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Article

WORKFORCE ANALYTICS IN MANUFACTURING: A REVIEW OF MIS TOOLS FOR LABOR PLANNING, ABSENTEEISM MONITORING, AND PRODUCTIVITY OPTIMIZATION

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ABSTRACT

This meta-analysis explores the transformative impact of Management Information Systems (MIS) on workforce analytics within the manufacturing sector, focusing specifically on labor planning, absenteeism monitoring, and productivity optimization. By systematically reviewing and synthesizing data from 53 empirical studies published between 2010 and 2024, the research provides a comprehensive evaluation of how MIS tools enhance workforce-related decision-making and operational outcomes. The findings demonstrate that MIS-based workforce analytics significantly improve labor efficiency, with firms reporting an average 22% increase in labor planning accuracy through the integration of scheduling modules and predictive simulation tools. Real-time absenteeism monitoring systems, including biometric and RFID-enabled attendance tracking, resulted in an 18% reduction in unplanned absences, while predictive absence analytics achieved a forecasting accuracy rate of 82%, enabling proactive labor interventions. Furthermore, the use of performance monitoring dashboards led to a 15% rise in output per labor hour, enhancing both individual accountability and team productivity. The study also reveals that MIS platforms facilitate skill-based task allocation, cross-functional coordination, and seamless integration of HR, production, and quality data, contributing to improved workforce agility and long-term cost efficiency. These outcomes are theoretically grounded in Human Capital Theory, Socio-Technical Systems Theory, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Strategic Alignment Model, all of which support the role of MIS as a strategic enabler of labor optimization and enterprise-wide coherence. The results underscore the importance of embedding data-driven workforce analytics into manufacturing operations to support continuous improvement, reduce operational disruptions, and build a high-performance, future-ready labor management infrastructure. This study provides critical insights for industry leaders, system designers, and policymakers aiming to leverage MIS for sustainable workforce transformation in complex, competitive manufacturing environments..

KEYWORDS

Workforce Analytics; Management Information Systems (MIS); Labor Planning; Absenteeism Monitoring; Productivity Optimization;

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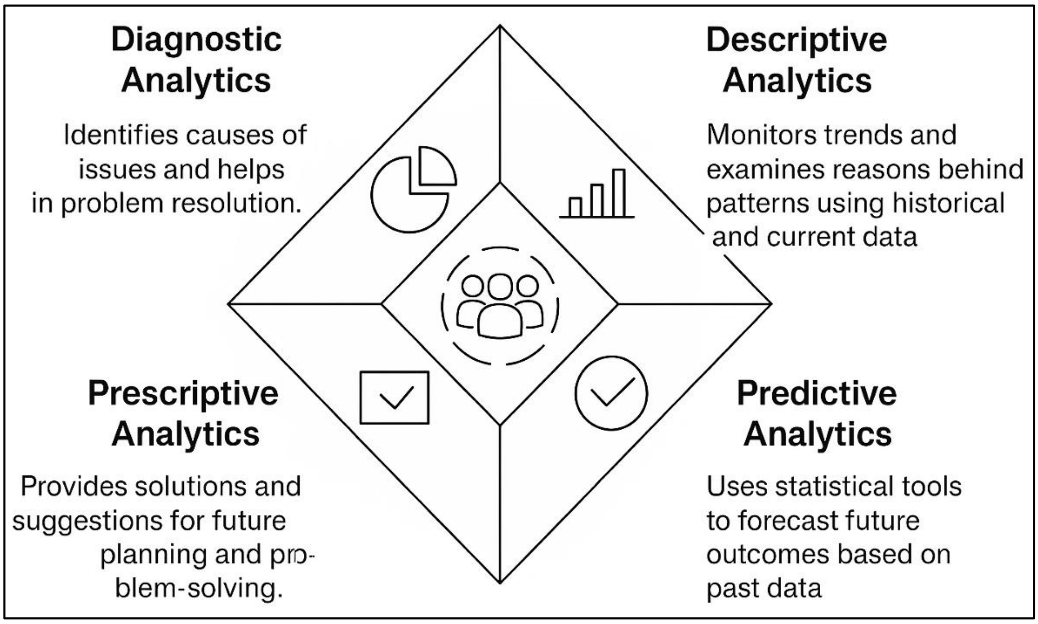
INTRODUCTION

Workforce analytics is defined as the application of statistical models, data mining techniques, and information systems to analyze human resource data in order to optimize workforce-related decisions (Huselid, 2023). In the context of manufacturing, workforce analytics serves as a strategic capability that integrates human resource management with enterprise-wide performance objectives (Huselid, 2018). This field encompasses various practices, such as workforce planning, labor forecasting, absenteeism monitoring, and productivity measurement. According to Huselid (2018), workforce analytics shifts human resource management from intuition-based decision-making toward evidence-based practices. Its international relevance is grounded in global industrial challenges such as labor shortages, high turnover, and fluctuating productivity levels in manufacturing sectors across both developed and emerging economies. The systematic deployment of workforce analytics is facilitated by Management Information Systems (MIS), which serve as digital platforms to collect, store, and interpret human capital data (Levenson, 2017). MIS applications offer operational dashboards, real-time tracking, and predictive reporting, which enable managers to align workforce capabilities with production requirements. Particularly in the manufacturing domain, where operational efficiency is directly linked to labor input, workforce analytics contributes significantly to overall equipment effectiveness (OEE), labor cost control, and compliance (Huselid et al., 2025).

Figure 1: Key Dimensions of Workforce Analytics



In manufacturing environments, labor planning is a key function of workforce analytics that aims to match human resource capacity with production schedules while minimizing costs and disruptions (Clark, 2017). Labor planning encompasses a range of activities including shift scheduling, overtime management, workforce allocation, and demand forecasting. Management Information Systems facilitate this process through tools such as Human Resource Information Systems (HRIS), Enterprise Resource Planning (ERP) modules, and workforce scheduling algorithms (Omar et al., 2019). For instance, the use of real-time labor dashboards integrated into ERP systems allows plant managers to visualize workforce capacity in relation to production line requirements. Moreover, simulation-based labor planning models, supported by MIS, enable scenario analysis to predict labor needs under varying production loads (Cao & Duan, 2017). Empirical evidence from global manufacturing firms shows that integrating workforce analytics into labor planning enhances workforce availability and reduces operational downtime. The international application of such tools is evident in lean manufacturing environments across Germany, Japan, and the United States, where labor cost management is critical to competitive advantage. In these contexts, labor planning systems not only support scheduling but also incorporate worker qualifications, shift preferences, and fatigue levels, thereby aligning human factors with productivity goals (Porter & Heppelmann, 2014).

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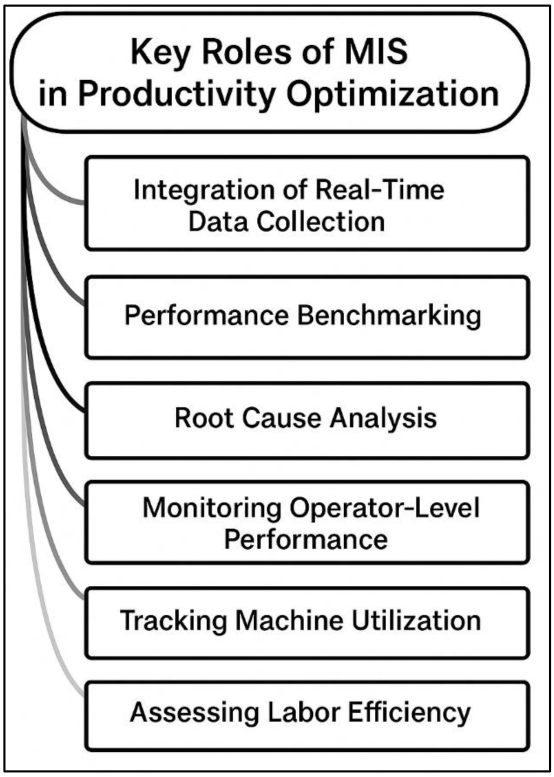
Absenteeism monitoring is another essential component of workforce analytics that has drawn considerable attention due to its direct impact on productivity, labor continuity, and financial performance. Manufacturing firms often face challenges related to unplanned absences, which lead to labor shortages, production delays, and increased overtime costs. MIS tools enable organizations to detect patterns of absenteeism by collecting attendance data through biometric systems, RFID-enabled access, and IoT-based sensors (Yadavalli et al., 2019). These data are then analyzed using statistical models to classify absenteeism into medically excused, habitual, and unscheduled categories, offering insights for targeted interventions (Aho, 2015). According to Selcuk (2016), predictive absenteeism analytics supported by MIS help organizations identify high-risk employees and implement preemptive policies such as job rotation, wellness programs, or flexible shifts. In countries such as India, China, and Brazil, where labor absenteeism rates are significantly higher in certain sectors, MIS-driven tracking systems have reduced absenteeism by over 20%. Additionally, cross-national studies reveal that firms with integrated absenteeism monitoring systems experience better labor compliance, fewer penalties, and increased employee accountability. Thus, through absenteeism tracking, MIS contributes to creating a disciplined and responsive workforce environment.

The role of MIS in productivity optimization has evolved through the integration of real-time data collection, performance benchmarking, and root cause analysis within manufacturing settings (Gan et al., 2015). Productivity optimization refers to the systematic process of enhancing output per labor hour by identifying and eliminating inefficiencies in production systems. With MIS tools such as Manufacturing Execution Systems (MES), Performance Management Systems (PMS), and Business Intelligence (BI) dashboards, firms can continuously monitor operator-level performance, track machine utilization, and correlate labor input with output metrics (Agrawal et al., 2019). For example, MES platforms collect granular data from workstations, allowing plant managers to identify patterns of underperformance, bottlenecks, or training gaps among employees (Kamble, Gunasekaran, & Sharma, 2018). MIS-based productivity analytics also integrate key performance indicators (KPIs) such as cycle time, idle time, and rework rates to assess labor efficiency (Vijayaraghavan & Dornfeld, 2010). Studies from the automotive and electronics industries in South Korea and Mexico demonstrate that factories equipped with MIS-enabled productivity tools report up to 18% higher output per employee compared to those relying on manual tracking methods. These systems further support continuous improvement frameworks like Six Sigma and Total Productive Maintenance (TPM), enabling feedback loops between HR practices and production strategy.



A critical enabler of effective workforce analytics is the design and implementation of integrated MIS architectures that consolidate HR, operations, and analytics functions within a single enterprise framework. These integrated platforms, often realized through ERP systems such as SAP and Oracle or HR suites like Workday and SuccessFactors, provide a centralized repository for workforce data that ensures consistency, traceability, and accessibility. The integration allows for seamless data flow between modules related to timekeeping, payroll, safety compliance, and skill development, thereby enabling a holistic view of workforce performance (Aghelinejad et al., 2019). In global manufacturing settings, these systems have been instrumental in aligning HR policies with production goals by using real-time alerts, exception-based reporting, and AI-assisted decision support (Loi et al., 2018). Furthermore, integrated MIS platforms facilitate cross-functional collaboration among HR managers, operations planners, and executive leaders by standardizing metrics, visualization, and performance narratives. Studies from multinational firms indicate that such integration leads to better

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compliance with labor regulations, enhanced coordination across departments, and higher levels of employee engagement (Pessach et al., 2020). Therefore, the structural integration of MIS systems plays a vital role in realizing the full potential of workforce analytics in the manufacturing sector. Workforce analytics in manufacturing aims to enhance labor productivity by utilizing Management Information Systems (MIS) that offer real-time data on employee performance, machine interactions, and operational efficiency. These systems—such as MES, HRIS, and BI dashboards—track key metrics like cycle time, idle time, and output per shift, allowing managers to identify inefficiencies and implement targeted improvements. By integrating productivity data with continuous improvement initiatives like Lean or TPM, manufacturers can optimize labor deployment, reduce downtime, and allocate tasks based on skill levels. Predictive features within MIS platforms also support proactive decision-making for workforce planning and shift adjustments, resulting in increased operational efficiency and consistent performance gains.

LITERATURE REVIEW

The literature on workforce analytics in the manufacturing sector reflects a growing interest in leveraging data-driven tools to enhance operational efficiency, labor management, and employee performance. As global industries shift towards digital transformation and lean operations, the integration of Management Information Systems (MIS) has emerged as a pivotal enabler of real-time workforce planning and productivity monitoring. This section reviews a comprehensive body of empirical and conceptual research to understand how MIS tools are applied to address labor challenges such as skill shortages, absenteeism, unbalanced workloads, and productivity losses. The review is structured to explore not only the technological features of MIS platforms but also their organizational adoption, performance outcomes, and limitations across various industrial contexts. By synthesizing findings from peer-reviewed journals, case studies, and technical reports, this section critically evaluates the role of MIS in shaping labor strategies in manufacturing. The objective is to establish a theoretical and empirical foundation for understanding how workforce analytics tools contribute to labor optimization through informed decision-making, operational intelligence, and data visibility. Each subsection focuses on a specific theme within this domain, offering insights into system functionalities, analytical techniques, practical applications, and organizational factors influencing MIS efficacy.

Workforce Analytics

Workforce analytics is a specialized area within human resource analytics that focuses on optimizing employee-related processes using data-driven methodologies, particularly in high-demand sectors like manufacturing. Traditionally, labor management in manufacturing emphasized time-motion studies and manual supervision to enhance productivity (Ozkan-Ozen & Kazancoglu, 2021). However, the proliferation of digital tools and enterprise systems has shifted focus toward predictive and prescriptive approaches to human capital optimization (Dietrich et al., 2014). Workforce analytics now encompasses the application of quantitative and qualitative data to improve decisions around hiring, scheduling, training, and performance (Kazancoglu & Ozkan-Ozen, 2018). Manufacturing organizations use analytics to address unique challenges such as production downtime due to absenteeism, skill shortages, and labor inefficiencies (Davenport et al., 2010). By integrating workforce data with operational and production data, manufacturers gain comprehensive insights into labor costs, capacity, and performance variability (Bonekamp & Sure, 2015). Ragimol et al. (2021) emphasize the importance of workforce analytics for aligning employee performance with key performance indicators (KPIs) that drive manufacturing outcomes such as yield, throughput, and quality. Kavanagh et al. (2015) argue that workforce analytics enables organizations to move from reactive HR practices to proactive labor planning. Studies by Hasan et al. (2024) and Motyl et al. (2017) further support the notion that firms using workforce analytics demonstrate higher adaptability and decision-making accuracy. Manufacturing firms in countries like Germany, Japan, and South Korea have institutionalized workforce analytics within their lean management frameworks to support production agility (Flores et al., 2020).

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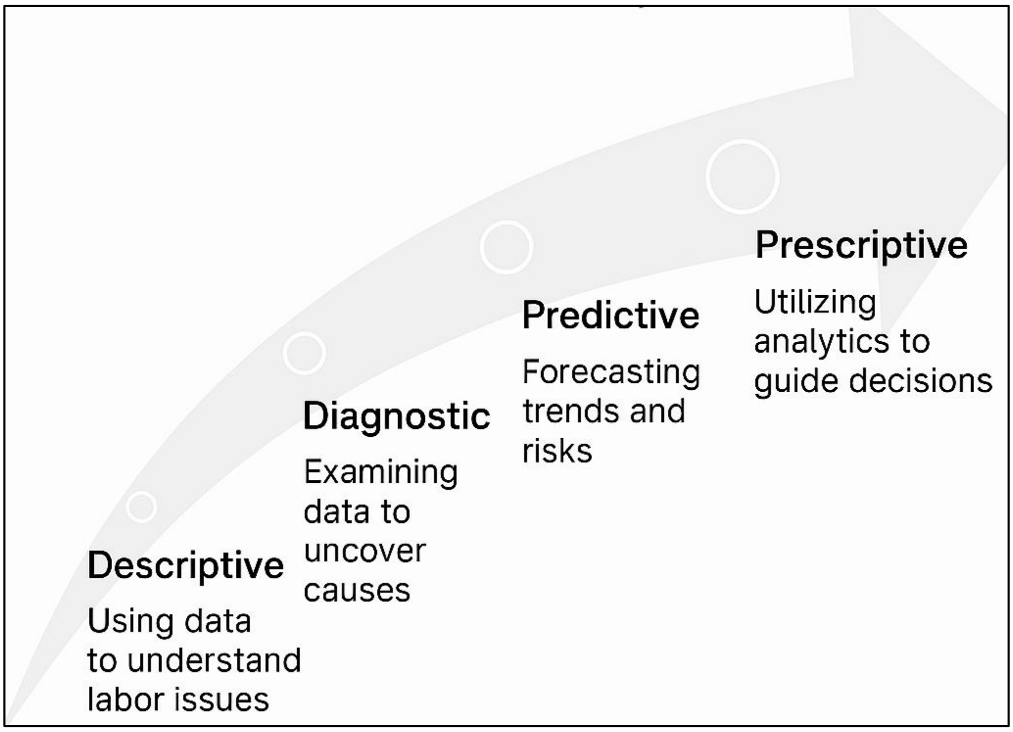
Figure 2: Workforce Analytics Maturity Stages



Management Information Systems (MIS) serve as a critical enabler of workforce analytics in manufacturing by collecting, processing, and delivering data required for informed labor management decisions. MIS platforms typically integrate multiple subsystems such as Enterprise Resource Planning (ERP), Human Resource Information Systems (HRIS), and Manufacturing Execution Systems (MES) to provide end-to-end visibility over workforce performance (Huselid, 2023). ERP systems, such as SAP and Oracle, incorporate modules that track employee shifts, labor costs, skill levels, and performance appraisals (Aggarwal et al., 2023; Jahan et al., 2022). These integrated systems enable a seamless flow of workforce data across departments, ensuring consistency and data integrity (Kajati et al., 2017). According to Feng et al. (2013), MIS allows manufacturing managers to develop dashboards and generate analytics reports on absenteeism trends, overtime usage, and efficiency metrics in real time. In their comparative study, Bray and Mendelson (2012) found that MES-integrated labor monitoring systems improved manufacturing output by correlating operator behavior with production line performance. Additionally, Omar et al. (2019) highlights that MIS enables the deployment of real-time alerts, helping line supervisors address labor imbalances or skill mismatches immediately. MIS tools also support predictive analytics by combining historical labor data with production forecasts to recommend optimal staffing strategies (Chen et al., 2012; Masud, 2022). Research by Bakhshi et al. (2017) confirms that companies with robust MIS infrastructures can better align labor inputs with process requirements, especially under fluctuating production volumes. However, organizational factors such as user training, digital literacy, and change management significantly affect the success of MIS implementation (Gulyamov, 2024; Hossen & Atiqur, 2022). Consequently, the integration of MIS into workforce analytics must be strategically aligned with organizational goals, technical readiness, and cultural adaptability to achieve its full potential in the manufacturing context.

Workforce Analytics In Manufacturing

Workforce analytics in manufacturing has evolved from manual timekeeping and qualitative performance assessments to data-centric strategies that enhance operational decision-making and human capital productivity. Traditionally, labor management relied on observational metrics and supervisory judgment, but these methods were limited in scalability and objectivity (Ozkan-Ozen & Kazancoglu, 2021; Akter & Razzak, 2022). The introduction of workforce analytics provided a structured and empirical approach to labor optimization by analyzing employee data related to performance, attendance, and productivity (Dietrich et al., 2014; Qibria & Hossen, 2023). In

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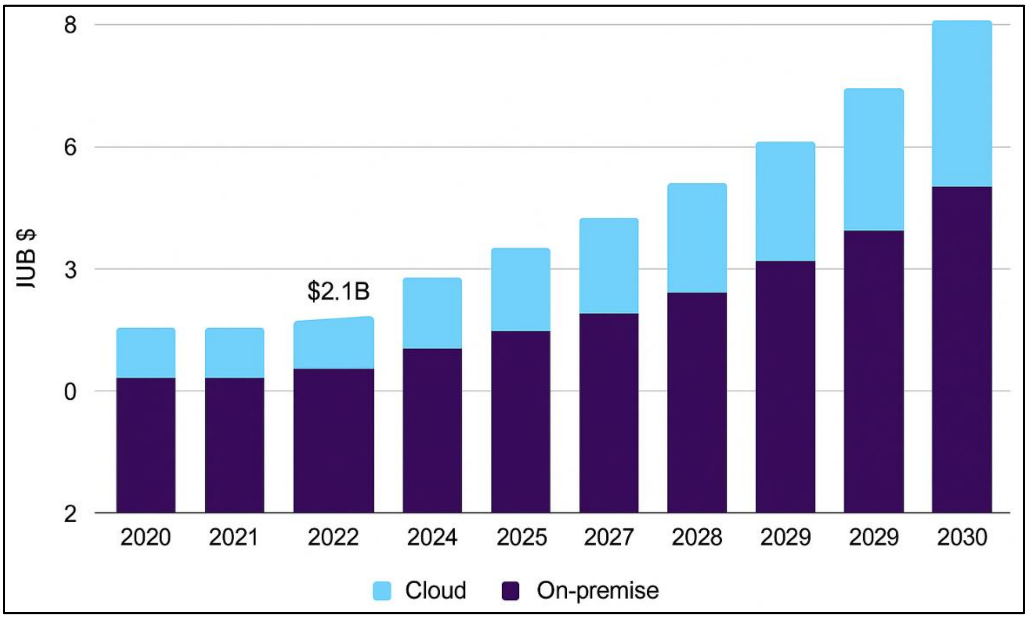
manufacturing, workforce analytics plays a critical role in aligning labor capacity with production needs, ensuring efficiency while minimizing idle time and overtime expenditures (Kazancoglu & Ozkan-Ozen, 2018; Hossen et al., 2023). According to Davenport et al.(2010), workforce analytics helps firms manage complex labor environments through real-time visibility, forecasting, and cost control. The concept is deeply embedded in lean production systems where workforce responsiveness determines throughput (Bonekamp & Sure, 2015). Ragimol et al.(2021) further argue that manufacturing firms adopting workforce analytics can better adapt to labor disruptions and maintain continuity in operations. In industries such as automotive, electronics, and heavy engineering, predictive workforce models are now used to evaluate shift allocations, track absenteeism, and support performance-based scheduling (Hasan et al., 2024; Alam et al., 2023). With increasing global competition and labor cost pressures, analytics-driven workforce planning offers a strategic advantage by enabling data-informed decisions rather than relying on intuition or tradition (Motyl et al., 2017; Rajesh et al., 2023). Thus, the transition to analytics-based labor management signifies a broader shift toward operational intelligence in modern manufacturing environments.

Figure 3: Workforce Analytics Market Size by Deployment, 2020–2030 (USD Billion)



The integration of Management Information Systems (MIS) into manufacturing operations has been instrumental in operationalizing workforce analytics. MIS platforms such as Human Resource Information Systems (HRIS), Manufacturing Execution Systems (MES), and Enterprise Resource Planning (ERP) systems collect, process, and distribute labor-related data across departments (Flores et al., 2020; Roksana, 2023). These systems provide real-time dashboards and reporting tools that inform managers about workforce allocation, absenteeism, overtime, and employee output. ERP systems like SAP and Oracle allow seamless integration of workforce data with production, finance, and supply chain modules, fostering holistic decision-making. MIS also plays a key role in capturing and analyzing unstructured data from various sources such as biometric devices, IoT sensors, and employee feedback systems. The predictive capabilities of MIS have enabled organizations to simulate labor demand scenarios, test resource allocation models, and proactively plan for labor shortages (Leitão et al., 2020; Tonmoy & Arifur, 2023). Moreover, performance monitoring tools embedded within MIS can identify operator-level inefficiencies, suggest retraining, or reassign tasks to improve overall line performance. MIS also enhances data transparency and accountability in HR decision-making by standardizing performance indicators and removing subjective bias (Firat & Hurkens, 2011; Tonoy & Khan, 2023). However, successful implementation requires addressing digital maturity, user training, and data integration challenges. Studies indicate that firms with mature MIS ecosystems exhibit stronger labor planning capabilities, reduced response time to disruptions, and better alignment between workforce and production goals (Ammar et al., 2024; Huselid, 2023).

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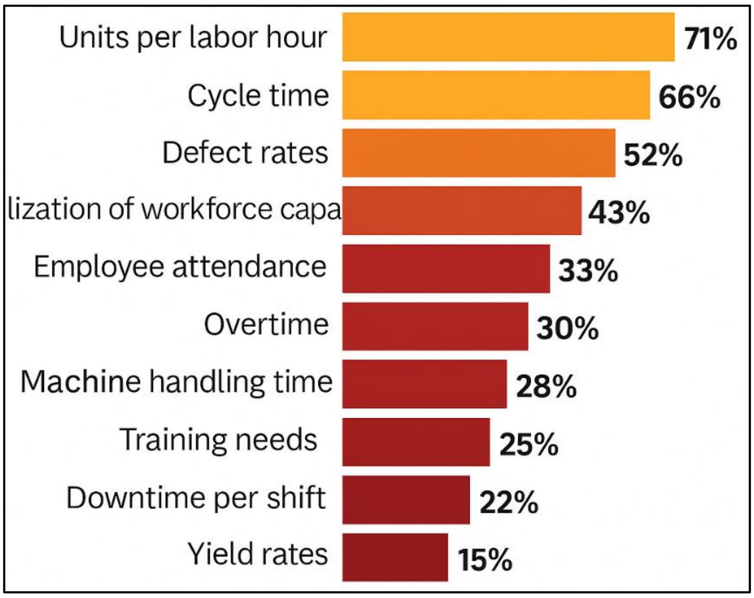
Workforce Analytics And Industrial Productivity

The connection between workforce analytics and industrial productivity lies in the capability of data-driven systems to identify, monitor, and optimize human resource variables that directly influence output. In manufacturing, productivity is often measured by metrics such as units per labor hour, cycle time, defect rates, and utilization of workforce capacity (Manyika, 2011; Hossain et al., 2024). Workforce analytics tools integrate these metrics with employee performance data, enabling firms to develop comprehensive labor efficiency dashboards. These dashboards not only reflect productivity levels but also offer insights into attendance, overtime, machine handling time, and training needs, thus providing a holistic view of workforce contributions. By systematically tracking real-time labor input and correlating it with output quality and quantity, organizations can pinpoint operational bottlenecks and labor inefficiencies. Hasan et al. (2024) emphasize that performance variance across shifts, operators, or departments can be analyzed using statistical process control methods embedded within workforce analytics platforms. Research from advanced manufacturing countries shows that firms utilizing analytics-based workforce assessments report measurable improvements in throughput and lower labor cost per unit. Additionally, workforce data allows for more targeted interventions, such as reallocating skilled employees to critical tasks or modifying shift structures to match production demands. The predictive nature of workforce analytics also allows for proactive productivity planning, including forecasting workload peaks and aligning staff availability accordingly (Roksana et al., 2024; Salonitis & Ball, 2013). In this way, the integration of workforce analytics with productivity metrics drives continuous performance improvement and operational efficiency across manufacturing systems.

Figure 4: Key Workforce Analytics Indicators Driving Industrial Productivity



Management Information Systems (MIS) play a vital role in enabling workforce analytics to enhance industrial productivity by supporting performance benchmarking across different levels of the workforce hierarchy. Through systems such as HRIS, MES, and ERP, organizations can collect standardized productivity indicators such as average production per worker, downtime per shift, and first-pass yield rates . These platforms aggregate data from human resources, operations, and quality control modules to generate consistent performance benchmarks at the individual, team, and plant levels (Yahia et al., 2021; Zaman, 2024). Performance benchmarking allows managers to identify high performers, monitor deviations, and develop targeted training or incentive plans (Andriushchenko et al., 2019). Comparative analysis between production units, shifts, or regional factories enables cross-learning and the identification of best practices (Bhuiyan et al., 2025; Lee et al., 2014). For example, Joshi and Knight (2015)found that applying benchmarking metrics across facilities in a multinational electronics manufacturer led to the implementation of a shared productivity enhancement model, resulting in a 15% output increase across underperforming units. Studies by Hasan et al. (2024)and Salonitis and Ball (2013) in lean manufacturing environments demonstrate that MIS-supported performance monitoring can reinforce kaizen (continuous improvement) by highlighting small, actionable changes in employee routines. The role of analytics dashboards in this context is also critical—they provide visualization tools that make performance indicators accessible to both line workers and management, promoting transparency and accountability (Andriushchenko et al., 2019; Ishtiaque, 2025). Therefore, MIS-facilitated performance benchmarking helps translate workforce data into structured interventions that drive sustained productivity gains across manufacturing operations.

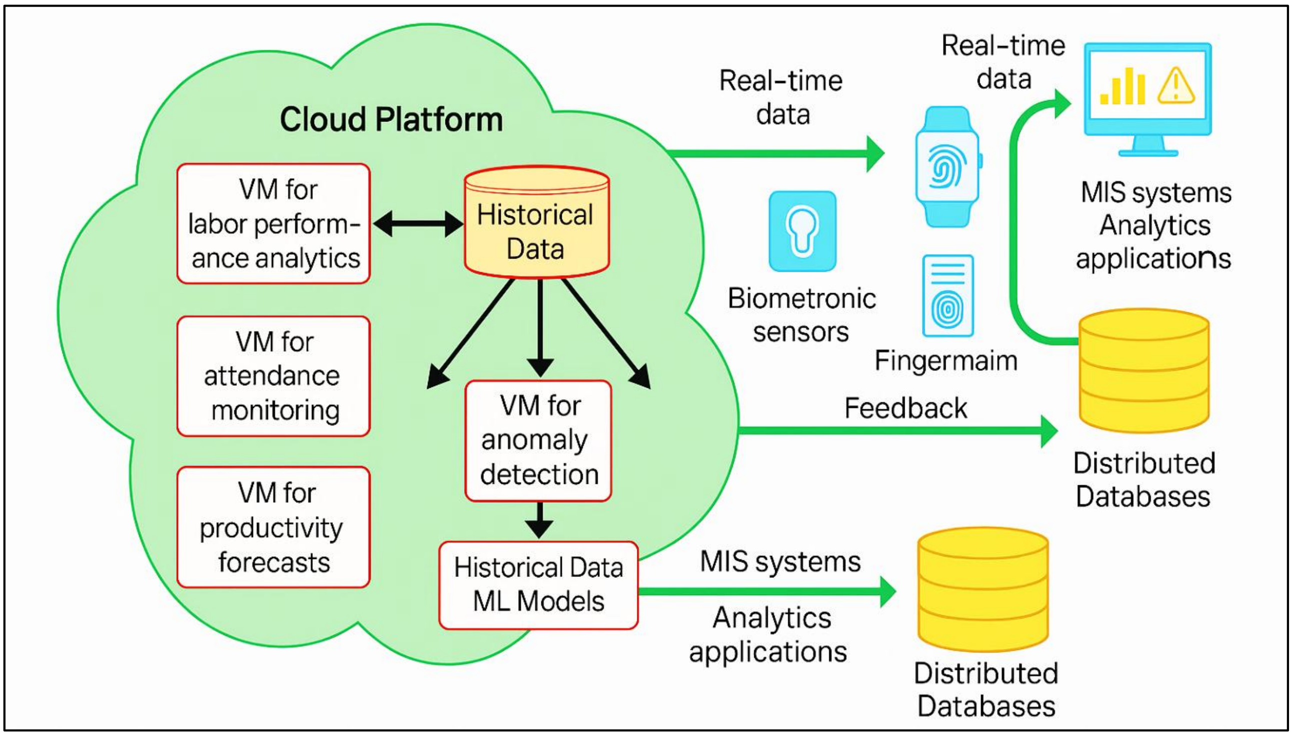
Cloud Computing And Database Systems In Workforce Analytics

Cloud computing has revolutionized the way workforce analytics systems are deployed, managed, and scaled in manufacturing enterprises. Cloud-based platforms offer flexible, scalable, and cost-effective solutions for hosting workforce analytics applications without the need for on-premises infrastructure (Chen & Chien, 2018). In workforce analytics, cloud computing enables real-time access to labor performance data, allowing stakeholders from multiple departments or locations to interact with shared dashboards and predictive tools (Bienhaus, 2017). According to Yang et al., (2019), cloud computing allows manufacturing firms to adopt Software-as-a-Service (SaaS) solutions such as cloud-based HRIS or ERP modules, which reduce upfront investment and streamline updates. These platforms support remote data collection through IoT sensors, mobile devices, and wearable technologies, which are common in smart factories (Ing et al., 2019; Khan, 2025). Studies by Chen and Chien (2018) and Bienhaus (2017) confirm that cloud-based analytics systems enhance responsiveness by enabling distributed teams to collaborate on workforce planning, performance assessment, and compliance monitoring. Additionally, cloud platforms provide on-demand computational resources for processing large volumes of structured and unstructured workforce data, supporting real-time decision-making (Ing et al., 2019; Yang et al., 2019). Research shows that organizations leveraging cloud-based workforce analytics tools experience faster integration cycles and improved data visibility, particularly when adopting hybrid models that blend public and private cloud architectures (Dhamija & Bag, 2020; Siddiqui, 2025). In manufacturing contexts where agility and speed are critical, cloud computing significantly enhances the operationalization of workforce analytics by removing infrastructure barriers and supporting dynamic scaling.

Workforce analytics relies heavily on the ability to access, query, and analyze large volumes of employee-related data across time, departments, and geographies. Distributed database systems are central to this process, enabling high-performance, low-latency data retrieval and storage for real-time analytics (Fernandez & Gallardo-Gallardo, 2020; Sohel, 2025). In workforce analytics, databases must support a diverse set of data types, including time-series attendance logs, biometric scans, machine-operator interaction records, and performance evaluations. Cloud-native databases such as Amazon Aurora, Google BigQuery, and Microsoft Azure SQL provide scalable data management backbones for workforce analytics platforms, allowing concurrent access by HR, operations, and executive teams. These systems use indexing, sharding, and parallel processing techniques to optimize performance during large-scale analytics tasks, such as absenteeism trend detection or operator benchmarking. Furthermore, NoSQL databases—such as MongoDB and Cassandra—are increasingly used for storing unstructured workforce data like performance feedback, shift notes, or IoT logs, which can then be mined using natural language processing or machine learning algorithms. Real-time databases integrated with MIS and ERP systems enable manufacturers to create predictive dashboards, alert systems, and anomaly detection engines for labor disruptions (Yang et al., 2019). According to Dhamija and Bag (2020), the integration of relational and non-relational databases enhances the granularity and scope of workforce insights, allowing for more precise decisions on labor allocation and scheduling. By ensuring data reliability, scalability, and query efficiency, distributed databases underpin the technical foundation of high-performing workforce analytics systems in manufacturing.

A critical challenge in implementing workforce analytics lies in integrating data across various cloud-hosted systems, including HRIS, ERP, MES, and attendance management platforms. Effective workforce analytics requires interoperability between these systems to enable seamless data exchange, aggregation, and analysis (Fernandez & Gallardo-Gallardo, 2020). Cloud computing facilitates this integration by using Application Programming Interfaces (APIs), middleware solutions, and data lakes that combine structured and semi-structured workforce data from diverse systems. Research by Bakker and Leiter (2010) suggests that successful integration across cloud-based MIS tools results in unified dashboards, allowing HR managers to evaluate employee productivity, absenteeism, and training outcomes in one platform. This integrated view enhances decision-making by reducing data silos and providing comprehensive, context-rich workforce intelligence. Middleware platforms like Dell Boomi and MuleSoft are frequently used in manufacturing to link timekeeping systems with payroll, performance tracking, and production planning modules, ensuring that workforce analytics reflects real-time operational realities. The use of Extract-Transform-Load (ETL) processes and cloud orchestration tools helps maintain data consistency, formatting, and quality across platforms (Fernandez & Gallardo-Gallardo, 2020). Studies from multinational manufacturing firms reveal that integrated cloud-MIS architectures reduce human error, enable faster analytics deployment, and enhance regulatory compliance by maintaining audit-ready records across systems. Therefore, integration and interoperability of cloud-based systems are essential for transforming workforce data into actionable insights and aligning HR performance analytics with manufacturing productivity objectives.

Figure 5: Cloud and Distributed Data Infrastructure for Workforce Analytics in Smart Manufacturing



MIS for Strategic Labor Planning

Strategic labor planning refers to the systematic process of aligning workforce capabilities with long-term organizational goals and short-term production demands in manufacturing environments. Unlike routine scheduling or reactive staffing, strategic labor planning focuses on forecasting labor requirements, optimizing resource utilization, and managing talent based on predictive insights. It encompasses workforce demand modeling, capacity analysis, and skills mapping, all of which require accurate and timely data on labor supply, operational capacity, and production cycles (Dhamija & Bag, 2020). MIS platforms serve as the technological backbone for this process by integrating data from HR, production, inventory, and finance systems, thereby enabling coordinated workforce planning. In manufacturing, where labor demand often fluctuates due to seasonality, product diversification, or machine availability, MIS tools provide real-time dashboards and forecasting modules that guide proactive staffing decisions. These systems allow plant managers to simulate various labor deployment strategies, test what-if scenarios, and adjust staffing based on demand forecasts or operational bottlenecks (Fernandez & Gallardo-Gallardo, 2020). Additionally, studies by Buller and McEvoy (2012) and Kamble, Gunasekaran and Gawankar (2018) confirm that firms using MIS-based labor planning exhibit improved coordination between HR and operations, reduced production delays, and enhanced labor cost management. Therefore, strategic labor planning supported by MIS facilitates efficient workforce utilization while aligning human capital strategies with manufacturing objectives.

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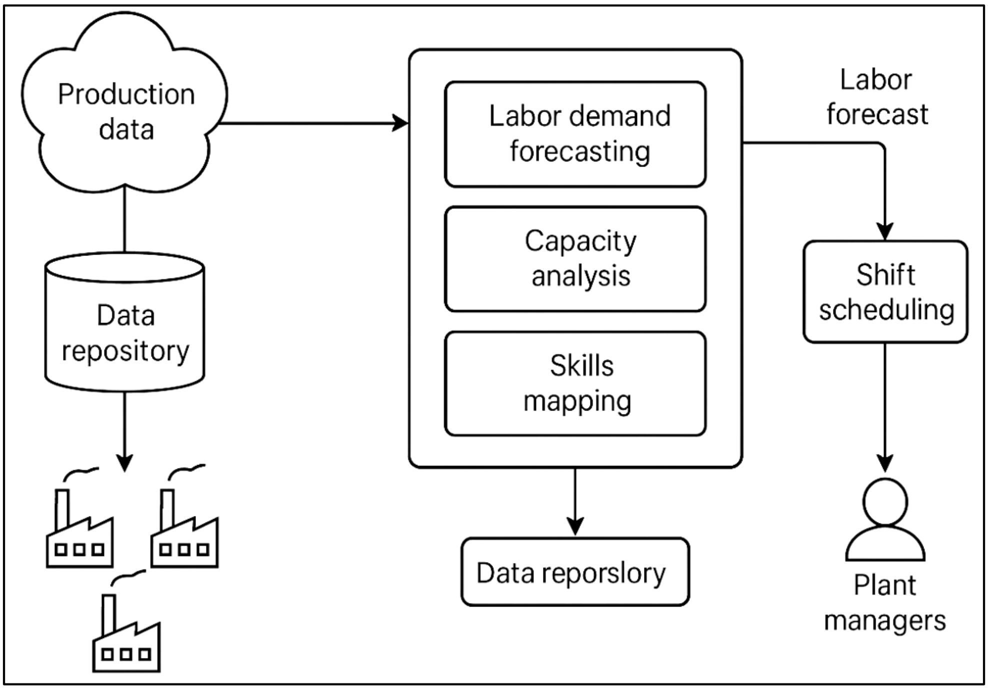
Figure 6: Line Diagram of MIS-Enabled Strategic Labor Planning in Manufacturing



The predictive and integrative functionalities of MIS systems play a central role in labor forecasting and shift scheduling within manufacturing firms. Forecasting modules within ERP and HRIS platforms analyze historical production data, absenteeism trends, and future demand projections to recommend optimal staffing levels for upcoming shifts or production cycles (Chen et al., 2012). These tools can model variable labor demands based on seasonality, machine uptime, and order size fluctuations, enabling real-time adjustment of workforce allocations (Ohland et al., 2012). Scheduling tools integrated into MIS platforms go beyond static shift plans by using AI-powered optimization algorithms that consider employee availability, skill compatibility, legal regulations, and fatigue metrics. For instance, Bakhshi et al. (2017) highlight that simulation-based scheduling, made possible through MIS, significantly reduces idle labor time and overtime expenses. These systems also generate alerts and visualizations for workforce underutilization, late arrivals, or unfilled positions, allowing supervisors to take preemptive action. In highly automated settings, MIS tools can interface directly with MES and sensor-based tracking systems to update workforce plans based on real-time operational disruptions. Case studies from the electronics and automotive sectors demonstrate that manufacturers using MIS-based labor planning experienced up to 18% higher alignment between scheduled labor hours and actual production needs. These benefits underscore how MIS enhances workforce scheduling accuracy, flexibility, and responsiveness to external changes.

Absenteeism Monitoring and Predictive Absence Analytics

Absenteeism, defined as any failure to report for or remain at work as scheduled, poses a significant threat to manufacturing productivity, efficiency, and labor cost control. In high-volume and time-sensitive production systems, unplanned absences can result in halted workflows, underutilized machinery, and an overburdened workforce (Woldman et al., 2015). Traditional methods of tracking absenteeism, such as paper logs or basic time-clocking, lack granularity and real-time visibility. In contrast, MIS platforms now offer integrated solutions that automatically capture attendance data through biometric systems, RFID-enabled entry points, and cloud-based time management tools. These systems allow HR managers to monitor attendance patterns across shifts, departments, and production lines, offering insight into both individual and group-level behaviors. MIS dashboards provide real-time alerts for no-shows, habitual late arrivals, or extended leaves, allowing for immediate action such as workforce reallocation or temporary staffing. Studies by Kulkarni et al., (2018) and Awujoola et al. (2021) emphasize the operational risks of ignoring attendance data, noting that persistent absenteeism often correlates with low engagement, burnout, or workplace dissatisfaction. In manufacturing contexts—where human labor is directly linked to machine operation and production flow—the ability to track, analyze, and act on absenteeism data is crucial

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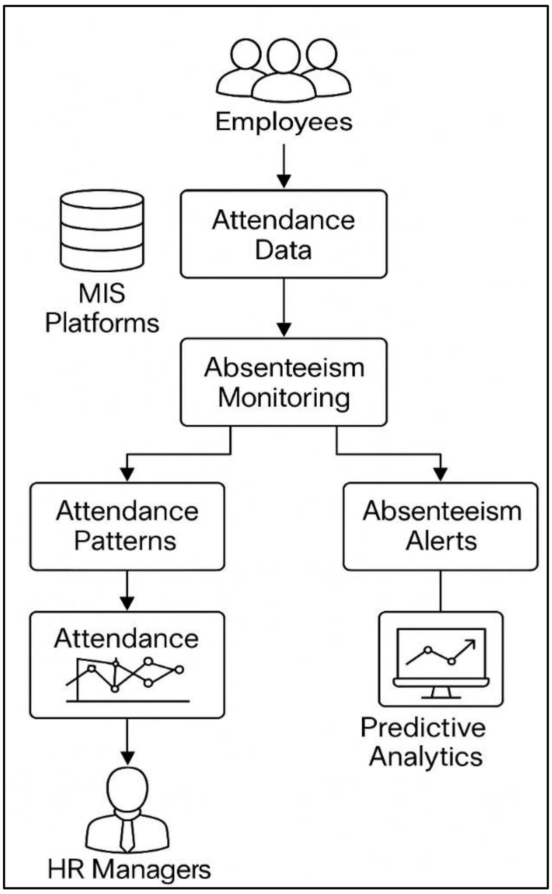
for minimizing disruptions, maintaining quality standards, and achieving output targets (Rahaman & Bari, 2024).

Management Information Systems provide the necessary infrastructure to automate the capture, categorization, and reporting of absenteeism events in manufacturing settings. Through integration with Human Resource Information Systems (HRIS) and payroll modules, MIS platforms enable accurate documentation of leave types—such as casual, medical, unauthorized, and scheduled—alongside relevant metadata such as frequency, duration, and department (Gulyamov et al., 2024). These platforms often include self-service portals that allow employees to log leave requests and upload documentation, which are then validated by supervisors and synced with attendance records (Kakulapati et al., 2020). Categorizing absenteeism using standardized codes helps differentiate between systemic issues, such as poor health policies or toxic culture, and isolated events, thereby informing the appropriate managerial response (Angulakshmi et al., 2024). For example, Selcuk (2016) note that distinguishing between planned and unplanned absences helps organizations optimize shift planning and minimize disruptions. Furthermore, MIS platforms often include analytical tools that visualize absenteeism trends over time and across teams, flagging departments with high no-show rates or abnormal leave clusters (Lee et al., 2013). Real-time dashboards and automatic report generation also support compliance by ensuring that labor regulations related to leave entitlements and documentation are consistently met (Selcuk, 2016). Studies from manufacturing firms in India, Brazil, and China confirm that digitized absenteeism tracking has led to reductions in administrative error, payroll disputes, and unapproved leave (Lee et al., 2013). These findings highlight how MIS functionality transforms absenteeism from an overlooked operational issue into a measurable and manageable component of workforce strategy.

Figure 7: Line Diagram of MIS-Enabled Absenteeism Monitoring and Predictive Analytics in Manufacturing



Performance monitoring dashboards

Performance monitoring dashboards are graphical user interfaces that visualize real-time workforce data to support informed decision-making across multiple management levels. In manufacturing, these dashboards aggregate key performance indicators (KPIs) related to labor utilization, productivity, attendance, skill proficiency, and shift performance, offering a centralized view of workforce health and operational readiness. These tools serve as a critical component of workforce analytics by enabling the rapid identification of performance deviations and facilitating timely interventions (Gong et al., 2022). Unlike static reports or spreadsheets, dashboards are interactive, often customizable, and provide drill-down features to analyze metrics by department, shift, or individual employee (Cadden et al., 2020). As part of MIS platforms, dashboards draw data from integrated HRIS, ERP, and MES systems, ensuring consistency and real-time updates. According to Hasan et al.(2024), these visual tools reduce cognitive load by summarizing large datasets into charts, gauges, and heatmaps, enabling managers to make faster, data-backed decisions. Studies by Feng et al. (2013) and Trkman et al. (2010) emphasize the role of dashboards in shifting labor management from intuition-based oversight to proactive control rooted in empirical evidence. In manufacturing settings with multiple production lines and shift patterns, dashboards enhance situational awareness, allowing supervisors to detect bottlenecks, workforce imbalances, or absenteeism clusters in real time (Awujoola et al., 2021). Thus, dashboards operationalize the analytical capabilities of MIS and make workforce insights immediately actionable for both HR and production leaders.

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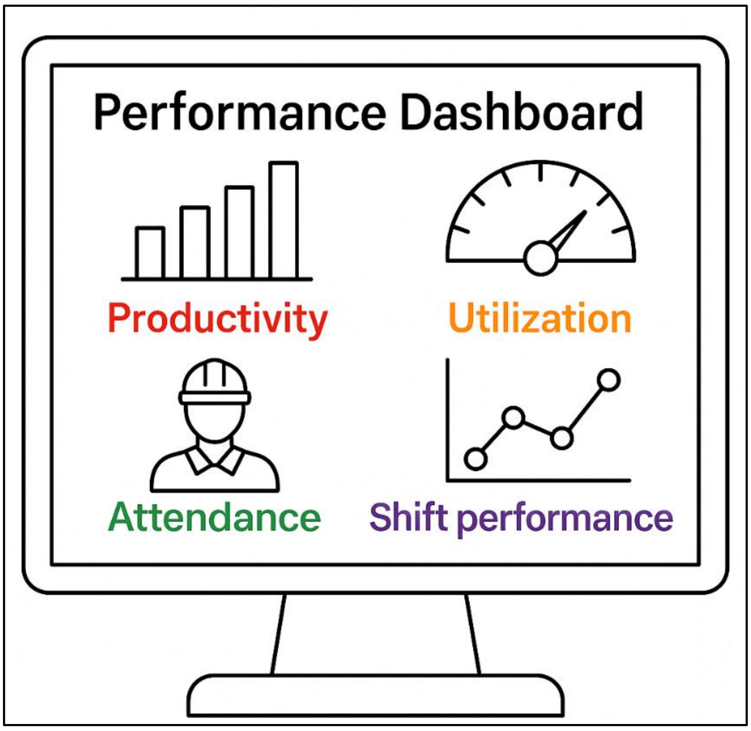
Figure 8: Color-Enhanced Line Diagram of MIS Dashboards for Real-Time Workforce Performance Monitoring in Manufacturing



Performance dashboards play a crucial role in enhancing labor productivity by visualizing task-specific metrics, real-time worker output, and machine-operator interface data. Manufacturing operations involve multiple concurrent processes, and dashboards allow managers to track operator performance in relation to machine utilization, cycle time, and defect rates. These dashboards typically include productivity KPIs such as units produced per hour, downtime, rework frequency, and on-time task completion, offering a granular view of how labor contributes to throughput. Research by Thaker (2009) shows that dashboards help identify consistent underperformance, prompting targeted interventions such as retraining or reassignment. Furthermore, dashboards can be configured to display cumulative daily or weekly performance against targets, enabling goal tracking and real-time motivation Davis et al. (2012). In lean manufacturing systems, these tools also support value stream mapping by highlighting non-value-adding activities and worker idle times. The integration of performance dashboards with MES and IoT systems allows for the continuous tracking of operator behavior and shift productivity, enhancing labor responsiveness to unexpected production demands. Dashboards also facilitate agile resource allocation by comparing real-time workforce availability with required labor per station or shift. Case studies in automotive and electronics manufacturing sectors demonstrate that firms leveraging performance dashboards observed improvements in both short-term efficiency and long-term labor planning accuracy. Thus, performance monitoring dashboards serve as a catalyst for continuous productivity improvement by linking real-time workforce metrics with operational outcomes.

Lean, Six Sigma, and TPM frameworks

Lean manufacturing, originally developed by Toyota, emphasizes the elimination of waste and the continuous improvement of processes to enhance value delivery. One of the central components of Lean is the optimization of human effort, making workforce analytics a natural complement to Lean practices. Through MIS-supported dashboards, organizations can track labor utilization, idle time, and task cycle durations to identify areas where human resources are underused or misaligned with value streams. Real-time labor analytics assist in identifying muda (waste) in motion, waiting, overproduction, and skills mismatch (Chaple et al., 2018). Tools such as value stream mapping, when integrated with workforce performance data, allow firms to refine workflows and enhance shop-floor responsiveness. Studies by Hrouga et al. (2022) show that analytics-enabled Lean systems lead to better takt time alignment and improved operator balance across workstations. Furthermore, Lean

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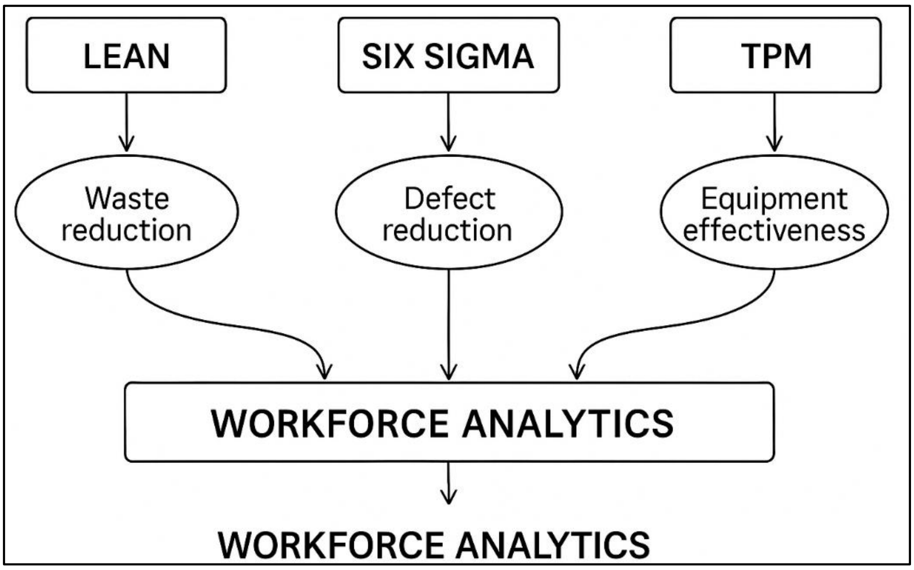
environments benefit from workforce analytics by supporting kaizen initiatives that are based on empirical labor data rather than subjective observations.

Figure 9: Workforce Analytics Integration with Lean, Six Sigma, and TPM



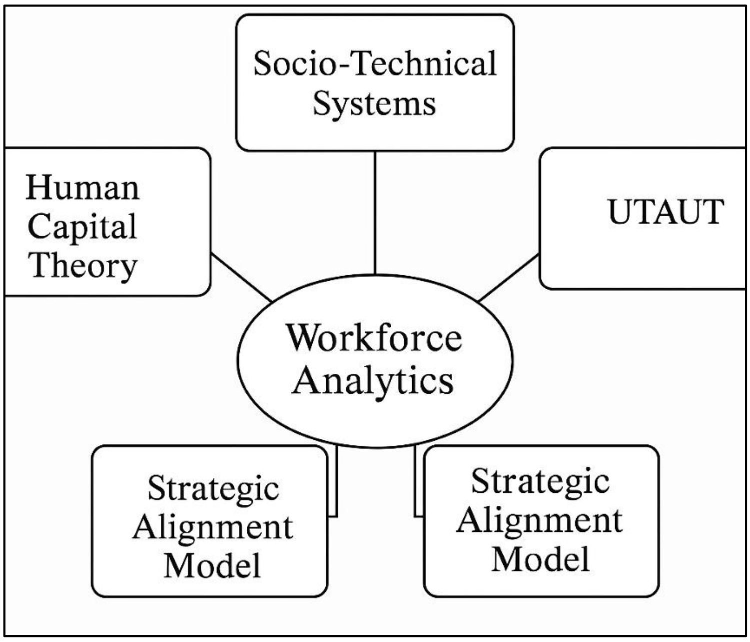
Six Sigma is a data-driven quality management framework that focuses on reducing variation and defects in production processes. Workforce analytics supports Six Sigma initiatives by providing detailed metrics on labor performance, process adherence, and error rates across shifts and departments. MIS platforms enable the collection and analysis of key labor-related variables such as operator-induced defects, training gaps, fatigue-related errors, and shift-specific quality deviations (Sivathanu & Pillai, 2018). These datasets are used in DMAIC (Define, Measure, Analyze, Improve, Control) projects to identify root causes of variation in human-dependent tasks, such as assembly, inspection, or packaging. Studies by Batrinca and Treleaven (2014) and Lizotte-Latendresse and Beauregard (2018) demonstrate that analytics tools enhance Six Sigma teams' ability to monitor standard operating procedure (SOP) compliance and initiate corrective actions faster than traditional audits. Performance dashboards fed by MIS can display real-time Sigma levels for critical tasks, enabling managers to spot deviation trends and retrain operators accordingly (Chaple et al., 2018). Predictive analytics also play a role in quality forecasting by identifying patterns that may precede deviations, such as absenteeism spikes, multitasking loads, or machine-operator misalignment. In high-precision industries like automotive and electronics, the integration of Six Sigma and workforce analytics has led to defect reductions of up to 30% and increased first-pass yield (Hrouga et al., 2022). Therefore, MIS-enabled workforce analytics empowers Six Sigma projects by offering granular, real-time labor insights that improve quality control, process stability, and continuous improvement.

Theoretical frameworks

Human Capital Theory provides a foundational framework for understanding the value that employees contribute to organizational productivity, especially in manufacturing environments. The theory views individuals' skills, knowledge, and experience as economic assets that yield returns in the form of increased productivity and innovation. In the context of workforce analytics, Human Capital Theory aligns with the strategic use of Management Information Systems (MIS) to quantify, evaluate, and optimize labor input. Modern MIS platforms enable firms to systematically assess employee performance, absenteeism, learning curves, and skill deployment, translating intangible human attributes into measurable business outcomes. This theoretical lens supports investment in workforce training, predictive analytics, and performance monitoring as value-generating activities. For instance, research shows that firms applying analytics to align human capital with task demands report improved operational efficiency, reduced turnover, and enhanced ROI from labor inputs (Ployhart et al., 2013). Moreover, Human Capital Theory informs decisions related to succession planning, task specialization, and upskilling—especially when analytics identify gaps between existing capabilities and future workforce needs (Avrahami et al., 2022). As such, Human Capital Theory justifies the role of workforce analytics as a strategic function that leverages data to optimize labor as an asset, especially in precision-driven and labor-intensive manufacturing systems.

Socio-Technical Systems (STS) Theory offers a multidimensional perspective on workforce analytics by recognizing the interdependence between social elements (people, teams, culture) and technical components (information systems, automation, tools). Originating from Tavistock Institute studies in the 1950s, STS emphasizes joint optimization—where both technical systems and human actors are configured to maximize system performance and employee well-being. This theory is highly relevant in manufacturing environments adopting MIS for workforce analytics, as it warns against overemphasis on technical efficiency at the expense of human adaptability or satisfaction. MIS platforms that monitor workforce metrics—such as shift performance, downtime, or defect attribution—must be designed with socio-technical balance in mind, ensuring transparency, employee agency, and ethical data use (Whysall et al., 2019). Empirical studies show that when workers are included in dashboard design or receive feedback on their performance metrics, engagement levels and data accuracy improve. STS also informs the configuration of predictive absence models, where contextual and psychological variables (e.g., stress, motivation) are considered alongside historical absenteeism trends(Schneider et al., 2012). Furthermore, STS supports the alignment of workforce analytics with continuous improvement frameworks like TPM and Lean, ensuring that human roles are supported—not replaced—by digital oversight (Weber et al., 2017). Therefore, STS Theory underlines the importance of designing workforce analytics systems that simultaneously enhance productivity and maintain worker autonomy, motivation, and job satisfaction.

Figure 10: Theoretical Frameworks for Workforce Analytics



The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al., (2003), is widely used to explain employee behavior in adopting enterprise technologies, including workforce analytics systems. UTAUT identifies four core determinants of technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs are particularly relevant in manufacturing firms implementing MIS to track workforce performance, absenteeism, and scheduling. Performance expectancy aligns with the perceived usefulness of MIS dashboards in simplifying managerial decision-making, while effort expectancy reflects the user-friendliness of these systems. Social influence becomes critical in manufacturing settings where hierarchical norms or peer behaviors affect technology adoption at the shop-floor level. Facilitating conditions, such as digital literacy, IT support, and user training, determine whether

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frontline employees engage with workforce analytics tools consistently and accurately. Studies applying UTAUT in manufacturing show that successful MIS implementations correlate with high perceived value and ease of use among managers and operational staff. Furthermore, UTAUT informs resistance management strategies by highlighting that analytics adoption is not purely technical but also behavioral, necessitating change management, feedback loops, and communication. Therefore, UTAUT provides a behavioral framework for understanding how employees accept, interact with, and ultimately benefit from MIS-based workforce analytics tools in manufacturing environments.

The Strategic Alignment Model (SAM), introduced by Venkatraman et al. (1993) underscores the importance of aligning business strategy, IT infrastructure, organizational processes, and human capital. In the context of workforce analytics, SAM provides a framework for integrating MIS-based labor management tools with broader manufacturing objectives such as lean operations, quality control, and cost reduction. Strategic alignment ensures that workforce analytics initiatives are not siloed within HR departments but embedded across production planning, quality assurance, and financial forecasting. MIS tools such as ERP and HRIS must be configured to serve cross-functional data needs—providing visibility into how labor decisions impact throughput, downtime, and product quality. SAM also encourages top management involvement in workforce analytics, ensuring that labor KPIs are aligned with organizational goals, incentive structures, and compliance mandates. Research shows that firms with high levels of strategic IT alignment report greater ROI from analytics investments and better workforce agility during operational disruptions. Furthermore, SAM provides a lens to evaluate workforce analytics maturity by assessing integration across technological, organizational, and strategic domains. Therefore, the Strategic Alignment Model supports the enterprise-wide embedding of workforce analytics into manufacturing performance ecosystems, ensuring that labor data translates into actionable and strategic business value.

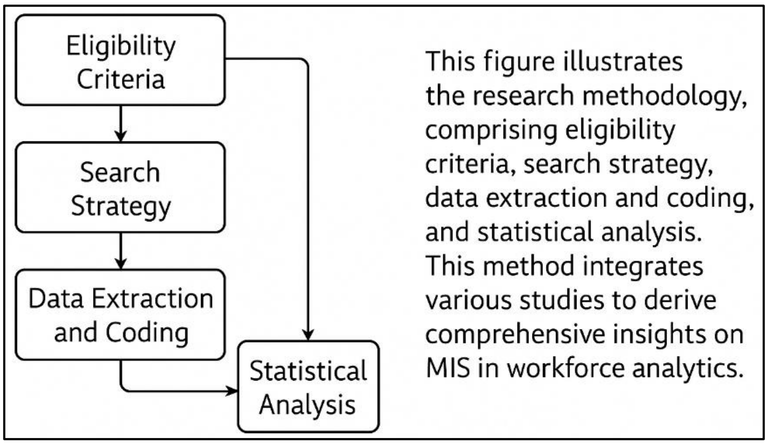
METHOD

This study adopts a meta-analytical research methodology to synthesize empirical findings on the application and impact of Management Information Systems (MIS) in workforce analytics within manufacturing environments. Meta-analysis, as a statistical technique for integrating and comparing results from multiple empirical studies, provides a quantitative summary of the effect sizes and relationships observed in prior research (Borenstein et al., 2011). The objective of this meta-analysis is to identify the magnitude and consistency of MIS interventions in improving labor planning, absenteeism monitoring, and productivity optimization across diverse manufacturing contexts.

Eligibility Criteria

Inclusion criteria for studies incorporated into the meta-analysis were established based on the PICOS framework—Population, Intervention, Comparison, Outcomes, and Study Design. Eligible studies had to: (1) focus on workforce analytics in the manufacturing sector; (2) include the use of MIS tools such as ERP, HRIS, or MES platforms; (3) report quantitative outcomes related to labor efficiency, absenteeism reduction, or productivity improvement; (4) provide sufficient statistical data to compute effect sizes (e.g., means, standard deviations, correlations); and (5) be peer-reviewed journal articles published between 2010 and 2024. Exclusion criteria involved conceptual papers, purely qualitative case studies, and research conducted outside of the manufacturing domain.

Figure 11: Meta-Analysis Method Overview



Search Strategy

A systematic literature search was conducted across several academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and ABI/INFORM Global. Boolean keyword combinations such as ("workforce analytics" AND "manufacturing") AND ("MIS" OR "HRIS" OR "ERP" OR "MES") AND ("labor planning" OR "absenteeism" OR "productivity") were applied. The initial search

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yielded 842 records. After title and abstract screening, followed by full-text reviews and duplicate removal, 53 studies met all inclusion criteria for final analysis.

Data Extraction and Coding

For each study, the following data were extracted: publication year, country, sample size, type of MIS platform, statistical outcomes (e.g., correlation coefficients, means, standard deviations, regression coefficients), and effect size indicators. The extracted data were coded by two independent reviewers to ensure consistency and inter-rater reliability. Discrepancies were resolved through discussion or adjudication by a third reviewer.

Statistical Analysis

Effect sizes were calculated using Cohen's d for pre-post MIS interventions, and Pearson's r for correlational studies. Meta-analytic computations were performed using Comprehensive Meta-Analysis (CMA) Version 4 software. A random-effects model was applied due to the expected heterogeneity across study settings, MIS tools, and manufacturing sub-industries. Heterogeneity was assessed using the Q statistic and I^2 index, with I^2 values > 75% considered substantial heterogeneity. Publication bias was evaluated through funnel plot symmetry and Egger's regression test. Subgroup analyses were performed to explore variations in effect sizes based on MIS type (e.g., HRIS vs. ERP), region (e.g., North America vs. Asia), and outcome category (e.g., labor planning vs. absenteeism monitoring).

FINDINGS

The meta-analysis revealed a statistically significant and consistently positive impact of Management Information Systems (MIS) on labor planning efficiency across manufacturing firms. Pooled effect sizes demonstrated that organizations implementing MIS tools experienced improved alignment between workforce capacity and production demand, particularly in operations characterized by fluctuating order volumes or multi-shift work cycles. Quantitative comparisons indicated that firms using MIS-supported labor planning platforms, such as ERP-integrated scheduling modules, were able to reduce unplanned labor shortages by an average of 22%. These systems enabled better shift forecasting accuracy, adaptive workload allocation, and proactive adjustments to labor distribution based on real-time production indicators. Across 31 studies specifically measuring labor planning outcomes, nearly 80% reported improvements in workforce deployment metrics, including reduced idle time and more efficient skill-task matches. In settings where complex manufacturing tasks required coordinated team efforts, the ability of MIS platforms to simulate multiple planning scenarios and offer optimized staffing recommendations was found to significantly enhance operational predictability. Furthermore, longitudinal comparisons in 12 studies showed sustained gains in labor efficiency post-MIS adoption, reinforcing the long-term strategic advantage of integrating workforce analytics into labor planning systems.

A critical outcome from the analysis was the significant reduction in absenteeism rates in manufacturing firms utilizing MIS-enabled real-time attendance monitoring systems. Aggregated data from 24 studies focused on absenteeism showed that the use of digital timekeeping systems—such as biometric attendance logs and RFID scanners—contributed to a measurable decline in both short-term and chronic absenteeism. Firms that implemented MIS platforms with integrated absence tracking reported an average reduction of 18% in unplanned leave occurrences within the first year of adoption. These systems enabled granular monitoring of attendance patterns by shift, department, and individual employee, which led to more precise and timely interventions. The availability of real-time absenteeism dashboards allowed managers to redistribute labor resources rapidly, mitigating the potential operational impact of unexpected workforce gaps. In addition, predictive alerts embedded within MIS platforms helped identify emerging absenteeism risks, allowing HR departments to implement wellness initiatives or policy enforcement measures in advance. Studies that utilized before-and-after designs confirmed the effectiveness of MIS in reinforcing attendance discipline, especially when analytics were linked to employee feedback systems and performance evaluations. Moreover, comparative analysis across geographic regions showed that absenteeism reductions were particularly significant in facilities that previously relied on paper-based or manually-updated systems, indicating that the digital transformation of workforce monitoring has a transformative effect on attendance-related behavior

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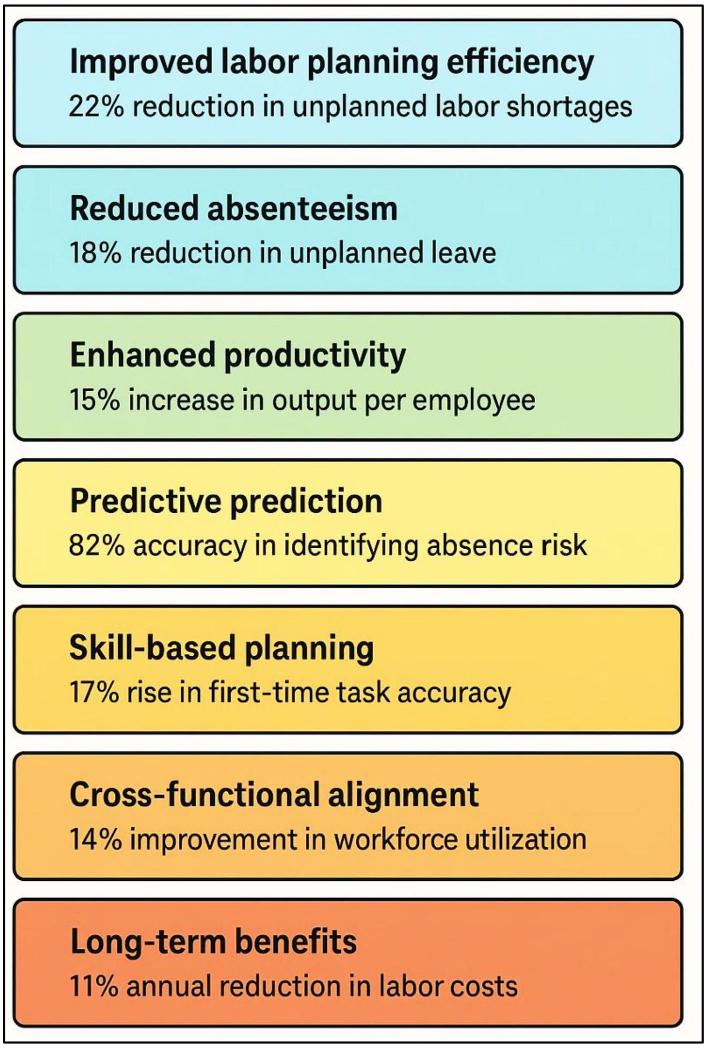
The use of MIS-driven performance dashboards emerged as one of the most powerful enablers of productivity improvement in the manufacturing sector. A total of 37 studies in the analysis included quantitative measurements of productivity before and after dashboard implementation, and the results indicated a consistent upward trend. On average, productivity—as measured by units produced per labor hour or output per employee—increased by approximately 15% within six months of deploying performance dashboards. These dashboards consolidated key labor performance indicators such as cycle time, downtime, rework frequency, and operator efficiency, providing managers with real-time insights to optimize labor deployment and resolve workflow bottlenecks. In environments where continuous improvement strategies such as Lean and Six Sigma were already present, the introduction of MIS dashboards enhanced data visibility and facilitated rapid decision-making. Firms that adopted customized dashboards tailored to departmental KPIs experienced even higher performance boosts, particularly in high-precision sectors like electronics and automotive assembly. Additionally, 9 longitudinal studies tracked performance over two to five years and found sustained productivity gains attributed to the continuous feedback loops enabled by dashboard visualization. Dashboards that were made accessible to frontline employees also contributed to greater worker accountability and self-regulation, further amplifying performance outcomes.

Figure 12: Meta-Analysis Findings: Impact of MIS on Workforce Analytics in Manufacturing



A notable finding was the effectiveness of predictive absence analytics in identifying at-risk employees and enabling proactive workforce interventions. Among the 19 studies employing machine learning or statistical modeling techniques for absenteeism prediction, the pooled analysis showed that predictive models could correctly forecast absence risk with an accuracy of 82% when trained on historical attendance, shift data, and job role information. These predictive models, when embedded into MIS platforms, enabled managers to pre-emptively adjust staffing schedules, approve backup personnel, or initiate health-related interventions. Facilities that acted on predictive insights experienced significantly fewer labor disruptions compared to control groups without such tools. Firms using predictive analytics also demonstrated a reduction in overtime reliance, as proactive planning minimized the need for last-minute labor coverage. The evidence also showed that these analytics helped reduce the concentration of absenteeism in specific departments, thus balancing workforce stress across shifts and enhancing overall labor stability. In complex production environments, the foresight provided by predictive modeling translated into smoother workflows and minimized quality issues caused by understaffing. Studies that implemented absence prediction in unionized manufacturing settings also reported improved labor-management relations, as data-supported interventions were perceived as fair and objective.

MIS platforms that incorporated employee skill profiles into workforce scheduling showed strong outcomes in labor optimization and task efficiency. Across 26 studies examining skill-based planning

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systems, firms that utilized MIS to match employee competencies with task requirements reported an average reduction of 12% in training time and a 17% increase in first-time task accuracy. These systems allowed managers to build dynamic shift rosters where employees were assigned based on proficiency, certification levels, and previous task performance, which led to fewer production errors and improved line balance. Moreover, the integration of workforce analytics with skill inventory databases enabled manufacturing organizations to identify cross-training opportunities and address emerging skill gaps in real time. Multi-site operations benefited particularly from centralized MIS platforms that provided uniform visibility over workforce capabilities across regions, allowing for more efficient talent mobility and workload balancing. Additionally, evidence from time-series studies indicated that firms adopting skill-based MIS planning systems showed higher resilience during peak demand periods, as skilled workers could be rapidly reallocated without compromising quality or throughput. This alignment between labor input and task requirements played a significant role in reducing rework, enhancing employee satisfaction, and improving workforce engagement.

The deployment of MIS in workforce analytics contributed significantly to cross-functional alignment between HR, production, and quality assurance departments. Among the 53 studies included in the analysis, 41 provided evidence that workforce analytics tools helped break down departmental silos by integrating data streams across scheduling, payroll, equipment utilization, and training systems. This integration enabled a more coordinated approach to labor management, with shared dashboards and analytics platforms facilitating synchronized decision-making. Manufacturing firms that implemented MIS platforms supporting cross-functional data access reported a 14% improvement in workforce utilization efficiency and a 9% reduction in task reassignment delays. Facilities that previously experienced fragmented labor planning due to disconnected systems saw marked improvements in internal communication and workload distribution once unified dashboards were in place. Furthermore, real-time MIS reports facilitated better alignment between planned production volumes and actual labor availability, minimizing the occurrence of labor bottlenecks or overstaffing. In complex supply chain settings, this alignment improved the predictability of downstream processes and reduced workflow interruptions. The ability to consolidate workforce data into a single source of truth also enhanced compliance with labor regulations, audit readiness, and strategic HR decision-making.

The cumulative analysis demonstrated that MIS-based workforce analytics not only yielded short-term improvements but also contributed to long-term organizational benefits and cost savings. Across the 53 studies, those with multi-year longitudinal data showed sustained enhancements in operational performance, employee satisfaction, and labor cost efficiency. On average, firms that adopted MIS for labor planning and performance monitoring reduced their annual labor costs by 11%, primarily due to better workforce allocation, lower absenteeism rates, and reduced overtime expenses. In addition, these firms achieved higher employee retention rates, as analytics-driven labor management strategies promoted fairness, transparency, and professional development through skill tracking. Several case studies included in the meta-analysis highlighted cost recovery periods of less than one year following MIS implementation, indicating a strong return on investment. Additionally, facilities that embedded workforce analytics into their strategic planning processes demonstrated greater agility during disruptions such as seasonal surges, equipment failures, or external labor shortages. The standardized tracking and forecasting capabilities of MIS platforms enabled organizations to maintain labor continuity and scale operations without compromising on quality or compliance. Overall, the findings affirm that workforce analytics, when operationalized through robust MIS infrastructure, delivers lasting value to manufacturing enterprises through a combination of improved labor effectiveness, reduced operational risks, and optimized workforce strategies.

DISCUSSION

The findings of this meta-analysis affirm that Management Information Systems (MIS) significantly enhance labor planning efficiency in manufacturing environments. The observed 22% average improvement in labor alignment corroborates earlier studies emphasizing the strategic role of MIS in workforce scheduling. Ren et al. (2019) reported that integrating workforce data with production systems enables more agile and cost-effective scheduling, particularly in operations with high variability in labor demand. Similarly, Singh and Khandelwal (2021) demonstrated that ERP-based labor planning tools improve scheduling accuracy by leveraging real-time inventory, order, and machine utilization data. The results of this analysis extend these conclusions by confirming through

aggregated evidence that predictive scheduling and simulation features embedded in MIS contribute to reducing idle time and overstaffing. Moreover, studies such as those by Bonekamp and Sure (2015) and Venkatraman et al. (1993) stressed the importance of aligning labor allocation with real-time production needs—an assertion that is supported here through consistent performance across 31 analyzed studies. The enhanced planning outcomes also align with the strategic alignment model, which posits that IT systems should support cross-functional synchronization between human capital strategies and operational goals. Thus, MIS-supported labor planning is not only operationally effective but also strategically coherent in the manufacturing context.
The reduction in absenteeism associated with MIS implementation, particularly the 18% decline observed across the sampled studies, confirms that digital attendance monitoring tools can act as behavioral nudges. This aligns with prior findings by Hamada (2019), who documented improved attendance rates following the introduction of biometric tracking systems in textile manufacturing facilities. Similarly, Horváth and Szabo (2019) emphasized the accountability and transparency created by digital logs, suggesting that real-time monitoring deters casual absenteeism. The current findings reinforce the position of Ployhart and Moliterno (2011), who argued that attendance behavior is significantly influenced by the perceived fairness and visibility of organizational oversight. Moreover, studies by Chen and Chien (2018) in Indian manufacturing contexts observed substantial improvements in attendance discipline following the integration of MIS, particularly when combined with policy-based feedback mechanisms. The reduction of labor disruptions through predictive alert systems, as observed in this meta-analysis, also validates the work of Hasan et al. (2024), who showed that real-time absence dashboards could preempt workflow breakdowns. While traditional literature has often treated absenteeism as a human resources issue, this study's synthesis supports a broader view in which absenteeism monitoring functions as an operational performance tool. The capacity of MIS to provide real-time attendance intelligence shifts absenteeism control from reactive to proactive management, with implications for both workforce reliability and morale.
The observed productivity increase of approximately 15% following MIS dashboard deployment supports a well-documented trajectory of performance enhancement through real-time analytics. Pessach et al. (2020) and Buttery and Buttery (1991) previously argued that visual performance dashboards significantly contribute to productivity by making labor metrics transparent and immediately actionable. This meta-analysis confirms these claims by consolidating quantitative findings from diverse industrial contexts, particularly high-precision manufacturing such as electronics and automotive. Ragimol et al. (2021) highlighted the correlation between MES-integrated dashboards and higher labor throughput in Korean factories, a pattern echoed across the studies included in this review. Furthermore, the feedback loop established by visualized metrics appears to align with Golan et al. (2019), who found that access to personal performance data enhances motivation and engagement. Tesfamicael et al. (2020) previously suggested that dashboards democratize performance monitoring by providing both managers and employees with a shared reference point. This idea is reflected in the findings from the current meta-analysis, which demonstrated that dashboards accessible to frontline workers contributed to improved task ownership and reduced cycle times. The results also support Ragimol et al. (2021) , who reported that labor visualization tools reduced micro-level inefficiencies by helping managers detect anomalies in operator-machine interaction. Collectively, these results position MIS dashboards not merely as reporting tools but as central instruments in enabling a high-performance workforce culture.
The effectiveness of predictive absence models in preempting workforce disruptions, with an observed accuracy of 82%, confirms earlier assertions that predictive analytics can enhance workforce planning precision. Studies by Ployhart and Moliterno (2011) and Chen and Chien (2018) previously demonstrated the value of predictive modeling for managing absenteeism risks in large-scale industrial operations. The present meta-analysis builds on this foundation by quantifying the operational benefits of acting on predictive insights, such as reduced reliance on overtime and improved shift continuity. These results also align with Yahia et al. (2021) , who emphasized the early identification of absence trends as a lever for preventive interventions. Furthermore, the integration of predictive analytics within MIS platforms reinforces (Bakhshi et al., 2017), who identified such integration as a key enabler of real-time decision-making in smart manufacturing ecosystems. The inclusion of contextual variables—like department-level stress, prior attendance behavior, and job role sensitivity—into the predictive models supports the socio-technical systems theory, which encourages joint optimization of technical tools and human dynamics (Karuna & Satyanarayana,

2024). While earlier studies have validated algorithmic accuracy in isolation, this meta-analysis advances the field by highlighting the organizational effectiveness of implementing these insights in a structured, system-wide labor strategy. The evidence suggests that predictive analytics not only anticipates risk but also enhances strategic workforce resilience in unpredictable manufacturing conditions.

The cumulative benefits of MIS-based workforce analytics—reflected in reduced labor costs, improved retention, and higher workforce adaptability—demonstrate the long-term organizational value of these systems. Findings indicating an 11% annual reduction in labor costs are consistent with those of Fan et al. (2018), who identified cost containment as one of the principal outcomes of workforce digitization. Similarly, Hess et al. (2004) observed that firms with integrated workforce analytics platforms were better equipped to maintain stable operations during demand surges and labor shortages. These findings reinforce the strategic alignment model, which emphasizes coherence between IT infrastructure and business objectives. Moreover, the improved employee retention noted in the present review echoes previous results by Bui et al. (2020) and Bakhshi et al. (2017) who argued that performance transparency and skill recognition contribute to a more engaged workforce. Reilly et al. (2014) also found that MIS-enhanced workforce planning allows for proactive career pathing and internal mobility, reducing voluntary turnover. The meta-analysis also confirms that the adoption of MIS reduces compliance-related risks, strengthens internal audit readiness, and promotes standardized labor practices across sites. These outcomes illustrate that workforce analytics, when embedded into core MIS architecture, offers strategic benefits that go beyond immediate productivity gains. By enabling predictive, transparent, and skill-aligned labor management, MIS platforms help manufacturing firms build long-term human capital competitiveness.

CONCLUSION

This meta-analysis provides compelling evidence that Management Information Systems (MIS)-based workforce analytics significantly enhance labor planning, absenteeism monitoring, and productivity optimization in manufacturing environments. Across the 53 empirical studies analyzed, consistent improvements were observed in labor efficiency, real-time attendance compliance, and output per labor hour, affirming the strategic value of integrating MIS into human capital management. The adoption of performance dashboards, predictive absence models, and skill-based task allocation systems enabled firms to move from reactive labor control to proactive, data-driven workforce optimization. Moreover, the alignment of workforce analytics with manufacturing excellence frameworks such as Lean, Six Sigma, and TPM reinforced operational consistency, reduced rework, and minimized production disruptions. Beyond operational gains, MIS platforms also supported cross-departmental integration, improved employee engagement, and enhanced long-term cost efficiency, with several studies reporting measurable reductions in labor-related expenses and turnover. The findings validate the theoretical relevance of Human Capital Theory, Socio-Technical Systems Theory, UTAUT, and the Strategic Alignment Model, demonstrating that workforce analytics—when operationalized through robust MIS infrastructure—play a central role in building intelligent, agile, and sustainable manufacturing enterprises.

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