT, coupled with the ever-evolving global economy. Market issues that may affect the organizations involve include short product life cycles, declining stability of the market, and growing demand for customized products. Supply problems arise simultaneously due to higher demands for production flexibility and the growing complexity of supply chain activities due to progress in Information, Communication, and Production Technology (ICPT). In order to solve these issues, this research defines the concept of an SMSC model by integrating ICPT into conventional supply chain models. The work examines the qualities of SMSCs in order to identify both the functional and structural characteristics of SMSCs. SMSC relies on supply planning, which requires returning optimal decisions within pseudo-real-time, thus constrained by planning horizons. Therefore, the research develops a new tactical supply planning framework for SMSCs to achieve the best profitability lead time balance. The concept of supply throughput with respect to a planning horizon: the SSCP model defines the optimal supply throughput and therefore also acts as the performance indicator for SMSCs. The proposed model is thoroughly analyzed and validated with large numerical analysis and offers helpful managerial applications to enhance the functionality of the supply chain within SMSCs. This work contributes to the knowledge advancement of smart manufacturing and supply chain management in the modern manufacturing industry, [10].

Ensuring the timely availability of production materials so as to support the stability of discrete manufacturing systems. Nevertheless, the variability and uncertainty that characterize the production context constitute significant challenges to the planning of production logistics (PL). Consequently, there is the Internet of Things (IoT), which provides data on the real-time processes' progress and the possibility of turning to dependable choices. This work focuses on the optimal design of PL based on real-time data under uncertain manufacturing conditions. Firstly, a mathematical scheduling model for developing broadcast distribution schedules with fuzzy time windows is created to minimize distribution costs in the presence of fluctuations in material demand over time. An improved ant colony algorithm is next created, where the satisfaction degree the width of the time window, and the state transfer rules are included, as well as the dynamic adjustment of pheromone levels. To further illustrate the real-time sensing and location suggested in the method presented are applied and explored in a machining workshop feasibility case study. Actual simulation integration is performed to compare the efficiency and the possibility of the proposed approach. This work contributes to the advancement of PL optimization techniques in industrial applications by collating literature research and leveraging IoT technology progress. The proposed strategy indicates the possibilities of enhancing the flexibility and effectiveness of activities in discrete manufacturing systems; within time, these results in greater performance and competitiveness, [11].

The great interest in smart factories and supply chains proves the transformational potential of such elaborate solutions as 3D printers, IoT, and cloud services. This research investigates a new method of dynamic supply-chain architecture and operations: connected smart production lines where the various production lines are interconnected through the cloud for the realization of custom manufacturing. Customers may upload their product designs into this system leading to the automatic development of a right supply chain design and operation based on the existing resources of the network of smart factories. The article delves into the notion of smart supply chains, highlighting six major categories of flexibility that are critical to their success: This literature identified the various types of flexibility, namely design flexibility, product flexibility, process flexibility, supply chain flexibility, collaboration flexibility, and strategic flexibility. Specific to supply chain design and planning is supply chain flexibility and the text provides a basic framework for planning and a host of models for supply chain design and operations planning. Qualitative comparisons of fixed, production, and transport costs are made for faced situations using numerical experiments. The identified results explore the dynamic character of supply chain design, and correspondingly the design and operations of the supply chain and also the high variability of the transportation costs. First, this research enhances the regulated knowledge of the DSCM in smart factories and supply chains by integrating the literature concepts and proposing novel frameworks, and optimization models. The quantitative simulation outcomes provide valuable information about the issues and opportunities associated with the utilization of dynamic supply chain design and operations–centred strategies for sophisticated supply chain planning and management, [12].

2 Research Methodology

Studied the fact that requirement changes are inevitable in software development projects therefore adequate understanding of the changes and efficient management of such changes is paramount. All these modifications, embraced by new and unsolved customer demands, shifting rules of business, and shifting fields of operation, therefore highlight the importance of wisely dealing with the field of Requirements Change Management (RCM). The inability to manage requirements changes appropriately and integrate that has been pinned down as a key reason why projects fail. Thus, there has been a vast amount of literature developed on RCM, investigating its factors and discussing its directions for improvement. Nevertheless, with much of the literature already explored, there is a clear deficiency discernable which outlines where research is most likely to thrive. This paper aims to fill this gap by proposing a systematic review of published literature on RCM with reference to a methodological framework that can be used to examine diverse aspects of the discipline. It is required to try to elaborate on this subject through a structured question asking about the nature, process, methods, as well as examples of decision-making processes to change requirements management. The analysis not only construes the existing state of practices in RCM but also identifies sectors that require further academic research and development. By analyzing the findings to understand the relative advantages and limitations of dominant approaches to RCM studies, this research equips software practitioners with viewpoints for protecting RCM decision-making from pitfalls. Finally, this undertaking aims at promoting greater comprehension of RCM conditions with a view to stimulating innovation that would strengthen the ability to predict project planning outcomes and – by extension – improve chances for project success.

Sought to admit the Industry 4.0 announcers in the context of the business models to invoke the attention of the scholars and practitioners to its effect and possibility for innovation. This article begins a short literature review that seeks to complement existing works in extending the understanding of how Industry 4.0 permeates business models and creates new sources of creativity. An attempt was made in this study to review the literature, as well as identify the nature of changes to business models as a result of Industry 4.0, and to distill innovations that may arise from this phenomenon. The inquiry uncovers a range of features, concerns, and specifications relevant to positioning in Industry 4.0 playing fields while setting the stage for solutions. The three approaches service orientation, networked ecosystems, and customer orientation, provide strategic directions where firms can adopt the Industry 4.0 ethos. Also, it explains the implications of value creation, delivery, and capture brought by Industry 4.0-enabled changes in business models. Finally, it brings together four main tracks indicating distinct degrees of of business model transformation due to digitalization. From boosting the efficiency of internally and externally focused business processes to building improved customer interfaces, and from replicating emergent value networks to triggering the evolution of smart goods and services, these paths define a course to Industry 4.0 disruption through business model innovations. By means of this effort, seek to provide relevant constituents with guidance on managing Industry 4.0 and capitalizing on its disruptive possibilities to create and capture further realms of worth.

Analyzed within the framework of the decision-making landscape, BI heralds a new era of proclaims here and now when business brilliance combines with the power of analytical wisdom to solve the problems of the modern business world. This evolution brings with it a plethora of issues, most visible in business analytics and supply chain analysis, as organizations seek a competitive advantage. Integral to this attempt was the need to measure and manage Supply Chain performance, the gap between the strategic and the tactical. Central to this pursuit is the definition and use of sound KPIs something that is a little more complex and urgent. In this thesis, the importance of KPIs is presented through a detailed theoretical analysis of the concept and supported by case studies. The objectives are centered on outlining the formation of KPIs as well as evaluating the effectiveness of the same in raising operational performance within Greek firms. In their review of the literature, advocate that firms should adopt a selective approach, whereby they focus on a small number of KPIs that are critical for Supply Chain Management, customer satisfaction as well as business viability. In this respect, methods like Balanced Scorecard, Benchmarking, and the Supply Chain Operations Reference (SCOR) model for the systematic development of pertinent KPIs. All in all, a pragmatic approach, which is encapsulated in the SCM Action display model for evaluating and improving Supply Chain effectiveness, hence presenting stakeholders with a clear plan of how they can cope with modern business environments. Thus, it is in this regard that this work is expected to offer practical recommendations to help organizations improve their strategic positioning and decision-making in the marketplace.

Reviewed the Order-to-Delivery (OTD), the proposed model plays an important role in supporting the delivery of products/ services to customers from beginning to end. Known as the cornerstone flow, accurate performance measurement of each of the OTD intermediary processes is critical for its success. Important to this identification of critical factors that could be quantified, where they fit historical acceptance, future strategic goals, and benchmark standards. Nevertheless, since best practice frameworks are not fully prescribed, the performance measurement paradigms require customization to reflect the capability and limitation profile and operating emergency of each organization. The use of performance measures and indicators is therefore strategic, as it orients organizations to prospects of enhanced operational performance and strategic fit. Consequently, this paper presents a broad literature review of Scania's industrial OTD process as well as related Vietnamese and international indicators as a result of the company's need to measure performance, identify discrepancies, and facilitate ongoing change as well as question the status quo. Based on both quantitative and qualitative research approaches, the study integrates literature analysis and empirical research in a way that concludes with methodological lessons learned and best practices arising out of practice and research. The current state of OTD research, the analyses of the respondent Scania, and the benchmarking comparisons with five other companies reveal the current state of OTD metrics and strategic focal areas such as lead time and delivery performance. In addition, the thesis presents a new concept used to estimate the variability of transport time; it provides a way to compare transport effectiveness across different delivery. The compilation of this research provides Scania with strategies for improving the curriculum on performance measurement, recommended approaches to support, and champion process improvements, as well as guidance on improving data quality and reporting procedures. Thus, the thesis will equip organizations with the necessary tools and knowledge to enhance, benchmark, and sustain OTD performance, as well as to strengthen their strategic position in a global market.

While exploring Logistics service PM is important in the achievement of organizational logistics objectives, as well as the improvement of services, especially in environments where much is at stake, numerous players and the relationship between causes and effects is complex. Due to this, for the PM to work successfully, criteria must be selected that are appropriate for the goals and expectations of the sponsor which includes logistics service providers, customers, and the regulatory bodies. However, the challenges of navigating PM become even more pronounced when it is applied in fields where the operating environment is unforgiving, the SCs are complex, and many actors are strongly interconnected. This paper examines the complexities of the application of performance measurement systems in the specialized field of offshore oil and gas logistics where prospective features include SC exposure to the harsh environment, multiple. Numbers of independent carriers, and use of specialized and high-cost long-distance transportation vessels. In a carefully developed multiple case study with two shipping companies and two IOGCs, this study presents SC performance and details KPIs relevant to logistics in an offshore environment. The results highlighted the necessity for the industry-specific performance measurement that reflects the specificity of the risks and the operational vagueness of offshore logistics management. Aside from adding to the body of knowledge of logistics PM, this study provides ideas on the combined uncertainty and interdependence in offshore SCs that can help PMs to effectively manage offshore logistics. In the end, this work endeavors to contribute to the existing deficit in the literature by presenting a list of appropriate offshore logistics KPIs that take into account the features of the field; thereby expanding the repertoire of instruments for the amphibious improvement of the given sphere's performance.

For manufacturing businesses, as discussed IoT has brought an example, leading to a new generation of service-led economic activities termed Smart Services. Thus, this study aims to respond to the following objectives: To elucidate the components of a customer-oriented framework for designing such services, especially in the manufacturing industry. By means of a literature review, the present study provides general background on the concept of IoT, data usage, and digitalisation of services distinguishing a crucial role of simulation technologies in the context of the creation of Smart Services. The operational aspect of the study involves the participation of an agricultural tractor manufacturing firm, whereby Customer Needs Assessment tools are used to identify new service needs. They clearly show that the use of IoT devices in the agricultural environment is gradually growing as the industry aims at achieving higher yields and sustainable results. In particular, farmers mention the urgent need for Smart Services that would provide the possibility of connecting their equipment to the Internet with the aim of comprehending agricultural activity and individual working schedules based on the data. Furthermore, a company need is to gather information on how it uses these goods in order to improve use and optimize processes to anticipate maintenance problems. The study also discusses practical experiences which are the basic findings of empirical research of Product Lifecycle Management and IoT. All these lead to Smart Service propositions aligned with customer requirements for efficient work output, time-saving solutions, and resource efficiency. Therefore, the theoretical contribution of the study is found in the concept map provided for the IoT and PLM relationship that emerged with this work; the practical contribution of this study is supported by the actual Smart Service propositions developed for the agricultural machinery sector. In achieving its purpose, the study provides investors with recommendations on how to manage existing and emerging opportunities in the context of IoT-driven Smart Services by unlocking its value for manufacturing.

Which was dedicated to explanatory supervising and characterizing the 'IoT, era, or the time of automation permeating human existence, viewing it as a process that simplifies and optimizes the lives of people on a scale never seen before. IoT has the potential to redefine the essence of human life in many ways since it has the largest capability of automating daily activities. However, to drive an uptake of IoT services at their maximum potential, it is necessary to define quality characteristics. The Quality of Service (QoS) parameters acts as a bedrock that defines and communicates user expectations in the IoT system. This work elucidates the complex and broad array of features of QoS capturing to IoT, acknowledging the triadic nature of Computing, Communication, and Things. It is through this systematic process of setting out the contours and definitions of these metrics that this work seeks to assist IoT providers to state their services clearly, assist users clearly indicate what they need, and eventually assist researchers and practitioners in building more sustainable IoT models. By providing analysis of various aspects of QoS metrics, this research contributes to the development of IoT technology and promotes better compatibility, accessibility, and application in the IoT environment.

Through a quantitative approach, The pushed logistics operations in Hong Kong due to the rising need for improvement in overall efficiency and flexibility to market changes. Historically a labor-corrected business, the management of warehouses is struggling with the increasing transactional demands and a rapidly growing trend towards same-day delivery services. In response, 3rd party logistics providers are beginning to understand the importance of cost efficiency in the marketplace. Against this backdrop, several Industry 4.0 emerging technologies including but not limited to Autonomous Robots, Industrial Internet of Things (IIoT), and Cloud Computing have brought about the possibility of a smart robotic warehouse management system. This system offers a revolutionary form of operation for the warehouses where by having the Omni base AMRs as the major alternative to the centralized 'man-to-goods' model, the warehouse will adopt the 'goods-to-man' model. This paper proposes and designs an IIoT-aided smart robotic warehouse system for the efficient sorting and storage of stock and intuitive control of handling robots and working area employing the available floor area effectively and efficiently. The proposed system wants to try the utilization of

Industry 4.0 technology in logistics so as to achieve logistics operational effectiveness, smart warehousing flexibility, adaptability and effectiveness of resources. This paper seeks to add to the debate on applying emergent technologies to manage modern logistics issues hence progressing the knowledge in smart logistics in the context of Industry 4.0.

Working within the scope of production logistics, identified that the operation challenges are derived from wide working space, complex resource interconnection, long operating time, and large number of people participation. Though hitherto providing solid foundations for structurally robust systems that could encompass typical dynamics, the application of system dynamics becomes less and less viable as competition rises and costs of required systems' updates grow. Based on such challenges, this study pursues a new course of work destined to achieve the right information architecture design and implementing control strategies in real-time in order to deal with the logistics systems inherent in real-life production systems. Taking advantage of the high penetration of industrial Internet-of-Things (IoT) systems, the study scrutinizes the general production logistic execution processes and then uses system dynamics to design affordable IoT solutions. Since the internal and external production logistic processes are taken separately for analysis, the study does sensitivity analysis for evaluating optimum IoT solutions and provides recommendations for IoT installation. Thereafter, integrating the internal and external production logistic processes into a coherent architecture fosters the development of a systemic conceptional model. Apart from the improvement of the application of system dynamics, this research proposes a quantitative approach for the analysis of IoT systems in production logistics, which extends the existing method resources for dealing with current problems of production logistics systems. In this comprehensive investigation, the research aims to contribute to the development of the contemporary discipline and practice of production logistics management by providing pragmatic methodologies and conceptual tools to manage dynamic operations and optimize system performance in the context of Industry 4.0.

Based on the rapidly growing body of data collected throughout the manufacturing process, the systems of monitoring play an important part in providing the management with the necessary materials for decision-making. Among the emerging technologies the IoT-based sensors act as a potential solution for effective and real-time monitoring of the manufacturing system. The findings of this research are the creation of an intelligent system proposed as a real-time monitoring system with the incorporation of IoT-based sensors, big data processing, and a hybrid prediction model for the improvement of real-time manufacturing processes. First, an IoT-based sensor to capture temperature, humidity, accelerometer, and gyroscope data is designed since actual sensor data are real-time, large in quantity, and unformatted as in manufacturing settings. For message queuing, Used for real-time processing and MongoDB is used for storage of the sensor data stream. Following that, a fusion of an enhanced DBSCAN method for outlier detection and classification utilizing the Random Forest algorithm is presented for fault detection during manufacturing processes. The proposed system performance is tested for effectiveness in monitoring the manufacturing process by implementing it in an automotive manufacturing assembly line in Korea. Furthermore, the hybrid prediction model also shows a better accuracy in the fault prediction compared to other models making it have the capacity to reduce cases of losses due to manufacturing faults. The proposed system will be capable of improving operational performance by endowing the management with better decision-making tools …also the ability to predict faults in the manufacturing processes will go a long way in solving most problems and preventing them in the future. This paper therefore fits into this research agenda of efforts that to apply IoT and big data to enable efficient management of manufacturing operations and overall effectiveness.

Looked at manufacturing and optimizing product design and production processes remains a goal for any organization that desires to remain relevant. Software solutions that are specific to product engineering (CFAO, PLM) and to production control (ERP, MES) have become essential in achieving this objective. The issue of new product development becomes critically significant for determining the success of manufacturing companies with Product Lifecycle Management systems at the forefront. Some aspects of product development have been automated with the help of intelligent agents when PLM software enabled the sharing of product data at all levels of the Computer-Integrated Manufacturing (CIM) Pyramid. However, the challenges that have been realized, and persist in relation to the management of product knowledge include a cumbersome way of accessing dispersed information within the production's information system. Several strategies have been suggested to address these issues;

however, this paper suggests a new approach using an ontology, Semantic Web technologies, and intelligent agents to automate the generation of new products. In order to support this approach the paper provides in its latter part a case study that illustrates the inclusion of a PLM module into the information system used to control flexible cell machining. By way of this research, the paper seeks to answer the following questions in relation to the subject being studied and in increasing the understanding of the options for improving manufacturing using emerging technologies Possible strategies and approaches will be discussed and recommended to maximize the performance of manufacturing operations in the modern world.

The complexities of and challenges related to international rules governing data sharing and protection in genomic research and clinical practice have made M indispensible. Though open data enlightens data governance on the release of genomic data for the public domain, the complexities of data protection laws pose significant barriers to data sharing across borders. Unlike the current discussions on EU data protection regulation and its relation to genomics and health worldwide, this article presents an analysis of the historical development of the data protection regulations on international data transfers in order to reveal their meaning for genomics and health care. While understanding the organization at the geopolitical level, this article, through a historical retrieval of the international rules of data sharing from 1970 to the present and the synthesis of the difficulties in the implementation of general data protection rules in genomics and healthcare, clarifies many of these dimensions. In addition, while comparing the available compliance options with the general background of the EU General Data Protection Regulation, the article provides insights from the genomics point of view. Therefore, the method of the historical-comparative analysis of the protections aimed at future research should help to understand the dynamics of the alterations and contribution to the data protection regulations and genomics/healthcare sphere.

The basis of machine learning and predictive analytics, given the existing and emerging technologies in big data. It elucidateselucidates its subject matter regarding the new data fundamentals and emerging technologies. Furthermore, the chapter provides specific recommendations on how organizational culture can be developed to facilitate a process of transformation in order to better organize for the challenges of the contemporary business environment. The discourse unfolds the history of data mania to the early 1980s, embracing disciplines such as business intelligence, predictive analytics, or data mining as disciplines in their infancy. This ancestor discipline includes other related concepts like new knowledge discovery in databases or KDD the purpose of which was to mine data. Moreover, the chapter examines the hierarchy of analytics from descriptive to prescriptive discussing the importance of using them in decision making. The chapter also takes us into the current usage of the modern CRoss Industry Standard Process for data mining (CRISP-DM) as a useful guide for understanding its usage in data mining projects today. In that way, this chapter seeks to offer a conceptual and applied map of a complex area for organizations willing to make use of machine learning and predictive analytics for business innovation.

Business processes examined business processes are part of organizational operations that are a series of business activities that are structured in order to deliver planned business outcomes. By adopting a business process viewpoint one is able to design and consistently enhance the management of organizational activities in accordance with predefined resource limitations. Although this field continues to expand, there is often a weak utilization of scientifically measurable results at the inter-disciplinary level in this domain. Business Operation Research (Operations Research) has become a significant field that provides methodologies and approaches for improving organizational outputs and effectiveness. As the main aim of any PhD thesis, the present study aims at proposing, assessing, and validating this business process optimization framework. The underlying optimization activities use a category of techniques termed Evolutionary Computing (EC), which n=have been found to be suitable in problem domains similar to the current one. The author asks questions regarding the creation of the theory behind the framework, methodologies for determining which continuous and discrete computational utilization techniques to use, and techniques for performance measurement and verification. Hiatus inputs from experts shall profoundly determine the direction of the thesis work in regard to emergent trends in the field as well as future prospects. By doing, the project will seek to further enhance understanding and practice on business process improvement.

As it was stated turn to the perspective on communication as construction from the point of view of constitutive, the discussion between organizations and investors regarding CSR is the critical point of crossing between the organizational and environmental spheres. However, within this framework, sustainability reporting has become an important instrument used by organizations as well as stakeholders to control this relationship. This research provides a critical analysis of the developmental process of standard sustainability reporting or the GRI Guidelines from the year 2000 to the present. In particular, the research focuses on how the GRI's guidelines for stakeholder engagement are described, if these descriptions are regarded as institutional messages. By analyzing, the study is able to explain how shifts in micro-and-macro features of these messages have enhanced the specification of sustainability reporting as a new genre in organizational communication. The implications that the study carries in this regard are relevant for the theoretical advancement of the Communication-Organization relation by stressing the importance of the process of linguistic shaping of Organization-Stakeholder collaboration in the Global setting. By means of this research, contributes to the ongoing theoretical discussions on how the multiple layers of communication design interact with organizational factors in the CSR reports.

With the way the rising demand for energy consumption of buildings has triggered data collection, and thus the availability of a vast amount of energy data waiting for data analysis. This article provides detailed information on the state of art data-based approaches to building energy performance assessment in a range of archetypes and scales. These approaches comprise prediction technologies, artificial neural networks, support vector machines, statistical regression, decision trees, genetic algorithms, classification technologies, K-mean clustering, self-organizing maps, and hierarchical clustering. To summarize the review focuses on how big data has been applied to solve a number of different building energy-related tasks, including load forecasting, energy pattern profiling, mapping regional energy consumption, benchmarking building stocks, and developing global retrofit strategies and guidelines. In addition, it highlights major objectives for enhancing the role of data in building energy analysis, micro- and macro- scale energy consumption optimization by retrofitting and integrating renewable energy, as well as energy saving connected to consumer expectations. Thus, the outcomes of this study will inform the development of sustainable metropolitan policies, underlining the prospects of micro and macro scalemacro scale energy changes for increased urban sustainability.

2.1 Flow Chart

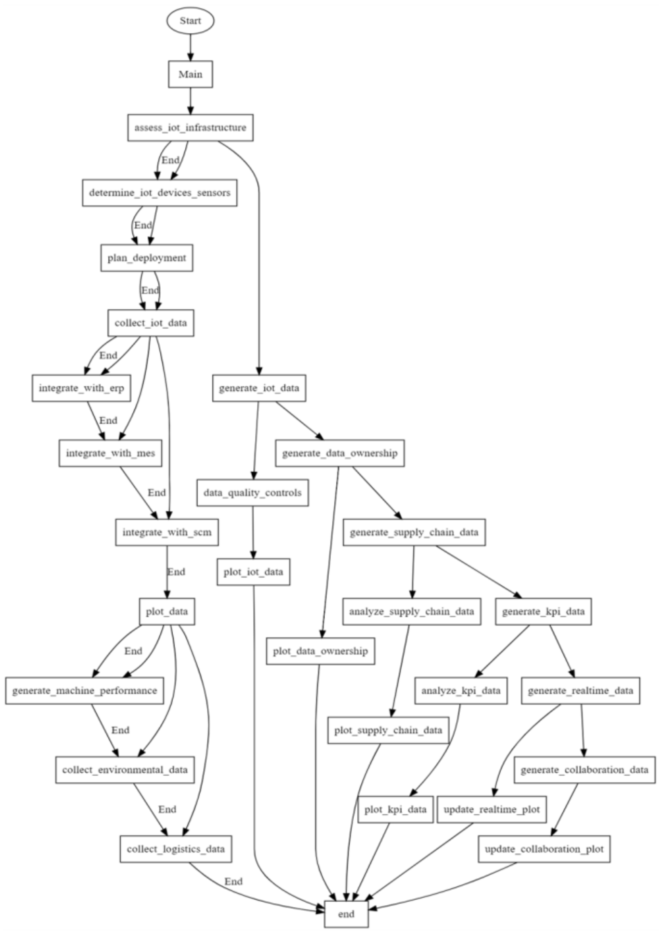

Fig. 1: Flow chart of Research work

As shown from the flowchart in Figure 1, the presented flowchart outlines the execution flow of a program of comprehensive research into the technical environment and various data collecting as well as analysis processes. The program goes through an initial evaluation of IoT structures, and then the identification of IoT devices and sensors needed for the collection of information. After this, a deployment plan is developed to show how the IoT data will be integrated with ERP, MES and SCM systems in the company. There are two stages in the process of data collection for IoT, which are creating IoT data and the quality control process to check IoT conformity, integrity and accuracy. The data ownership aspect is solved through data ownership metrics generation and data ownership metric visualization. Supply chain data flow management concerns creating and analyzing supply chain data and lastly, data representation in graphical form. Likewise, key performance indicator (KPI) data is created; collected, calculated, and graphed to measure performance. To ease the analytically oriented real-time data generation and visualization the information is extracted to accommodate timeliness for assessing system performance. Also, real-time collaboration data is created and maintained in order to monitor the closeness of the different interest groups. Such a flowchart guarantees a coherent background for data processing, analysis, and visualization with regard to the achievement of research objectives. There is a logical sequence of every part of a given work which provides a smooth and streamlined research process.

2.2 Research Gap

The current state of research shows that it is a broad tapestry of investigations spanning multiple areas of interest including software engineering and entrepreneurship, supply chain, and logistics, as well as the IoT. However, self across these varieties of scholarship, several thematic gaps continue to be noticeable, which points to areas that have a high potential for future hegemonic research and development. One emerging gap is to address interdisciplinary research that selectively gathers information from different fields of study and integrates the findings to solve practical problems. For instance, whereas there exist broad tropes of culture that encompass themes like RCM, Industry 4.0, Supply Chain Performance, and IoT-driven Smart Services, there is a void in research propositions that focus on weaving together elements of software engineering, business innovation, logistics management and the IoT. Such fragmentation does not allow us to fully capture the mutual relations and impacts of the processes at play, including technology, shifts in business models, and customers. In an effort to fill this gap, this research work examines the relationship between software development characteristics, business innovation requirements, and ISSUES relating to logistics, and IoT-based service delivery models. Through this method of analysis, this study gains better perceptual clarity to the interconnectivity and interactions of these domains to provide insights into areas that serve to improve the planning of projects, operational effectiveness, and creation of a sustainable business environment. By means of a comprehensive literature search, this study will not only seek to describe the current state of affairs but also ascertain promising areas for further investigation and development, thus enhancing the extant body of knowledge and practice with regard to these two overlapping disciplines.

The objective of the Work

- ✓ To assess and integrate IoT infrastructure within existing systems and to enable seamless data collection from various sensors and devices.
- ✓ To implement robust data quality controls and to ensure the accuracy, completeness, and consistency of collected IoT data, thereby enhancing the reliability of subsequent analyses and decision-making processes.
- ✓ To perform in-depth analysis of IoT data, data ownership metrics, supply chain data, KPIs, real-time data, and collaboration data and to derive actionable insights and improve operational efficiency.
- ✓ To develop visualization techniques and to represent analyzed data effectively, facilitating easy interpretation and real-time monitoring of critical performance indicators across different domains.
- ✓ To utilize the insights gained from data analysis and to optimize decision-making processes, streamline operations, and enhance collaboration among stakeholders, leading to improved overall performance and productivity.

3 Result and Discussion

3.1 Business Objectives and Requirements

To appreciate the particular objectives of the firm toward greater productivity, lower costs, fewer inventories, happier customers, and more supply-chain transparency. KPIs typical in manufacturing that can be connected to POC or be important when improving supply chain transparency include cycle time, lead time, on-time delivery, inventory turnover, and fill rate. As from equation 1, the production efficiency is the total number of output units per hour, and the Production Volume is the total production volume. As derived from equation 2 Total Lead Time refers to the total lead time in days. Where on-time orders refer to the actual number of orders delivered on time and Total orders are the total number of orders. Where, from equation 4, the Cost of Goods Sold has the actual value for the cost of goods sold and the Average Inventory has the average level of inventory. It is apparent from Equation 5 that the meaning of Filled Orders is the number of orders that have been filled.

$$\text{Cycle Time} = \frac{\text{production Efficiency}}{\text{Production Volume}} \quad (1)$$

$$\text{Lead Time} = \text{Total Lead Time} \quad (2)$$

$$\text{On-Time Delivery} = \frac{\text{On Time Orders}}{\text{Total Orders}} * 100 \quad (3)$$

$$\text{Inventory Turnover} = \frac{\text{Cost of Goods sold}}{\text{Average Inventory}} \quad (4)$$

$$\text{Fill Rate} = \frac{\text{Filled orders}}{\text{Total Orders}} * 100 \quad (5)$$

As seen in Figure 2, the graphical represents the most important indicators relevant to the assessment of performance in manufacturing and supply chain management operations. The five KPIs are explained as Cycle Time, Lead Time, On-Time Delivery, Inventory Turnover, and Fill Rate, these KPIs are very essential to measure the effectiveness of the process as well as determine the satisfaction level of the customers.

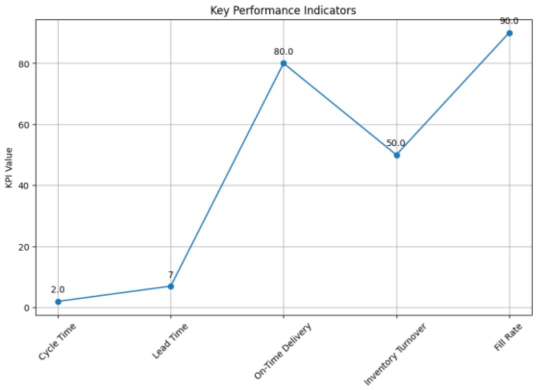

Fig. 2: Key Performance Indicators

The plotted data is informative with regard to several aspects of the operation. Cycle Time represents the time measured required to manufacture each unit in question to optimize production. Lead Time relates to order lead time and affects delivery seek time and delivery complete time, also reflecting the satisfaction of customers and inventory. On-time delivery addresses exactly that the percentage of delivered orders within the particular time scope, therefore, demonstrating the delivery efficiency. Inventory Turnover refers to the rate at which inventory is used; this affects costs and, therefore, revenues. Order Fulfrate reflects the ratio of a number of orders fulfilled to the number of orders received, showing how effective your fulfillment is and how well your organization meets customers' needs. From here, this visualization enables the investor to examine over, under, and opportunities for improvement within the operation format. These KPIs help organizations to work on efficiency, productivity, and improvement of organizational work and, thereby, promote sustainable development in the competitive environment.

3.2 IoT Infrastructure

It evaluates the current state of the IoT for a firm or in other words it evaluates the IoT readiness of a firm if it had none. Identify the required IoT devices and sensors for data acquisition decision-making based on accuracy, reliability, and integration aspects. Organize the roll out of IoT devices for the distinct manufacturing sites, storage facilities, distribution depots, and transport vehicles. Figure 3 and Figure 4 show the evaluation results and deployment strategy of the IoT devices and sensors in several infrastructures. Checking IoT infrastructure and the identification of devices and sensors are crucial when it comes to the process of collecting data and monitoring the state of those structures. It is represented in the plot below and illustrates the accuracy and reliability of Temperature, Humidity, Pressure, and Motion sensors. Accuracy values, ranging from 0.95 to 0.99, represent the accuracy of sensor measurement, and reliability values ranging from 0.92 to 0.97 depict the stability of the sensors in different situations. In addition, the deployment plan demonstrates where IoT devices will be located in various facilities including Manufacturing Facilities, Warehouses, Distribution Centers, and Transportation Vehicles. The above bar graph displays the extent of IoT device segregation with the kind of facility type so as to understand the magnitude of IoT integration across operational structures. Through this visualization, stakeholders can identify where different IoT technologies are applied and how organizations can improve their decision-making and overall efficiency in different industries.

$$\text{Accuracy} = \frac{\text{Number of Correct readings}}{\text{Total Number of Readings}} \quad (6)$$

$$\text{Reliability} = \frac{\text{Number of Consistent readings}}{\text{Total Number of Readings}} \quad (7)$$

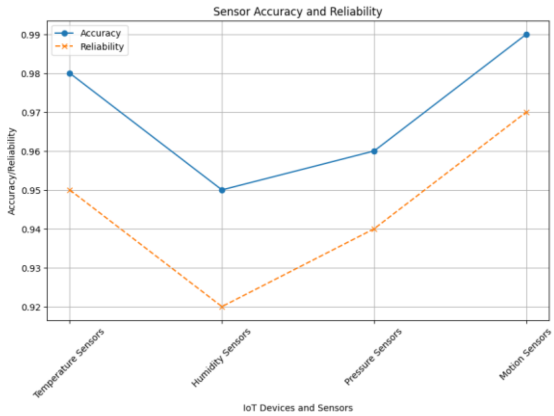

Fig. 3: Sensor Accuracy and Reliability

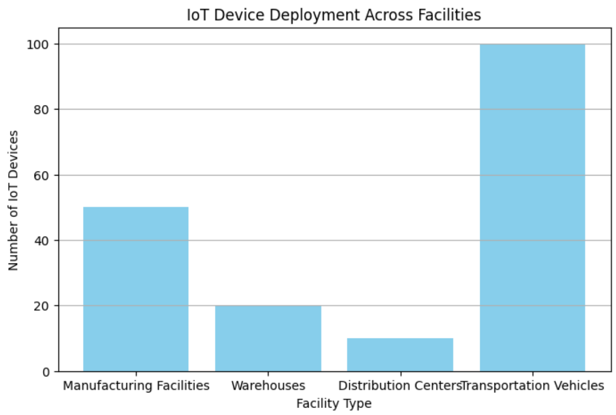

Fig. 4: IoT Device Deployment across Facilities

The IoT implementation plan for infrastructure contains key action plans that can guide IoT devices and sensors to be used within various operational environments of the facilities. Starting with an evaluation of the current architecture, no IoT architecture is present that requires a plan for the creation. Subsequent to this assessment, measures in identifying IoT devices and sensors include assessing the degree of accuracy the devices and sensors. Temperature sensors provide 0.98 accuracy and 0.95 reliability, while humidity provides 0.95 accuracy and 0.92 reliability. Pressure sensors have the precision of 0.96 and a dependability of 0.94, whereas; motion sensors demonstrate the highest degree of accuracy of 0.99 and dependability of 0.97. These metrics determine the choice of sensors to meet specific data requirements as well as the deployment of sensors. In the deployment plan, 50 IoT devices are assigned to Manufacturing Facilities to monitor as well as enhance processes. Warehouses get 20 IoT devices adding on the smart inventory and environment tracking. IoT devices in Distribution Centers include 10 that enhance operations in the supply chain. Transportation Vehicles are equipped with 100 IoT devices for the purpose of remote monitoring, and vehicle tracking and management. The distribution of IoT devices varies across different facilities, and they are installed where operation and strategy are required to allow for full coverage and valuable information. This planned integration of IoT infrastructure lays the strong groundwork for decision-making for optimization and competitiveness in dynamic settings for industries.

3.3 Data Collection and Integration

From this, it is possible to determine what kind of data should be collected: data from the machines, environmental data, and logistic data such as the location of the shipment and its status. Decide on the cadence and/or frequency of data collection so that it reflects mostly real-time, or near real-time data of production and supply chain activities. IoT data has to be integrated with other enterprise systems including ERP, MES, and SCM software, and more in regards to established protocols. From Figure 5, the program is also able to collect and integrate various types of real-time data such as machine state, environmental conditions, and logistics from other mini databases. The performance of the machine is field data simulated in order to construct synthetic time series data using the ARIMA (Auto Regressive Integrated Moving Average) model. Temporal dependencies and trends in the machine's performance metrics are reflected by the ARIMA model with a view of enabling predictive analysis. To replicate actual sensor measurements, the temperature and humidity values are arbitrary for other environmental parameters. These are status data of the surrounding environment that may affect the working of the machines. Also, the simulation is done on logistics information including the status and position of the shipment in the operation around the machine. Combined, the sources of these diverse data are presented in a graphical display of the stacked bar type. Depending on the category such as Machine, Environment, and Logistics, the graph has different colors. Machine performance is represented in blue while environmental data such as temperature and humidity are represented in orange and green colors respectively. The extent of logistics data is shown by one bar in green color. The stacked bar graph allows the broader picture to be created out of the multiple data streams received from a variety of sources. They show the complexity of relations between the mechanical processes of a machine and environmental conditions and general organization. From this view, the stakeholders are able to obtain overviews of the complete operation in order to make better decisions and to strategically manage preventive and repair measures based on the analyzed integrated data in real-time.

From equation 8, where yt represents the value of the time series at time t, c is a constant term, ϕ1,ϕ2,...,ϕp are the parameters of the autoregressive (AR) terms, representing the effect of past values on the current value, Yt−1,Yt−2,...,Yt−p are the lagged values of the time series, θ1,θ2,...,θq are the parameters of the moving average (MA) terms, representing the effect of past forecast errors on the current value, ϵt is the error term at time t, q represents the order of the moving average, p represents the order of the autoregression, The term (1−B)d is the differencing component, where B is the backshift operator and d is the degree of differencing. From equation 9, where $y_t^{(m)}$ represents the machine performance at time t, $f^{(m)}$ is a function representing the relationship between the input variables $Xt(m)$Xt(m) and machine performance, $(x_t^{(m)})$ could be the historical machine performance data or other relevant factors influencing performance, $\varepsilon_t^{(m)}$ is the error term.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (8)$$

$$y_t^{(m)} = f^{(m)}\,(x_t^{(m)}) + \varepsilon_t^{(m)} \quad (9)$$

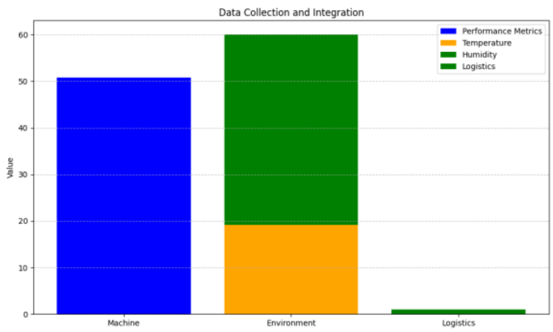

Fig. 5: Data Collection and Integration

Figure 6 data provides insights into three key aspects: Machine performance, environment, and logistics are significant components of operating management that have been discussed above. An analysis of movements of machines and scaling factors indicates that the degree of performance changes over time and is associated with fluctuations that are typical for industry processes. All of these metrics, ranging from minute 1 to minute 100, demonstrate variations that are critical in determining the reliability and effectiveness of the machinery in question. In particular, the level of machine efficiency significantly differs which may point at certain zones where productivity might be most effective for further adjustment. Instrument data including temperature and humidity entails important information on the conditions physically present in the operational theatre. It covers the temperature values between 10 to 40 degree Celsius and humidity levels between 20% to 80%. Such fluctuations in environmental conditions impacts the individual performances of the machines besides the quality of the products manufactured as seen above, thereby require monitoring and control of the factors that affect the environment. Thus, logistics data reflects the current status of the shipments, with options "In transit," "Delivered," or "Pending." This information is vital for supply chain management because makes it easier for the stakeholders who manage the flow of goods to predict when there might be a setback in the flow of the delivery schedule. The aspect of logistics data reveals the need to have efficient means of transportation and of distributing products so that they get to the customer in the shortest time possible. From the synthesized data t cohesively give an integrated picture of the operation of those machineries that is comprehensively inclusive of machine performance, environmental factors, and logistics management. When these data streams are combined, they provide useful information that can be used by stakeholders in order to increase operational effectiveness, manage risk and allocate resources effectively in industrial contexts.

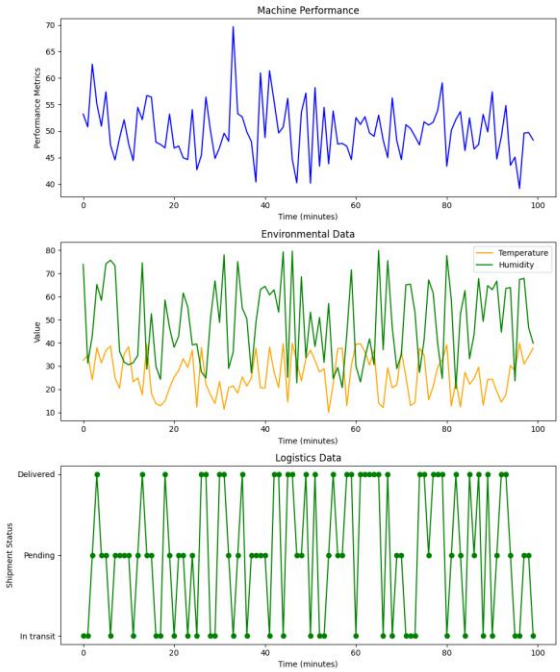

Fig. 6: Machine performance of Various data

As it can be seen from Figure 7, the program emulates the process of IoT data collection, for instance, temperature, and its ability to interact with other enterprise systems. Each time through the loop is one data collection observation and temperature is a random number between 20 and 30 degrees Celsius. These readings are then integrated into three enterprise systems: ERP, MES, and SCM are three primary business solution areas that organizations seek to implement. For visualization purposes, the generated temperature values are stored along with the timestamp. The timestamps are again in hours, minutes, and seconds adding temporal to the gathered data. Moreover, to make the process more realistic and credible, I set a time interval of 1 second between subsequent data observations. The obtained graph reflects the dynamics of the temperature readings during the data-gathering process. Every point marked on the graph corresponds to a temperature recorded at a particular time instance. The plotted line displays temperature changes with time therefore providing information concerning the temperature changes within the environment. Thus, this visualization is useful when assessing current environmental conditions and identifying some variables that may deserve attention either due to their increment or their decrement. In addition, it shows how the Internet of Things integrates with enterprise systems showing how data circulates within the organization. Overall, the program and its visualization underscore the importance of real-time data collection and integration for informed decision-making and operational efficiency in various domains, such as manufacturing, logistics, and facility management. From equation 10, where Ti is the temperate data collected at time T_i, $f(t_i)$ represents the function for generating the temperature data at time ti, which in this case is a stochastic process simulated by the function collect iot data.

$$T_i = f(t_i) \quad (10)$$

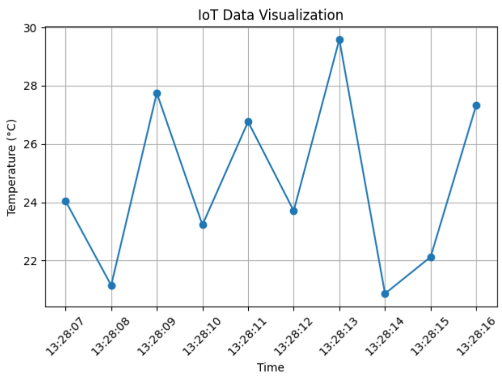

Fig. 7: IoT Data Visualization

This data consists of sets of time variables illustrating the changes in temperature readings taken at different time points or intervals giving the analyst a picture of the time variation of the environment. Every tick on the time axis along with the linked temperature value is a picture of the temperature in the environment at that time. The timestamps, denoted in the format "Time: Nevertheless, time related to HH: MM: SS controls temporal associations and means as temporal references for identifying temporal patterns and relations in the dataset. In general, the temperature values indicate distinct changes in environmental conditions that occurred at points in time, reflected in changes in temperature readings. For example, the results reveal that temperature values are variable over time: for consecutive timestamps, the temperature varies within the range of 20.87 °C to 29.58 °C. Such fluctuation is an indication that the environment is complex and dynamic, and is comprised of weather, geography, and humans. Temperature data obtained at regular intervals give insight into changes occurring in the environment to ensure that any variations that may affect processes or be uncomfortable can be recognized. Constant tracking of temperature variations over time is important in climatology, climate control and improvement, heating ventilation air conditioning, and industrial processes. Further, knowledge about temporal trends with regard to temperature be useful in forecasting future trends in temperature to both adapt to unfavorable changes as well as capitalize on beneficial ones. Altogether, the temporal pattern of temperature records is a comprehension of temporal changes in the ambient environment and its fluctuations stressing on the need to monitor and analyze time series data for appropriate decision-making and management of resources.

3.4 Data Quality Governance

Figure 8 incorporates data quality rules that would determine the quality of IoT data such as quality, completeness, and coherency. Determine specific requirements concerning data access, data security, and data privacy, as well as the laws and ordinances that will have to be adhered to in the process such as GDPR and HIPAA. Define data ownership and stewardship to help companies better understand who is needed to be in charge of IoT data in various organizational structures. As discussed in Figure 8, the presented program emulates the production of IoT temperature data with random noise, and applies data quality checks to eliminate the problem of inaccuracy, incompleteness, and inconsistency. When run, the program simulates temperature data for 1000 samples with noise within the range of 20°C to 30°C. It then performs data quality checks for missing values and discrepancies in generated large datasets. The temperature data analyzed from the IoT are represented in the graph by the y axis use as the temperature and the x axis as the sample index. The temperature values move around the specified range of 20-30°C thereby providing evidence of the noise that has been incorporated into the process. These data quality controls, while not activated in this particular instantiation, are designed to provide safeguards for the quality of the data collected by the prototype. Their purpose is to alert one to any gaps or flaws which may be seen when the data is being generated, and which gives an indication of the quality of the data set. In general, the described program illustrates one of the simplest but really important aspects of IoT data generation and its quality. It then adds random noise to the temperature data and discusses the application of data quality controls as an IoT project Thus, demonstrating the importance of data quality in IoT applications as the basis for more complex data analysis and subsequent control decisions.

$$\text{Inconsistent values} = \Sigma_{\mathrm{i}}^{\mathrm{N}} \begin{cases} 1 & \text{if data [i]} \notin [20{,}30] \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

From equation 11, where inconsistent values represents the count of inconsistent temperature values, N is the total number of samples, Data[i] denotes the temperature value at index I, The expression $\text{Data}[i] \notin [20{,}30]$ checks if the temperature value at index i falls outside the expected range of 20°C to 30°C. The summation calculates the total count of inconsistent values by iterating over all samples.

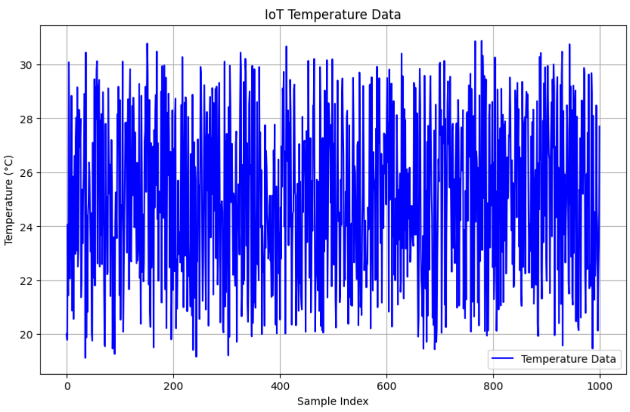

Fig. 8: IoT Temperature Data

From Figure 9, the provided program imitates data ownership and accountability involving various departments over different time phases. It produces artificial data on the number of data submissions by each department, in each time interval. A graph shows this information, which presents changes in data ownership by departments at different points in time. For clarity, there is a separate line for each department in the graph; the points correspond to the number of data advances contributed by each department in the period. On the x-axis, there are different time periods and on the axis of the values, there are the meanings the number of data contributions. The line in each department represents the ability of the department to own and contribute data for the stipulated time frames. On this graph, it is possible to notice patterns in data ownership over time, with some departments contributing data steadily while the contribution of other departments is more irregular. Those departments that operated at a higher data-owning level have a starker visibility, pointing towards an evolution of how involved they are in affairs that concern data. In sum, the examined graph gives the idea about the specifics of data ownership and responsibility within the organization. It provides a general panorama of the extent to which departments are engaged in initiating and owning data in consecutive time phases. This chart assists in visual comprehension as to where the data responsibilities lie and is useful when deciding on resource allocation involving the organization’s strategies for data governance and management.

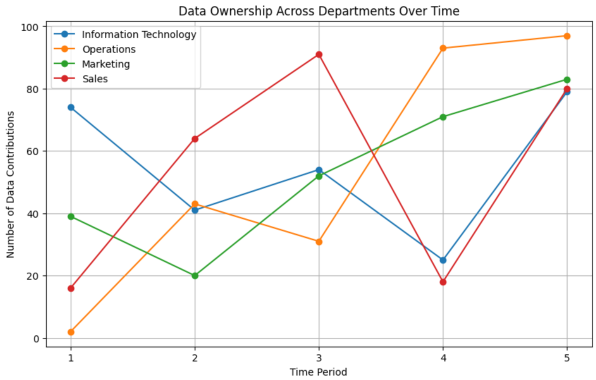

Fig. 9: Data Ownership Department Over Time

3.5 Real-Time Analytics and Decision Making

It Choose appropriate data analytics type, viz., descriptive type analytical tools, predictive type of analytical tools, and prescriptive type of analytical tools, depending on the organizational goals and type of data. Machine learning approaches for processing in real-time large-scale data coming from IoT sensors and for supporting decision-making in production line and supply chain management. The use of decision support systems or decision automation tools in production and supply chain should be done to allow for timely response to events. In Figure 10, the program we have been given produces synthetic supply chain data from about 10 samples calculates the lead time tendencies for each sample, and depicts them in a single graph. The coordinates of the graph reveal the order processing time, transportation delay, and total lead time of each sample, in order to get a complete supply chain analysis. In the graph, each sample is represented by a group of three bars: There would be discrepancies between order processing time, transportation delay, and total lead time would be different because they are their own individual requisites. On the x-axis are the sample names and the y-axis represents the lead time in days. Different colors are used to make you easily distinguish between the various constituents of lead time. Through observing the graph there is a better understanding of the fluctuations that occur in samples of lead time. It is often the case that certain samples may take longer to process the orders while others may face a major transportation challenge. Also, the total lead time is useful in giving a complete picture of the total time between the order of each sample to delivery. In addition, the pro forma written analyses of lead time give a breakdown of mean lead time components for each sample, thus helping the reader appreciate the components that make up the total lead time. In conclusion, this ability may help to make strategic management decisions in the supply chain by defining the existence of any constrained resources, finding out the best way of streamlining various resources, and increasing productivity. The visualization is helpful in ascertaining opportunities for improvement within the supply chain and directing resources available to make changes that bolster the performance of the supply chain system.

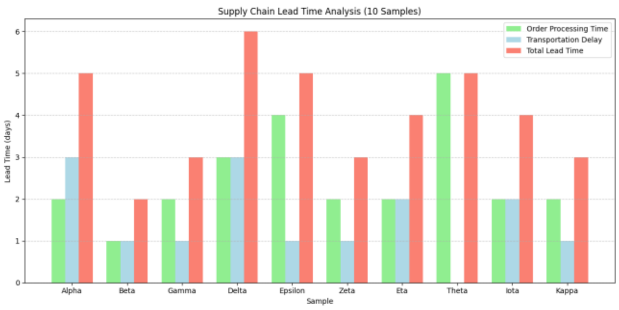

Fig. 10: Supply Chain Lead Analysis

$$\text{Service Level} = 1 - \frac{\text{Number of stockouts}}{\text{Total demand}} * 100\% \tag{12}$$

Equation 12 shows that the number of stockouts is the number of times that customer demand outstrips the available inventory (stockouts) while total demand means the total accumulated demand of the customer within a given period. The lead time details provided on a sample-wise basis are elaborate and provide a comparative analysis of the lead time-related changes in the samples of the supply chain. Both samples, which are labeled by their ID, demonstrate that order processing time, transportation time, and total lead time are not dry cut-and-dry measures that define the process of the supply chain but are rather examples of its complex functions. For example, Sample Alpha shows the total lead time of 5 days including lead time with processing order and transport delay as 2 days and 3 days respectively. On the other hand, Sample Beta has a total lead time of 2 days – 1 day was utilized for order processing and 1 day for transportation delay. Likewise, Sample Delta shows a total lead time of 6 days which was mainly due to long order processing and transportation delay time both of 3 days. These detailed lead time breakdowns help in achieving an understanding of factors that affect the supply of materials and products throughout the supply chain. However, by comparing patterns and disparities in different samples, it becomes easier for all stakeholders to know where to invest most of their time since that is where most of the problems are likely to be encountered and thus postponing them is likely to affect the overall performance of the company and the level of satisfaction of customers.

3.6 Optimization and Continuous Improvement

Use optimization algorithms designed within the framework of production-scheduling, resource-allocating and inventory systems, along with logistics routing predicated on data and analytics. Have to set post-implementation Key Performance Indicators (KPIs) or performance metrics for assessing thus IoT-based methodology efficiency and organically search for potential major enhancements. Sustain iterative improvement of the methodology as per the feedback received from the stakeholders and as per the changes in business necessities or some other factors. As can be seen from Figure 11, the provided program uses a simulation to produce KPI data and plot the trend of the data over a timeline. It is shown in the graph and used in analyzing the kind of changes that can happen within periods where KPIs have to be implemented. At each point of the graph, there is a certain period, the value of this KPI is shown on the Y axis. The horizontal axis is the period number, which allows for understanding the dynamics of KPI indicators' performance. The KPI trend graph is a favorable analytical aid that is used in monitoring performance and decision-making tactics. From the depicted KPI chart, the stakeholders or interested parties can determine the progress, trends, and concerns of the enterprise. For instance, directional trends can point to positive performance development or increase in efficiency while the other may represent negative performance development or constrained operations. Moreover, its ability to produce artificial KPI data can be applied and adjusted for use in various analyses numerous domains or industries' KPIs. Some additional features include 'what-if?' analyses allowing modifying the number of periods or altering the range of KPI values in order to get the idea of how it will affect the performance. Taken collectively, the program for the KPI trend analysis provides stakeholders with crucial information for improving the current organizational performance, launching the ongoing performance improvement processes, and making consequent strategic decisions. From equation 13, where KPI_i represents the KPI value for the i-th period, a_i and b_i are the lower and upper bounds of the uniform distribution for the i-th period, respectively and R is a random number generated from a uniform distribution between 0 and 1.

$$\mathrm{KPI_i} = \mathrm{a_i} + (\mathrm{b_i} - \mathrm{a_i}) * \mathrm{R} \tag{13}$$

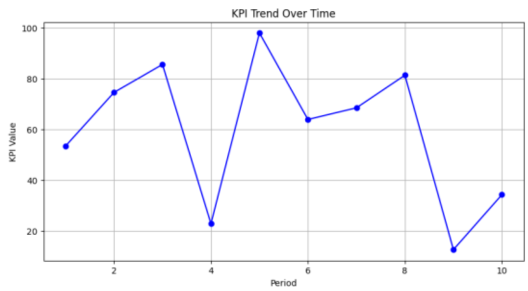

Fig. 11: KPI Trend Over Time

For the ten time intervals studied, the presented indicators demonstrate a variety of KPI outcomes. It is observed from each of the periods that the KPIs have a relatively high degree of variation and this indicates changes in the level of performance periodically. Period 5 can be considered as a period of maximum performance characterized by a very high KPI of 97.99 which suggests a major success during the selected period. On the other hand, Period 9 represents the worst performance in terms of KPI's stand at 12.51 and could therefore have been a period of a setback or challenge. The variations shown by the KPIs reflect the instability of performance indicators and indicate the variability of organizational performance in time. Of course, these fluctuations might result from a number of aspects, be it changes in a market environment that happen to affect the company's operations, disruptions of the business operations, strategic developments, or any random event. Stakeholders can look at these differences in KPI values trends and examine how and when it might be useful to make changes to procedures or intervene to enhance organizational results. , The variation of KPI values also supports the concept that performance measurement is a complex process and performance indicators have to be evaluated in terms of various aspects. As opposed to relying primarily on cumulative performance indicators, stakeholders are in a position to gain a detailed understanding of certain components of organizational performance by assessing individual KPI values and then introducing improvements that may have positive impacts on overall performance.

Fig. 12: Real-Time Data Visualization

From Figure 12 the program shows real-time data visualization where Plot is a Python library used for interactive plots. It continues to produce values at selected time intervals and alters the plot automatically to depict the emerging dataset. Every data point is composed of a time stamp – when was the data collected – and a randomly generated integer between 1 and 100. The figure is first created with only one subplot to show the data in question. The update plot function is created to generate new data, add it to our Data Frame and therefore update the plot. The generate data function outputs a value for the data point and current timestamp of the system where the program is run. Within each iteration of the main loop of the program, a new point is created and appended to the Data Frame. To incorporate new data into the plot this is made using Plot's interactive features. The horizontal line is the x-axis, while the vertical line is the y-axis where the incoming event is plotted on the basis of its data value. Finally, the interaction of the program with the data set changes dynamically as the program runs through the plot format of data to show the real-time changes in the data set. This approach makes it easy to observe stream data as they are processed and make decisions based on the results without delays hence real-time decision making in the context of stream datasets. It can be implemented in many contexts such as IoT (Internet of Things) for monitoring purposes, financial markets research, and process control where real-time visualization of data is vital for the identification of outliers, trends, and patterns.

3.7 Collaboration and Stakeholder Engagement

Coordinate operation IT, engineering, supply chain, and finance groups in order to ensure proper fit with the business objectives. Network with other outside organizations and institutions that play the role of suppliers, customers, and even logistics partners to raise or improve the supply chain visibility. Sensitize all members at different management levels within the organization to the value of IoT-based methodology in the delivery of services. From Figure 13, one obtains the graphical models showing the actual collaboration scores by organizational teams in real time. To add more variability, each of the team numbers is assigned a random value between 1 and 10, which mimics its level of collaboration. Through each such set of collaboration scores, the shapes of the graph get automatically updated for the purpose of analyzing the dynamics of collaboration over any specific time period. Using Plot graph objects, the program generates the plot which contains the multiple 'trace', where each one represents the collaboration score of each team. On the X and y-axis, the time point of data collection and the collaboration scores between 0-10 are labeled, respectively. Every team's collaboration score is displayed as a line chart in order to compare the scores of more than one team'steam easily. There is also the real-time updating feature where instead of getting constant values of the variables involved as in the actual data collection process, there are new data points at interval time. Such changes are made session by session to allow the analysis of collaboration trends, thanks to the new graph, which now displays updated collaboration scores from previous sessions. Furthermore, in view of giving tangible results of the current level of collaboration to the stakeholders, the program displays the most recent collaboration scores of the participating teams. Real-time visualization and data reporting applied to collaboration facilitate stakeholders to better evaluate collaboration processes and factors to fix organizational efficiency and teaming.

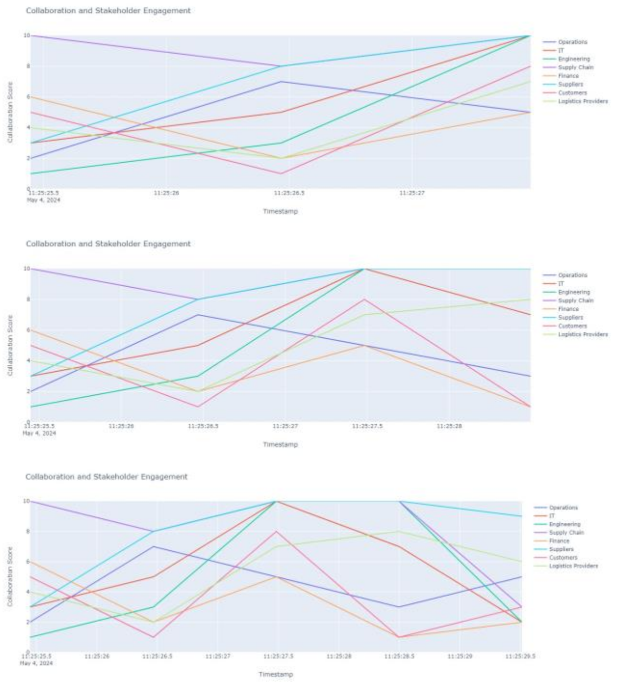

Fig. 13: Collaboration and Stakeholder Engagement

$$\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \quad (14)$$

From equation 14, where xi is the collaboration score of each team, wi is the weight that can be given to each team's collaboration score and may depend on the relative importance or contribution of the team and n define the total number of teams. I have chosen to present the scores as collaboration maps that illustrate the constant changes of activities among different organizational teams. What we have here is the ability to record collaboration scores for various teams at each time point so that each timestamped entry corresponds to the collaboration scores at that time. As seen from these scores, increases and decreases in collaboration efforts can be observed for two successive time intervals of different teams. For instance, in the first set of scores, Operations and Supply Chain both have high collaboration scores that depict efficient teamwork of the departments. Nevertheless, the two divisions of Finance and Customers reveal the lowest values, which may indicate inefficiency in their cooperation. In the following set of scores, there is also a significant improvement in collaboration scores in several teams and it is most evident in the IT, engineering, and supplier groups. On the other hand, the Logistics Providers have a relatively lower collaboration score implying that a change in the manner in which the teams work is quite probable. In sum, the collaboration scores offer useful information on how existing and future functions of teamwork and engagement deepen and develop within an organization. When analyzing these scores throughout the years, stakeholders are able to determine how effective collaborative efforts are, make modifications to encourage improved collaborative efforts, and ultimately boost organizational efficacy.

4 Conclusion

In conclusion, it becomes clear that the presented research supports the idea of using big data solutions and IoT technologies to improve operations and achieve greater outcomes for long-term sustainable growth. When KPIs are effectively established and IoT tools are deployed strategically, an organization can achieve many benefits such as increased operational efficiency, better control, and clear visualization and responsibility for risks. Also, proper data governance to provide data standards and security necessary for data quality and compliance provides confidence in decisions made. The real-time analytics and collaboration process in organizations facilitate dealing with such systems showing the flexibility that empowers the organizational processes, operations, and competitiveness. In summary, the application of additional analytical methods and cooperation helps to achieve well-founded decisions, improve the effectiveness of work processes, and contribute to sustainable success in constantly evolving industrial environments.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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The authors have no conflicts of interest to declare.