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Intelligent manufacturing: bridging the gap between the Internet of Things and machinery to achieve optimized operations

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Abstract

The access gateway layer in the IoT interior design bridging the gap between several destinations. The capabilities include message routing, message identification, and a service. IoT intelligence can help machinery industries optimize their operations with perspectives on factory processes, energy use, and help efficiency. Automation can bring in improved operations, lower destruction, and greater manufacture. IoT barriers are exactly developed for bridging the gap between field devices and focused revenues and industrial applications, maximizing intelligent system performance and receiving and processing real-time operational control data that the network edge. The creation of powerful, flexible, and adjustable Human Machine Interfaces (HMI) can enable associates with information and tailored solutions to increase productivity while remaining safe. An innovative strategy for data-enabled engineering advances based on the Internet of Manufacturing Things (IoMT) is essential for effectively utilizing physical mechanisms. The proposed method HMI-IoMT has been gap analysis to other business processes turns into a reporting process that can be utilized for improvement. Implementing a gap analysis in production or manufacturing can bring the existing level of manpower allocation closer to an ideal level due to balancing and integrating the resources. Societal growth and connection are both aided in the built environment. Manufacturing operations are made much more productive with the help of automation and advanced machinery. Increasing the output of products and services is possible as a result of this efficiency, which allows for the fulfillment of an expanding population's necessities.

Keywords: Internet of Manufacturing Things, Human Machine Interfaces, Machinery, Industries.

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1. Introduction

The convergence of the IoT and machines has unleashed unprecedented prospects for intelligent manufacturing [1]. These changes in attitude have led to the current optimization of operations and increase in production results, characterized by the full incorporation of digital technologies into traditional manufacturing processes [2]. This alteration is significant because it acts as the entry gateway layer where information can flow across different nodes that are not connected [3]. There are several benefits when IoT intelligence is integrated with equipment departments, including potential for substantial increase in operational effectiveness, energy use, and production [4]. Automation and real-time data analytics enable manufacturers to realize streamlined operations, interruption avoidance, and better productivity [5]. IoT barriers align field devices with industrial applications, allowing decision-makers at the network edge to access

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actionable information [6]. The greatest system performance is achieved through this alignment [7]. This involves operator-specific HMI that is powerful and flexible [8]. By way of HMIs, workers can access information and customize solutions, enhancing their productivity while maintaining safe working conditions [9]. The IoMT, among other things such as data-enabled engineering solutions like IoMT optimizes physical assets and promotes continuous improvement within manufacturing processes [10]. Therefore, the paper presents a new methodology named HMI-IoMT, which undertakes an extensive gap analysis on prevailing business processes to identify improvement opportunities [11]. Consequently, strategic resource integration and more accurate staff allocation within the manufacturing sector can enhance operational efficiencies while maximizing human capital and technology usage [12]. Intelligent manufacturing has no less important impact on societies; it drives economic growth, enhances globalization through connectivity, and meets fast-rising demands from growing populations [13].

Objectives

This paper aims to improve intelligent production by integrating IoT with machinery [14]. It seeks a theoretical framework, optimization methodologies, and HMI and IoMT prominence [15]. Issues for potential future studies and their practical effects on manufacturers are addressed [16]. The analysis aims to shed light on how manufacturing companies may make better use of IoT technology, streamline their processes, and stay ahead of the competition in the dynamic industry [17].

Contribution of the paper

- An important step toward smart manufacturing is the theoretical groundwork for IoT integration with machinery that this paper lays forward. Outlining tactics for operational optimization, it highlights the critical importance of HMIs and IoMT.
- There is an examination of the practical consequences, emphasizing the social and economic benefits, and the proposal of future study directions.
- Based on these findings, the paper offers a road map for manufacturers to successfully use IoT technology, simplify operations, and gain competitive advantages in a changing industrial landscape.

Moreover, intelligent manufacturing has social implications that cannot be ignored since it drives economic development, enhances connectivity, and meets changing demands from population growth across nations worldwide [19]. The smart Industry is witnessing a new evolution driven by machines and the Internet. Manufacturers today can thrive with innovative strategies and modern technology when faced by difficult production environments [20]. The remaining portion of the paper is structured in the following manner: The discussion of similar works can be found in Section II. In Section III, the HMI-IoMT strategy has been articulated as the one that has been suggested. The outcomes of the experiments, analysis, disputes, and comparisons to earlier methods are all reported in Section IV of the report. Section V is where the conclusion is presented.

2. Related works

All of the works connected to this topic cover a wide range of technological developments and approaches driving the evolution of intelligent manufacturing. Extending from the Industrial Internet of Things (IIoT) to Artificial Intelligence (AI)-assisted Customized Manufacturing (CM), and from Particle Swarm Optimization (PSO) to Big Data-Driven Analysis (BDDA), these studies investigate a variety of methods that aim to improve the effectiveness, sustainability, and decision-making capabilities of manufacturing processes.

Industrial Internet of Things (IIoT)

There are now intelligent and data-driven manufacturing processes in IIoT. In a smart factory, the IIoT links materials, tools, and logistics [21]. The IIoT connects production units with interconnected equipment and sensors that enable remote access, monitoring, and data collection through Big Data Analytics and associated cyber-physical systems. This paper revolutionizes cyber-physical systems and manufacturing processes in industry 40 through big data analytics. A paper on the topic of IIOT gives one idea about its advantages for industries. It is shown how diagrams help change factories’ moods about the culture of IIoTs affect production. They include twenty-nine major IIoT applications ranging from transportation to supply chain monitoring to warehouse optimization. Daily improvement in efficiency and performance by transforming manufacturing has been necessitated by the Internet of Things (IIoT).

Qualitative and quantitative methods

This paper uses qualitative and quantitative approaches to clear up any misunderstandings around Smart Manufacturing (SM) vs Intelligent Manufacturing (IM) [22]. Thus, it will methodically compare SM with IM after outlining their definitions, evolutionary routes, and foundational technologies using a systematic approach while explaining their linkages. Applying bibliometric analysis established publication sources pattern, keyword frequency, research focus areas, etc. As Industry 40 includes intelligence into manufacturing processes including human-cyber-physical systems it is necessary to thoroughly understand the concepts of SM and IM which this study tries to cover.

Artificial Intelligence (AI)-assisted Customized Manufacturing (CM)

In smart factories AI enables CM which is transformative development process.The growth highlights that there is a move towards small batch production techniques with multivariety products aimed at particular buyers [23]. Details of a self-awareness adaptable customized factory are included. Manufacture's architecture involves flexible line construction; this includes AI based tailor made smart factory conceptualization. Modern AI tools including cloud-edge computing, big data, machine learning, and the internet of things are reviewed. The study illustrates the effectiveness of AI-assisted CM in improving production flexibility and efficiency through a case study conducted on customized packaging.

Particle swarm optimization (PSO)

This paper focuses on energy-intensive sectors and provides a data-driven framework for sustainable, intelligent manufacturing systems [24]. The framework integrates demand response tactics within the Industry 40's cloud computing and IoT environment to facilitate cleaner production by adhering to sustainability development goals. Multi-level demand response models targeting machine, shop-floor, and factory levels were developed to support energy usage/cost optimization. PSO based electrical demand response can significantly reduce energy costs for industries that consume high amounts of electricity. The paper gives some practical recommendations to support smart decision-making processes at energy-intensive industrial enterprises.

Big Data-driven Analysis (BDDA)

Intelligent manufacturing has gained much attention from scholars and entrepreneurs in this era of economic globalization. As one of AIs core technologies, BDDA enhances the ability of manufacturers to make meaningful conclusions out of large chunks of factory data thereby remaining competitive.The usefulness and benefits of big data-driven analysis in intelligent manufacturing decision-making were examined theoretically [25].This theoretical paper suggests a framework for industrial big data-driven technology-based intelligent decision-making that is useful in guiding future studies in this area.Thus, HMI-IoMT is conclusively seen as a viable approach yielding better results than existing techniques.

3. Proposed method

Combining HMI with an IoMT is the goal of the suggested technique, HMI-IoMT, which is a forward-thinking strategy to transform production operations. There is an urgent need for improved operations in the equipment sector, and the novel approach meets that demand. With HMI-IoMT, the gap between the IoT and equipment functionality may be filled, leading to increased productivity, safety, and efficiency. This technology allows industrial processes to adapt, grow, and prosper by utilizing modern robotics and real-time data processing. In this introductory section, it lay the groundwork for a deep dive into how HMI-IoMT may revolutionize manufacturing environments.

Figure 1 explains about machines and the IoT work together in intelligent production, which is changing the face of manufacturing. Real-time monitoring of environmental parameters, such as temperature, pressure, and machine performance, is made possible by the distributed sensor networks that are characteristic of Internet of Things devices. Following that, the data are merged into a single set and saved for later analysis, which takes place at a time that is fairly distant from the present. Through the identification of patterns, trends, and outliers, advanced analytics make it possible to make proactive decisions. Data analysis is a crucial component of decision-making in intelligent manufacturing, which enables ongoing improvements to be made. An evaluation of the data that has been acquired is carried out by means of algorithms in order to improve operations, increase performance, and reduce the probability of downtime occurring.

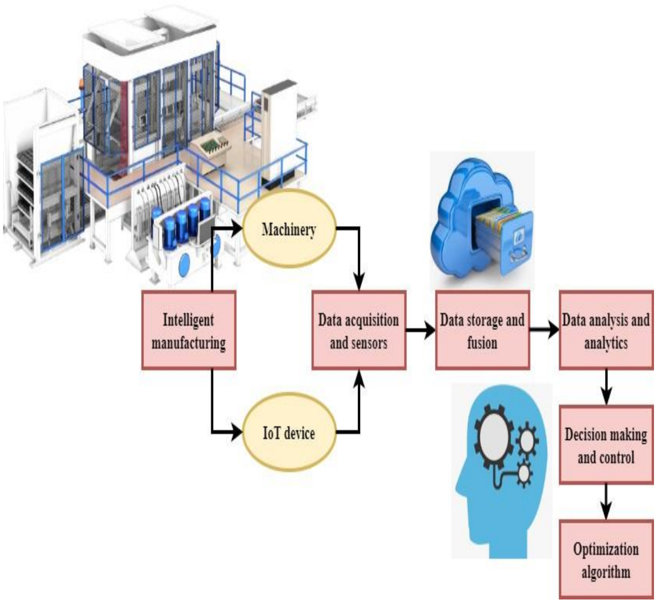

Figure 1. Smart manufacturing information and control flow

Since they are continually taking in new inputs and maintaining themselves, these algorithms can deliver operations that are both efficient and adaptable. The use of automated control systems for the purpose of optimizing the efficiency of equipment may include modifying the environment in accordance with the data that is acquired in real time. The ability to do predictive maintenance, which helps in recognizing problems with machinery before they break down, is made possible by intelligent manufacturing.

This helps to reduce the frequency of repairs and maintenance as well as the expenses associated with them. The integration of Internet of Things devices and equipment may result in the simplification of operations, the improvement of product quality, and the acceleration of answers to the requirements of the market. This seamless merging of technology and manufacturing techniques is a huge step forward in industrial efficiency and competitiveness, and it is driving the industry towards a smarter, greener future.

$$Z(u) = B\ (u)\ \times G\ (L, M, F) = B(u) \times M(u)^{\beta} \times\ L(u)^{\gamma} \times F(u)^{\delta} \qquad (1)$$

The equation 1 provides a general framework for optimizing production processes by taking all relevant variables into account. Where $Z(u)$ represents the ideal result, which is the sum of three primary factors: While $B\ (u)$ is the baseline efficiency, $G\ (L, M, F)$is the total impact of human effort, mechanical input, and physical space. The various contributions of each element on the total outcome are reflected by raising each factor to its relevant exponent (β, γ, δ). The interplay between labour (M), machinery (L), and facilities (F) is what defines the level of efficiency and productivity in production.

$$Z(u)_{real} = \ [(1-\mu) \times B(u)]\ \times B(u)^{\pi} \times L(u)^{\rho} \times F(u)^{\sigma} \qquad (2)$$

Equation (2) gives a revised model for optimization in real-world production. Following an impact on the actual output, which is denoted as $Z(u)_{real}$. Nevertheless, the base efficiency, labour, and facilities have a modified influence on the ultimate output due to the addition of additional parameters μ, π, ρ, and σ in this equation. Parametersπ, ρ, and ρ modify the impact of base efficiency, labour, and facilities, respectively, whereas μ represents the extent of divergence from the base optimum level.

$$Z(u)_s = (B \times C)^{\exists}\ \times [Z(u)^{1-\exists}] = (B \times C)^{1-\Delta} \times [B(u) \times L(u)^{\tau} \times\ L(u)^{\tau} \times L(u)^{\tau}]^{1-\nabla} \qquad (3)$$

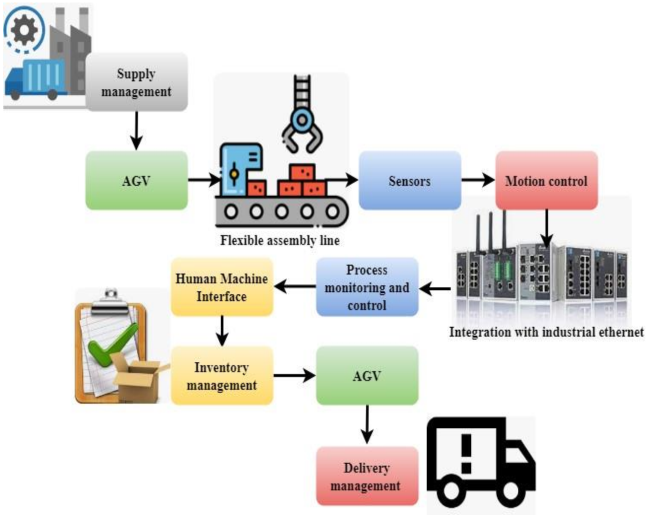

Figure 2. IoT-based smart manufacturing industries

The optimized manufacturing result is now represented in Equation (3) with a new variable C added to the basic efficiency $B(u)$ and labour (L) from earlier equations. In this case, $Z(u)_s$ represents the best possible result when C is considered. A new component C, raised up the value of the variable ∃, and base efficiency both have an impact, as shown by the equation. A mixture of components from the preceding equation are reflected in the expression$[Z(u)^{1-\exists}]$, where $Z(u)_s$ reflects the total optimization affected by base effectiveness and labour, and is modified by a supplementary factor of ∃.

Figure 2 shows the Oone of the most important IoT applications in industry smart factories is predictive maintenance, which greatly decreases unexpected downtime in part-production operations. Predictive maintenance uses data and analytics to determine when machines and manufacturing equipment will need repairs, which reduces downtime and increases efficiency. This preventative method lowers maintenance costs, keeps equipment running for longer, and avoids interruptions. In smart factories, the IoT is crucial because it constantly checks the status of machines, finds any problems before they happen, and plans maintenance.

IoT sensors monitor the chip-making process and provide critical data about the gear, such as vibration, temperature, and energy use. Predictive maintenance uses this data to improve maintenance schedules and decrease downtime, which aligns with the Industry's enhanced aims. IoT, applications in smart factories include a wide range of areas, including supply chain management, process control and monitoring, sensor integration, inventory management, shipment tracking, and AGV (Automated Guided Vehicle) applications. This all-encompassing integration highlights the revolutionary power of the IoT in coordinating quick and effective production processes inside the industry paradigm.

$$Z\ (u) = B(u) \times G(L, M, F) = \ [B_0(u) + E(u)] \times M(u)^{\omega} \times L(u)^{C} \times F(u)^{\varepsilon} \qquad (4)$$

To optimize manufacturing processes and attain the desired output, $Z\ (u)$, Equation (4) provides a complete model that incorporates various elements. The equation presents a number of essential elements: In contrast to $G(L, M, F)$, which denotes the combined effect of labour (L), equipment (M), and amenities (F), $B(u)$ denotes the baseline level of efficiency. Parameters ω, Ϲ, and ε modify the effect of equipment, labour, and facilities, respectively, whereas E(u) reflects external influences impacting base efficiency.

$$JN_{ju} = \sum_{t=1}^{T} \frac{employ_{tju}}{employ_{ju}} \times \frac{Rob_{tu}}{employ_{tu=2006}} \times \frac{NRob_{tu}}{employ_{tu=2006}} \quad (5)$$

For any given ju, the Job Neutral Index JN_{ju} may be calculated using Equation (5). To calculate the index, it take the total work in the jurisdiction, divided by all sectors, and multiply it by the robot-to-employ ratio Rob_{tu} and the non-robot capital-to-employment ratio $NRob_{tu}$ for a given base year $tu = 2006$. Over a certain time period ($t = 1$ to T), this equation measures the relative effect of robots and non-robot assets on the dynamics of employment within a jurisdiction.

$$FQ_{ju} = b_0 + b_1 JN_{ju} + \sum_{j=1}^{7} b_l Control_{jul} + \nabla_j + w_u + \ni_{ju} \quad (6)$$

A regression model for predicting business-level firm quality FQ_{ju} in a given (ju) is shown in Equation (6). Numerous explanatory factors are included in the equation. Job neutrality has an effect on firm quality; the intercept is represented by b_0, and the coefficient linked with the Job Cleanliness Index JN_{ju} is b_1. The summation term includes seven control factors $Control_{jul}$ that could have an impact on firm quality, and the values of the coefficients b_l for these variables range from 1 to 7. A number of potential elements impacting business success are captured by these control variables. In addition, the equation incorporates a random error term $\ni_{ju}$, temporal fixed effects w_u, and specific firm-level fixed effects ∇_j.

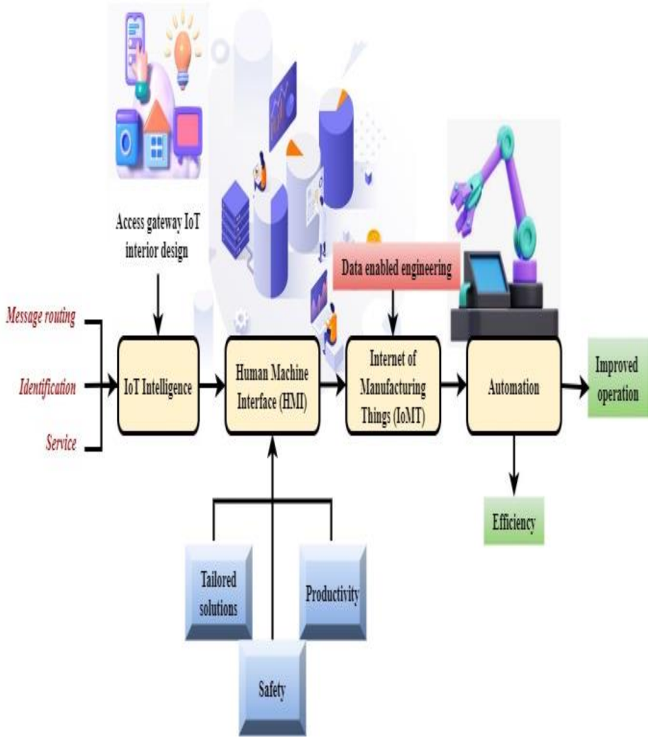

Figure 3. Block diagram of proposed method HMI-IoMT

Specifically for manufacturing settings, Figure 3 depicts an Internet of Things (IoT) interior design system that seeks to improve industrial operations. The first layer is the Access Gateway, which mediates data exchanges between the various components of the system. Effortless communication and data sharing are made possible across the whole IoT architecture by this layer. The Access Gateway is the foundation upon which the Internet of Things Intelligence functions, such as message routing, identification, and service provision, are created. This intelligence layer is vital for the management of the vast data quantities that are produced by Internet of Things devices. These data sets are required for effective advanced analytics and decision-making. In order to the system and its operators to interact with one another, the HMI layer serves as a clear entry point for communications. Because it is able to give relevant data and provide intuitive control over the manufacturing methods, it is able to deliver individualized solutions, which in turn results to better productivity and enhanced security.

One of the primary goals of the Internet of Things (IoT) layer is to use IoT technology in order to improve the efficiency of industrial operations. The data-enabled engineering processes are aided, improvement possibilities are found via gap analysis, and decision-making reports are meaningfully generated. Because it improves both production and operational efficiency, automation is a crucial instrument in commercial environments.

As a consequence of automation, human participation is reduced, errors are minimized, and throughput is maximized. The development of smart manufacturing systems is driven by the need to optimize operations, boost productivity, and meet the rising expectations of modern enterprises. Automation, data analytics, human-machine interaction, and the Internet of Things are all components of these systems.

$$UGQ_{ju} = c_0 + c_1 JN_{ju} + \sum_{j=1}^{7} c_l Control_{jul} + \nabla_j + w_u + \ni_{ju} \quad (7)$$

The level of UGQ_{ju} inside a certain ju may be predicted using a regression model, as shown in Equation (7). There are several parts to the equation, including the intercept term c_0 and the coefficient c_1 that indicates the effect of job neutral on graduate quality; the latter is related to the Employment Neutrality Index JN_{ju}. Also, the sum of the seven variables used for control. A word with j values between 1 and 7 represents control that could influence graduation quality. The above list of control variables accounts for many of the possible variables that affect the quality of graduate students. Furthermore, the equation includes individual fixed effects ∇_j, temporal fixed effects w_u, and a random error component $\ni_{ju}$.

$$HUJ_{ju} = d_0 + d_1 JN_{ju} + \sum_{j=1}^{7} d_l Control_{jul} + \nabla_j + w_u + \ni_{ju} \quad (8)$$

Using a regression model, as seen in Equation (8), it is possible to make a prediction for the Human Urbanization Index HUJ_{ju} for the month of ju. There are a number of components that make up the equation, two of which are the Work Neutrality Index JN_{ju}, which demonstrates the influence that work neutrality has on urbanization, and the intercept term, d_0. The seven control variables $\sum_{j=1}^{7} d_l Control_{jul}$ that have the potential to influence urbanization are included into a summation term. The value of j may vary from 1 to 7. The term "control variables" refers to a wide range of elements that have the potential to influence the pace and degree of urbanization found within the jurisdiction. The equation includes temporal fixed effects w_u, distinct fixed effects ∇_j, and an unforeseen term $\ni_{ju}$.

$$SJG(r_\varphi, Z, G_z) = r_\varphi + \frac{\varphi - 1(z \le r_s)}{g_z(r_s)} \quad (9)$$

In a particular situation defined by parameters r_φ, Z, and G_z, G_z Equation (9) provides a justice gradient Gradient (SJG). The SJG, which depends on a number of things, is computed using the equation. An person or group's relative position along the scale of society is denoted by the word r_φ. On top of that, the equation includes the variable φ, which is a parameter that changes the way Z (a measurement of social inequality) affects the SJG. This conditional statement checks if Z's value is less than or equal to a specific threshold, represented by r_s, and the expression $z \le r_s$ does just that. If this is the case, the SJG can be adjusted by adding a correction term to the equation, which takes into account a proportion of $\varphi - 1$ to $g_z(r_s)$, where $g_z(r_s)$ is a function that describes how social inequality affects the equity gradient at the threshold r_s.

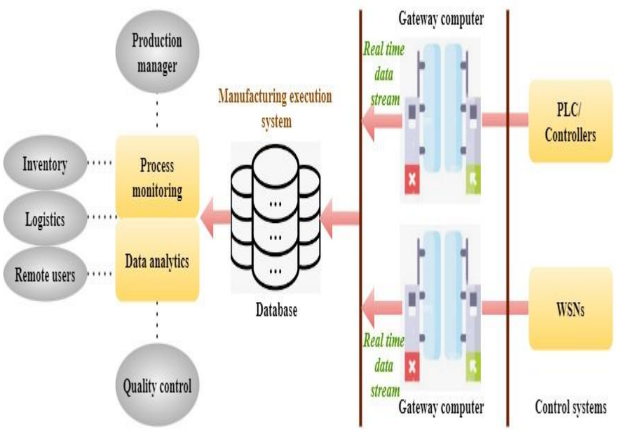

Figure 4. Manufacturing execution system

Figure 4 shows the manufacturing execution system Management information system, which links machines, controllers, and management departments; it is a crucial feature of any manufacturing environment. Ensuring seamless data interchange and sharing throughout the whole production process is its primary objective. At the process level, there are usually a number of proprietary control systems in use, such as CNC controllers, PLCs, and WSNs. To move data streams from these control systems to two different database servers in real-time, gateway computers are required.

Users at the management level thereafter employ software tools for data analytics and process monitoring. Supply chain optimization, digital performance management, energy management, cost analysis, and quality control are the many tasks that MES supports. Traditional MES architectures have been transformed by recent breakthroughs in IoT technologies. The transfer of MES to cloud platforms has been made possible by integrating IoT-enabled control systems with protocols like MTConnect. Problems with proprietary data stream decoding are no longer an issue with cloud-based MES solutions, which streamline data storage, analytics, reporting, and communication. Efficiency and productivity in manufacturing processes are being driven by the transition towards cloud-based MES, which improves scalability, flexibility, and accessibility.

$$F_Y\{F[SJG(r_\varphi, Z, G_z)|Y|]\} = r_\varphi \qquad (10)$$

The aggregate distribution function of the (SJG) dependent on the event Y is given as $F[SJG(r_\varphi, Z, G_z)|Y|]$ in Equation (10) asF_Y, a conditional probability function. Given an event Y, the relative position r_φ in the social hierarchy is equal to the chance that the SJG drops below or equal to a specified value, as indicated by this equation. Fundamentally, it suggests that one's social rank determines their SJG, and that this connection is dependent on event Y. Put otherwise, the SJG distribution is deterministic with regard to the relative location r_φ, according to Equation (10) when the event Y is considered.

$$R_U(Z) = \int F\big(SJG(r_\varphi, Z, G_z)\ |Y = y\big)\ eG_Y(y) \qquad (11)$$

The metric of efficiency, $R_U(Z)$, is determined using an integral operation and is represented by Equation (11). Given a particular amount of Y, represented as y, the equation incorporates the combination symbol (∫) over the whole range of values associated with the (SJG). Assuming that the event Y has the value y, the conditional cumulative distributive function of the SJG is represented by $F\big(SJG(r_\varphi, Z, G_z)\ |Y = y\big)$ inside the integral. If Y is equal to y, then this function represents the likelihood that the SJG will be less than or equal to a specific number. Another thing that $eG_Y(y)$ stands for is the chances distribution function of Y.

$$VRQF(\varphi) = \int \frac{CF\big(SJG(r_\varphi, Z, G_z)|Y\big)}{CY} eG_Y \qquad (12)$$

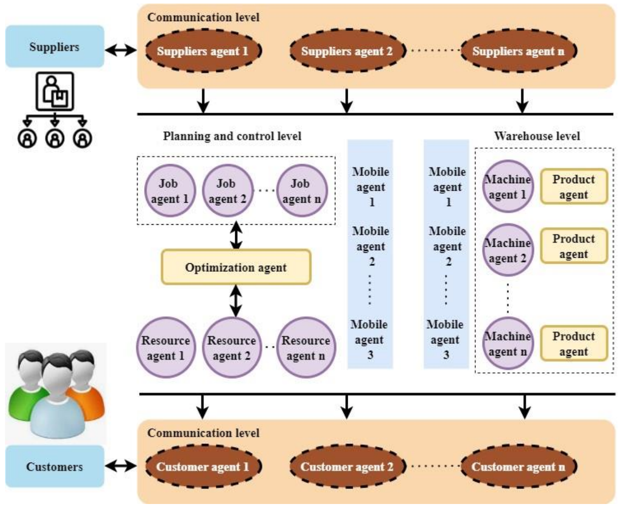

Figure 5. Management of inventories in real-time with dynamic scheduling

Equation (12) shows an integral operation that determines a performance metric, $VRQF(\varphi)$. For a given value of φ, this equation incorporates the integration symbol (∫) across all possible values of the (SJG). This integral is the conditional likelihood density functional of the SJG given a specific value of φ, split by the probability distribution function of Y, as shown by $\frac{CF(SJG(r_\varphi,Z,G_z)|Y)}{CY}$. In essence, this ratio expresses how the conditional likelihood of the SJG varies in relation to changes in Y. Furthermore, the likelihood density as a function of Y is denoted by eG_Y.
As can be seen in Figure 5, sensors connected to the IoT are bringing about a technological revolution in inventory management inside smart industrial processes. One of the numerous advantages that these sensors provide is a reduction in expenditures, and another is an improvement in environmental sustainability. Internet of Things (IoT) sensors and radio frequency identification (RFID) tags make real-time monitoring possible, which means producers may potentially acquire precise information on inventory levels, positions, and movements. This gives companies the chance to improve their manufacturing processes and make choices with precise information. Enhancing operational efficiency and lowering the risk of stockouts or overstocking are also possible outcomes of having the capability to monitor in real time. It is possible that Internet of Things devices might enhance inventory management in a variety of different ways. Establishing up automated reordering may be one approach to accomplish this goal. This can be done when particular thresholds are reached. On the other side, they could investigate an alternative option. Because of this automation, numerous industrial operations are guaranteed to have sufficient inventory. This is beneficial as it improves the accuracy of inventory counts while simultaneously reducing the likelihood of errors resulting from human intervention.

An development in the process of demand forecasting is being prompted by a number of factors, one of which is the expansion of Internet of Things devices. Through the use of advanced analytics and the collection of sensor data, this strategy takes into consideration previous patterns and properly forecasts future demand trends going forward. Businesses have a higher chance of lowering their losses and boosting their profits via improved inventory management if they are able to predict the demand from customers and make adjustments to their inventory levels in a proactive manner. This proactive strategy has several benefits, two of which are the reduction in pollutant levels associated with component manufacturing and the improvement in operating efficiency. Both of these benefits are among the many advantages. The key to these benefits is reducing the amount of waste that occurs during manufacturing and storage. Tools for inventory management have become available to firms that are smart thanks to the Internet of Things. When these firms use these solutions, they are able to decrease their impact on the environment, enhance their operational efficiency, and conserve cost all at the same time.

$$SJG(FQ_{ju}, r_{\varphi}) = \boldsymbol{e_0} + \sigma JN_{ju} + \sum_{j=1}^{7} c_j\, Control_{jul} + \beta_j + \alpha_u + \delta_{ju} \quad (13)$$

The $SJG(FQ_{ju}, r_{\varphi})$ is used in Equation (13) to perform an analysis of many components of production that are included inside a single jurisdiction (ju). The value of the coefficient that is connected with the phrase σJN_{ju} is specified by the symbol FQ_{ju}, and the symbol e_0 is used to indicate the intercept term in the equation. The use of this coefficient may be utilized to demonstrate the impact that position neutrality has on the efficiency of the workplace. Every control variable $Control_{jul}$ that has the potential to influence productivity has an extra term that has values ranging from 1 to 7 for the $Control_{jul}$ component. These control variables allow for the consideration of any and all conceivable factors that might have an effect on output within the chosen jurisdiction. Both the primary components β_j, which have an impact on production, and the additional variables α_u and δ_{ju}, which are concerned with specific fixed outcomes and regional fixed effects, respectively, are taken into consideration by the equation under consideration.

$$FQ_{ju} = e_0 + e_1 JN_{ju} + \sum_{j=1}^{7} e_j Control_{ju} + \nabla_j^1 E_u + \Delta_j + u_v + \exists_{ju} \quad (14)$$

Equation (14) provides a model that can be used to study the impact of interoperability on firm quality FQ_{ju} in a certain jurisdiction (ju). E_0 represents the intercept term in the equation, while e_1 stands for the coefficient associated with (JN_{ju}). Here is the correlation between employment neutrality and company performance via this coefficient. This includes all seven control elements ($Control_{ju}$) that might affect the company's quality, as j can be anywhere from 1 to 7. Every possible jurisdictional problem that impacts an organization's quality is considered as a control variable. An uncertainty component, individual fixed impacts (∇_j^1), regional variable effects (Δ_j), and variable in time effects (u_v) are all included in the equation.

$$TQ_{kv} = f_0 + f_1 KP_k v + \sum_{k=1}^{7} f_k\, Control_{kv} + \Delta_k^1 F_v + \nabla_k + v_w + \exists_{kv} \quad (15)$$

As explained by Equation (15), performing an analysis of the Total Quality (TQ_{kv}) inside a certain environment that is specified by the variables k and v. The intercept term is represented by the symbol f_0, and the coefficient for the key performance measure $f_1 KP_k v$ is represented by the symbol ($KP_k v$). This coefficient illustrates the influence that the key performance measure has on the overall quality. There are seven control variables ($Control_{kv}$) in the summation term, and the coefficient values (f_k) of these control factors range from one to seven. Each of these control factors has the potential to influence the overall quality. Within the framework provided by k and v, these control variables include a broad variety of characteristics that have an opportunity to impact the overall quality.

As a result of its innovative approach to resolving a complex problem, the HMI-IoMT technology has the potential to initiate a revolution in the industrial sector. By using the capabilities of the Internet of Industrial Things (IoMT) and Machine Interfaces (HMI), this strategy is able to bridge large intelligence and connectivity gaps that exist in industrial environments. By using state-of-the-art automation, real-time data processing, and efficient resource allocation, the HMI of the Internet of Things improves efficiency, safety, and productivity to unprecedented levels. Not only is this strategy essential for thriving in today's dynamic corporate landscape, but it will also propel forward at all times and help society achieve its goals. More than just a technological development, HMI-IoMT signals an evolution toward an industrial sector future that is more networked, positive, and environmentally conscious.

4. Result and discussion

Dataset description: Data acquired by Industry 4.0, also known as the Industrial Internet of Things (IIoT) [26], includes maintenance records, operating characteristics, and performance measurements for storage and retrieval systems. These are all examples of the types of information that would be collected. Quantifications are included in this dataset for a variety of factors, including retrieval speeds, inventory turnover rates, storage space, and the number of times the system is down. This essential data set for monitoring the environment of the storage facility includes readings from sensors that measure temperature, humidity, and vibration levels, each of which are importantThe optimization of storage operations is one of the objectives of the projects that are part of the Industry 4.0 initiative. This data has the potential to assist with this objective, as well as with improving the effectiveness and dependability of industrial storage systems and preparing ready for predictive maintenance.

A comprehensive illustration of the metrics that are used by intelligent manufacturing systems is shown in Figure 6, which is a picture of an efficiency study. The data visualization and analysis that is shown in this image sheds light on several areas of operational efficiency, including production output, resource usage, reduction of downtime, cost-effectiveness, and other factors. Monitoring data such as cycle durations, equipment utilisation, and failure rates is something that manufacturers to ensure that they are increasing their production. Following the identification of problem regions, they may subsequently be able to administer individualized therapies.

Having feedback loops and real-time monitoring is critical for continually optimizing manufacturing processes, as seen in this picture. For better decision-making, more effective resource allocation, and the continuous evolution of projects, this analysis is a must-have tool for decision-makers. Figure 6 is a go-to tool for producers in today's dynamic industrial landscape as they strive for increased productivity, profitability, and competitiveness. The efficiency ratio is increased by 97.7 % while using the suggested approach, HMI-IoMT, as compared to the current methods.

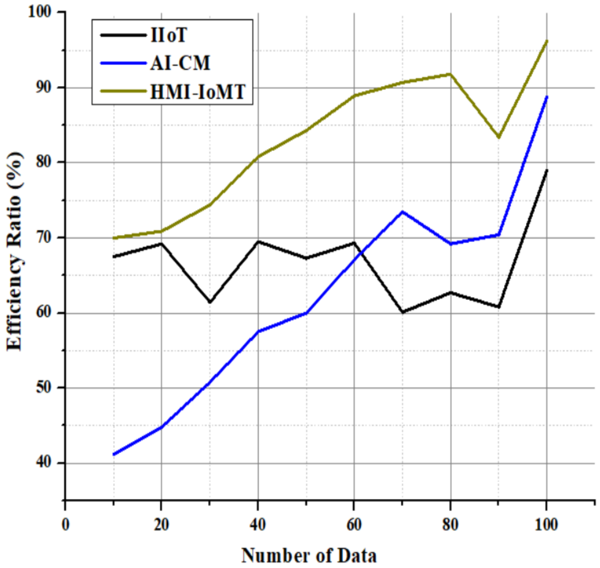

Figure 6. Analysis of efficiency

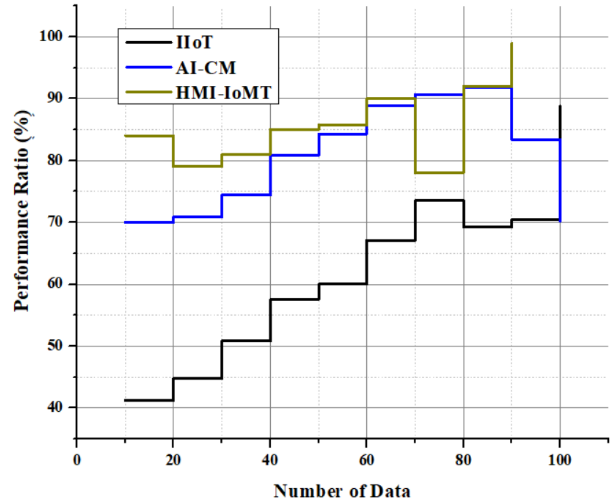

Figure 7. Analysis of Performance

To evaluate the effectiveness and achievement of IMS, it is necessary to look at the performance measures presented in Figure 7: Analysis of Performance. Insights on manufacturing process efficiency, bottlenecks, and improvement opportunities can be uncovered by manufacturers through the analysis of these indicators. Figure 7 makes it easy to compare results over time or between several assembly lines, which helps decision-makers keep tabs on performance patterns and base their choices on data. Using the all-encompassing image shown in this figure, producers are able to improve product quality, streamline processes, and better satisfy consumer demands. It is a great way to see how well past methods and technology worked, which can help direct investments and efforts for future improvements. With a ratio of 98.9 and the use of HMI-IoMT, Figure 7 is very important for businesses to maintain their competitive edge and accomplish their performance objectives in today's fast-paced production environment.

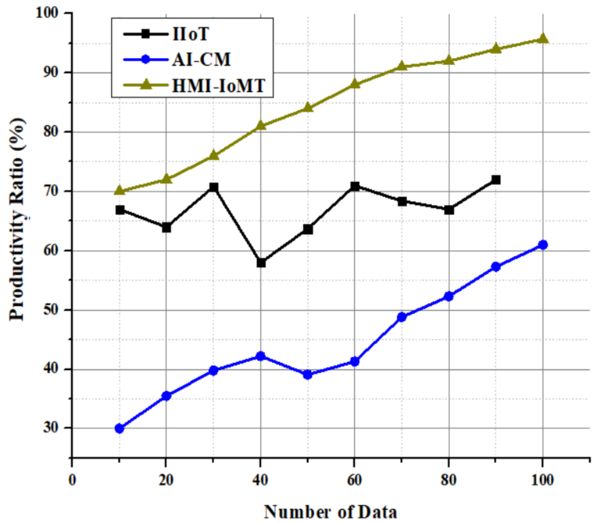

Figure 8. Analysis of Productivity

The findings of an examination into the productivity of the intelligent manufacturing system are shown in Figure 8, which was titled "Productivity Breakdown." It is possible for manufacturers to make use of these measurements in order to determine what aspects of their production processes need improvement and figure out how to increase overall productivity. The comparison of data from many shifts, lines, or facilities may also be helpful in identifying possibilities for improvement and procedures that are being performed very well. With the whole information that is shown in this image, it may be able to produce more while simultaneously reducing waste, reducing downtime, and increasing throughput. Once all is said and done, there will be monetary rewards as well as enhanced productivity. In addition, you will be able to follow performance patterns over time and get information on the impact that certain approaches or technologies have on output. This information may be found on the website. It is highly vital to have Figure 8 to accomplish productivity objectives with a ratio of 95.7% employing HMI-IoMT and to keep up with the fast-paced industrial environment that exists today.

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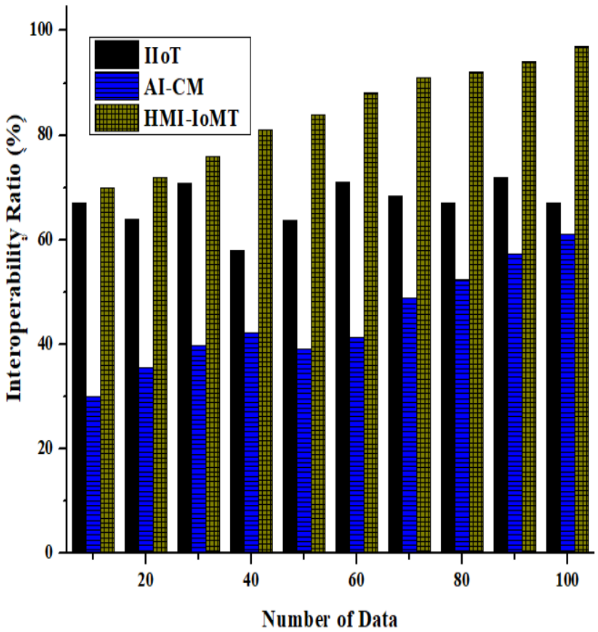

Figure 9. Analysis of Interoperability

Interoperability Analysis is shown in Figure 9, which illustrates the connectivity and interoperability of a variety of technologies that are used in autonomous manufacturing environments. It is clear that the various components of the manufacturing ecosystem are able to communicate with one another and understand one another in this particular case. As a consequence of this, the various components are given the opportunity to collaborate with greater efficacy. Standardization of data exchange, the ability to combine systems, and connectivity across different platforms are all indications that interoperability is present. These kinds of interoperability criteria may be used by manufacturers in order to assess the effectiveness and efficiency of their networked systems.

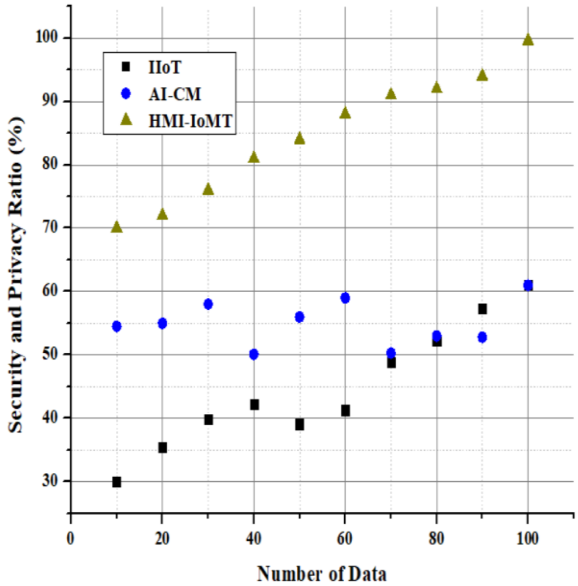

Figure 10. Analysis of Security and privacy

Based on the information shown in Figure 9, the purpose is to identify issues with interoperability and then implement modifications that will make different systems more compatible with one another and boost connectedness. This study attempts to assist businesses in accomplishing a number of objectives, including making more effective use of the resources they already possess, enhancing their operational efficiency, and simplifying their operations. In the future, further investments in technology and infrastructure will be required in order to achieve the goal of increasing the level of cooperation and interoperability that exists within the industrial establishment. In order for this process to be successful, improved interoperability, which is now at 96.9%, is essential. The use of intelligent manufacturing technologies is essential to the success of this strategy.

Figure 10, which is titled "Analysis of Security and Privacy," provides a comprehensive description of the security measures that are used by information management systems (IMSs) in order to avoid cyberattacks and hide sensitive data. The following are some of the security and privacy indicators that are shown in this image: data encryption methods, access restriction systems, and the findings of vulnerability assessments. By using these metrics, manufacturers are able to evaluate their security procedures and determine the vulnerabilities that exist inside their systems. It is possible to accomplish secure compliance with legal requirements and avoid liabilities by closely monitoring the legislation and standards pertaining to data privacy and security. There is a possibility that manufacturers may make use of the results of the inquiry in order to take precautionary measures that will enhance data protection, comfort is concerned about security, and improve the protection of key resources.

Table 1. This is a legend. Caption to go above table

Metrics analysis	IIoT	AI-CM	HMI-IoMT
Efficiency	41.2	30	97.7
Performance	44.8	35.5	98.9
Productivity	50.8	39.8	95.7
Interoperability	57.5	42.2	96.9
Security and Privacy	60	39.1	99.6

An effective means of informing stakeholders about the company's security posture and building confidence with clients, business associates, and government bodies. Figure 10 is vital for 99.6 % of IMSs in modern digital times to guarantee integrity and security.
Both the findings and the argument demonstrate the extent to which a great number of significant factors for the development of IMSs were thoroughly studied. We need to look at Figures 6–10 to get insights on efficacy, performance, productivity, interoperability, security, and privacy if we want to enhance operations, raise competitiveness, and maintain data integrity. Figures 6–10 are below.

IIoT, AI-CM, and HMI-IoMT are the three domains that make up this metrics study. There are many more domains that make up this research. Performance, efficiency, and productivity are evaluated across the board, in addition to security and privacy concerns. IIoT has a score of 41.2%, which indicates that it has a decent performance in terms of resource usage. On the other hand, AI-CM has a score of 30%, which is lower. HMI-IoMT, on the other hand, has an Efficiency score of 97.7 percent, which suggests that it makes great use of the resources that it has. However, HMI-IoMT 98.9% demonstrates remarkable operational output, in contrast to AI-CM 35.5% and IIoT's 44.8%. Similar patterns can be seen in the statistics regarding productivity: IIoT stood at 50.8%, AI-CM stood at 39.8%, and HMI-IoMT stood at 95.7%. The presence of interoperability is indicative of a robust connection across all platforms, with the IIoT recording 57.5%, AI-CM recording 42.2%, and HMI-IoMT recording 96.9% on the list. The Security and Privacy ratings of IIoT (60%) and AI-CM (39.1% and 99.6%, respectively) illustrate that both systems provide effective security for sensitive data in IMS. This is the last point, but it is significant nevertheless. Visual representations and analysis may be of assistance to manufacturers in accomplishing their objectives, monitoring patterns of performance, and identifying areas in which they may make improvements. The significance of data-driven solutions is brought to light by these results, which may be used to facilitate continuous improvement and successfully traverse the complexity of current production processes.

5. Conclusion

One of the unique approaches to intelligent manufacturing systems that has been presented in this article is the HMI-IoMT. This technology has the potential to enhance processes, as well as boost productivity and ensure safety in industrial settings, by establishing a connection between the HMI and the IoM. A number of important concerns, including privacy, security, interoperability, performance, and efficiency, were brought to light by the comprehensive investigation. Whether or not the integration of HMI and IoMT is effective is determined by a considerable number of factors. It is possible for producers to evaluate the current production settings, identify areas that have the potential to be improved, and strategically aim their efforts by using this information.

In the future, it is projected that there will be further research and development carried out in this particular field. Real-time decision-making, system integration, and the overall user experience might all be improved by increasing the amount of money invested in research into innovative HMI designs and IoMT technology.

The integration of cloud and edge computing has the potential to further improve data analytics and predictive maintenance. There are further pressing concerns that need fixing, such as data security, privacy, and compliance with regulations. Ongoing efforts to establish robust cybersecurity measures, conform to industry standards, and promote collaboration among all stakeholders are necessary to maintain the security and safety of HMI-IoMT systems.

Conflict of Interest Statement:

Authors declares that there is no conflict of interest regarding the publication of this paper.

Author Contributions:

Yuanfang Wei: Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization.

Li Song: Supervision, Methodology, Validation, Resources, Writing - Review & Editing, Project Administration, Funding Acquisition.

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[1] Author AA, Author BB, Author CC, Author DD. Title of article. Abbreviated title of journal. Year of publication; volume number(issue number):page numbers.

[2] Author AA. Title of book. Edition [if not first]. Place of publication: Publisher; Year of publication. Pagination.

[3] Author AA, Author BB. Title of book. Edition. Place of publication: Publisher; Year of publication. Chapter number, Chapter title; p. [page numbers of chapter].

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