

CHAPTER II

REVIEW OF RELATED LITERATURE AND STUDIES

This chapter looks at how Artificial Intelligence (AI) can be used in project management to improve workplace efficiency, automate procedures, and ensure fair task distribution. It seeks to provide a complete understanding of these components in order to facilitate the development and deployment of AI-based systems that promote equitable task allocation and improve workplace interactions. The researchers present an overview of the study from several scholarly viewpoints and relevant literature, outline existing research in the subject, and identify major discoveries and knowledge gaps that this study aims to fill.

Overview

In today's project management, establishing fair and effective task allocation is critical for increasing productivity and maintaining a balanced workload among team members. Traditional task assignment systems frequently rely on subjective assessment, resulting in inefficiencies, workload imbalances, and possible biases. AI-driven project management systems address these issues by using artificial intelligence to improve job distribution, assuring equal allocation based on skill sets, availability, and performance history.

This chapter investigates the role of AI-driven project management in fair job allocation, with an emphasis on how machine learning algorithms, predictive analytics, and automation improve decision-making processes. AI-driven systems assign jobs objectively by considering staff competencies, workload capacity, and historical data, hence removing favoritism and human prejudice. Furthermore, these systems improve workflow management by automating

regular tasks like scheduling, progress monitoring, and reporting, lowering administrative loads and human errors.

Equitable task distribution promotes a transparent and productive workplace in which employees are assigned jobs based on merit and ability rather than subjective preferences. AI-driven insights also provide project managers with data-driven decision-making capabilities, resulting in better resource utilization and project schedules. Finally, incorporating AI into project management improves team communication, increases efficiency, and fosters a fair and ethical work environment.

AI-Driven Project Management for Equitable Task Allocation

In today's fast-evolving software industry, the demand for efficient, adaptive, and intelligent project management solutions has never been greater. Artificial intelligence (AI) is emerging as a transformative force, revolutionizing how teams operate by automating routine tasks, offering predictive insights, and enabling data-driven decision-making. These tools empower project managers to anticipate challenges, streamline resources, and optimize workflows, resulting in more efficient project execution. By reducing the time spent on administrative tasks like scheduling and reporting, AI allows managers to focus on strategic objectives, fostering innovation and team collaboration. This paper explores the latest advancements in AI-driven project management, including predictive analytics, task automation, and tools for enhancing collaboration in remote environments. It highlights real-world applications, such as improving project delivery speed, enhancing scalability, and mitigating risks, while also addressing challenges like system integration, data privacy, and skill gaps. Through industry case studies and examples, this study offers actionable strategies for adopting

AI in project management and outlines its potential to reshape the future of software development. By bridging the gap between human expertise and machine intelligence, AI promises to redefine project management as an indispensable asset for success in an increasingly competitive landscape.

Artificial intelligence (AI) is transforming project management by increasing efficiency and ensuring fair task distribution. AI-driven systems use predictive analytics to anticipate resource requirements and optimize allocation techniques while taking into account team members' talents, availability, and workloads. This guarantees that assignments are assigned to the most appropriate persons, increasing productivity while reducing resource waste.

AI reduces administrative responsibilities for project managers by automating basic processes like scheduling and reporting. This enables them to focus on strategic objectives, promote innovation, and improve team communication.

Integrating AI into project management not only streamlines operations but also promotes fair workload distribution among team members. As a result, it improves team satisfaction and contributes significantly to overall project success.

AI-Driven Project Management Systems and Their Role in the Workplace

Project Management Systems (PMS) have become crucial tools in today's workplaces, allowing firms to fast-track project planning, execution, monitoring, and completion. As enterprises become more complicated, the demand for effective project management solutions has increased, prompting the creation and integration of a variety of software systems aimed at improving productivity, cooperation, and accountability. This section reviews existing literature

and studies on project management systems, discussing their evolution, benefits, challenges, and impact on organizational performance.

Choi, J., & Ha, M. (2022). Project Management Information Systems (PMIS) have been widely used for effective construction project management especially for EPC (Engineering, Procurement, and Construction) projects. It saves a significant amount of time and effort, making project management tasks more effective and efficient. However, most Korean EPC firms develop and use PMIS without validating the system's compliance with global project management standards. This research presented a methodology to validate the composition and functions of PMIS to ensure it conforms to the global project management standards of project management practice. The researchers defined the core and sub-management processes as well as the required capability level. Proposed global practice, which serves as evaluation criteria, was developed in the form of a work process. Sample PMIS evaluation results confirmed that the core management processes and their functions are compliant with overall global practice. The proposed work processes and evaluation criteria can serve as a global project management requirement for developing PMIS in the future.

DL Gilbert II · (2024). Some project managers lack strategies to mitigate project failures in detailed execution. Project leaders are concerned that an inapt definition and planning are used to deliver successful projects. Grounded in contingency theory, the purpose of this qualitative single - case study was to explore effective strategies used by industrial chemical plant project managers to mitigate failure in detailed execution. Five project managers from the southern United States who successfully led the execution of capital projects participated in the study. Data were collected from semistructured interviews and a review of company procedures. Four themes emerged from the thematic analysis: proactive complexity and risk management,

knowledge and expertise utilization, project planning and scope management, and stakeholder engagement and communication. A key recommendation for project leaders is implementing early risk identification and mitigation protocols by involving the team in decision - making processes and establishing clear and regular communication with all stakeholders. The implications for positive social change include the potential for improved project management practices and the promotion of a more inclusive and collaborative work environment, which can lead to increased customer satisfaction, job creation, and societal advancements.

Syalevi et al. (2024) examines the role of Project Management Offices (PMOs) in enhancing organizational performance across various industries. The study emphasizes how crucial PMOs are to enabling effective task organization and monitoring across a variety of industries. There is a need for focused study to better understand these dynamics, as indicated by the observed research gap on the relative impact of PMOs on IT vs non-IT sectors.

Through several models and measurements, the Competing Values Framework application offers a detailed view of how PMOs contribute to corporate success. Because the IT and non-IT sectors have different goals, PMOs need to modify their approaches to meet the demands of the respective industries. The emphasis on technological competence and prompt delivery in the IT industry emphasizes how crucial specialized expertise and effective procedures are. The focus on competency-based training and interpersonal ties in non-IT industries implies that human aspects are more important in these settings.

Overall, the study highlights how important it is for PMOs to modify their strategies according to industrial circumstances in order to improve organizational performance. Future

studies should look more closely at these variations and create frameworks that help PMOs use best practices that are suited to the demands of their particular business.

Ngo, J., & Hwang, B. G. (2022). Smart technologies in the Fourth Industrial Revolution can improve the performance of the construction industry with corresponding changes to project manager's knowledge and skills. This study investigated the impact of smart technologies on project management knowledge and skills required of project managers with the following research objectives: (1) to investigate the project management knowledge areas and skills that are important in managing projects with smart technologies; (2) to evaluate the changes in the relative importance of project management knowledge areas and skills in managing projects with smart technologies; and (3) to determine if project managers from different organisation domains perceive the importance of the knowledge and skills differently. Project communication, cost, and risk management were found to be most important, with changes in the importance of project integration, stakeholder, scope, and procurement management when managing projects with smart technologies. The top skills required were found to be problem solving, information management, communication, project management, and planning and organizational skills. Higher importance was placed on technical and operational technology skills, information management skills, creativity, ethical awareness, strategic planning, active learning, decision-making, and motivation skills when managing projects with smart technologies. The findings from this study contribute to the knowledge through better understanding of the impact of smart technologies on project management knowledge and skills. This can serve as guidelines for practitioners to remain competent and consistently deliver successful projects with smart technologies.

In addition, Yagyamitra Chouhan et al.'s essay "Project Management Tool: A Review" (2022) explores the importance of project management systems and assesses a range of tools and methods that support efficient job management.

The study highlights how important it is to choose the right project management tools in order to overcome the difficulties that come with managing software projects. The authors offer a framework for assessing and selecting tools that correspond with particular project requirements by outlining important selection criteria. The "Projectify" approach is an attempt to incorporate these crucial elements into a unified solution intended to improve task management and project performance in general. Ultimately, the study concludes by highlighting the significance of carefully choosing and utilizing project management solutions that are suited to the particular needs of software projects in order to increase productivity and better outcome.

On the other hand, Andy Behrens et al.'s essay "A Systematic Literature Review: How Agile is Agile Project Management?" (2021) investigates how closely Agile Project Management (APM) adheres to the fundamental principles listed in the Agile Manifesto, which connects to Project Management Systems. In order to evaluate APM's compliance with these values, the study examines literature published between January 2015 and March 2021.

The results indicate that APM techniques generally align with the fundamental principles of the Agile Manifesto. By placing a strong emphasis on teamwork, functional deliverables, customer engagement, and flexibility, APM offers a framework that complements agile concepts. The report does, however, also point out areas in which APM can develop further to improve its agility, such as striking a balance between flexibility and the required structure and making sure that all agile values are completely incorporated into project management procedures.

Furthermore, the book *AI-Driven Project Management: Harnessing the Power of Artificial Intelligence and ChatGPT to Achieve Peak Productivity and Success* by Kristian Bainey (2024) is thoroughly reviewed in the article *AI-Driven Project Management* by Soheila Sadeghi, which was published in the *PM World Journal* in August 2024. The paper looks at how artificial intelligence (AI), particularly ChatGPT and other AI-driven technologies, is changing project management by enhancing decision-making, boosting productivity, and spurring creativity.

Each of the book's six sections focuses on a distinct facet of integrating AI into project management. Predictive analytics for risk assessment and performance monitoring, automation of repetitive processes, and AI's role in data-driven decision-making are important subjects. Bainey highlights how AI technologies may be used practically in a variety of project management approaches, such as Waterfall and Agile, and talks about ethical considerations such as bias in AI decision-making.

The book's emphasis on efficiency and optimization is emphasized in the review, especially how AI can help project managers handle massive amounts of data, produce insights in real time, and streamline processes. Sadeghi recognizes the book's advantages, including its practical approach to AI adoption and real-world examples. She does, however, also highlight some possible difficulties, such as the necessity for project managers to upgrade their skills and the dangers of relying too much on AI without human supervision.

Consequently, Marcus Glowasz (2022) explores how incorporating artificial intelligence (AI) into project management can change organizational decision-making procedures in his article, "The Impact of AI-Driven Project Management on an Organization's Decision-Making

Culture," which was published in Cost Engineering. Key components of an AI-driven project management strategy are identified in the study, along with its implications for practitioners' norms and values around decision-making. Glowasz highlights that although AI presents chances to improve service quality and efficiency, using it would need a significant change in organizational attitudes and practices in order to promote a data-driven culture. In order to increase the predictability of project outcomes, the paper ends by suggesting methods for adjusting to this modified cultural environment.

In addition, by automating processes and enhancing communication, Karamthulla et al. (2024) contend that AI technologies are profoundly changing project management. The International Journal for Multidisciplinary Research published an article in March 2024 titled "Navigating the Future: AI-Driven Project Management in the Digital Era," which examines how artificial intelligence (AI) is revolutionizing contemporary project management. The study looks into how AI technologies are changing resource management, decision-making, and project workflows. Project managers may increase communication, automate repetitive work, and improve predictive analytics by using AI-driven solutions, which will result in more effective and efficient project results. The authors offer insights into how AI will influence the future of the field by addressing the difficulties and moral dilemmas associated with its application in project management.

Smart Scheduling

The study by Zahid, A., Leclaire, P., Affonso, R. C., Hammadi, L., & Elballouti, A. (2024, May) explained that in the dynamic landscape of Industry 4.0, the transition from traditional to smart scheduling is crucial for efficient manufacturing processes and sustainable

practices. The fourth industrial revolution, reshaping traditional practices, underscores the need for eco-friendly manufacturing due to environmental concerns and rising energy prices. This paper systematically reviews existing literature on manufacturing scheduling, dynamic scheduling models, and optimization approaches, providing insights into current challenges in adapting to Industry 4.0 technologies and opportunities for sustainable objectives. By illuminating the existing state of the field and highlighting the imperative transition from traditional to smart and sustainable scheduling practices, this review contributes to a detailed understanding of smart scheduling and its profound implications for sustainable manufacturing. A valuable resource for researchers, practitioners, and policymakers, this study addresses a critical research gap. Notably, the intersection of smart scheduling, Industry 4.0 technologies, and sustainable development is relatively underexplored, underscoring the novelty and importance of this study in advancing the field.

Rossit, D. A., Tohmé, F., & Frutos, M. (2018) highlighted that Smart Manufacturing and Industry 4.0 production environments integrate the physical and decisional aspects of manufacturing processes into autonomous and decentralised systems. One of the main aspects in these systems is production planning, in particular scheduling operations on machines. They introduce here a new decision-making schema, Smart Scheduling, intended to yield flexible and efficient production schedules on the fly, taking advantage of the features of these new environments. The ability to face unforeseen and disruptive events is one of the main improvements in the proposed schema, which uses an efficient screening procedure (Tolerance Scheduling) to lessen the need of rescheduling in the face of those events.

According to Rjoub, G., Bentahar, J., Wahab, O. A., & Bataineh, A. (2019, August), with the widespread adoption of Internet of Thing (IoT) and the exponential growth in the volumes of

generated data, cloud providers tend to receive massive waves of demands on their storage and computing resources. To help providers deal with such demands without sacrificing performance, the concept of cloud automation has recently arisen to improve the performance and reduce the manual efforts related to the management of cloud computing workloads. In this context, they propose in this paper, Deep learning Smart Scheduling (DSS), an automated big data task scheduling approach in cloud computing environments. DSS combines Deep Reinforcement Learning (DRL) and Long Short-Term Memory (LSTM) to automatically predict the Virtual Machines (VMs) to which each incoming big data task should be scheduled to so as to improve the performance of big data analytics and reduce their resource execution cost. Experiments conducted using real-world datasets from Google Cloud Platform show that the solution minimizes the CPU usage cost by 28.8% compared to the Shortest Job First (SJF), and by 14% compared to both the Round Robin (RR) and improved Particle Swarm Optimization (PSO) approaches. Moreover, this solution decreases the RAM memory usage cost by 31.25% compared to the SJF, by 25% compared to the RR, and by 18.78% compared to the improved PSO.

Serrano-Ruiz, J. C., Mula, J., & Poler, R. (2021) claimed that within the scheduling framework, the potential of digital twin (DT) technology, based on virtualisation and intelligent algorithms to simulate and optimise manufacturing, enables an interaction with processes and modifies their course of action in time synchrony in the event of disruptive events. This is a valuable capability for automating scheduling and confers it autonomy. Automatic and autonomous scheduling management can be encouraged by promoting the elimination of disruptions due to the appearance of defects, regardless of their origin. Hence the zero-defect manufacturing (ZDM) management model oriented towards zero-disturbance and zero-disruption

objectives has barely been studied. Both strategies combine the optimisation of production processes by implementing DTs and promoting ZDM objectives to facilitate the modelling of automatic and autonomous scheduling systems. In this context, this particular vision of the scheduling process is called smart manufacturing scheduling (SMS). The aim of this paper is to review the existing scientific literature on the scheduling problem that considers the DT technology approach and the ZDM model to achieve self-management and reduce or eliminate the need for human intervention. Specifically, 68 research articles were identified and analysed. The main results of this paper are to: (i) find methodological trends to approach SMS models, where three trends were identified; i.e. using DT technology and the ZDM model, utilising other enabling digital technologies and incorporating inherent SMS capabilities into scheduling; (ii) present the main SMS alignment axes of each methodological trend; (iii) provide a map to classify the literature that comes the closest to the SMS concept; (iv) discuss the main findings and research gaps identified by this study. Finally, managerial implications and opportunities for further research are identified.

The study by Shiue, Y. R., Lee, K. C., & Su, C. T. (2018). Previous studies of the real-time scheduling (RTS) problem domain indicate that using a multiple dispatching rules (MDRs) strategy for the various zones in the system can enhance the production performance to a greater extent than using a single dispatching rule (SDR) over a given scheduling interval for all the machines in the shop floor control system. This approach is feasible but the drawback of the previously proposed MDRs method is its inability to respond to changes in the shop floor environment. The RTS knowledge base (KB) is not static, so it would be useful to establish a procedure that maintains the KB incrementally if important changes occur in the manufacturing system. To address this issue, we propose reinforcement learning (RL)-based RTS using the

MDRs mechanism by incorporating two main mechanisms: (1) an off-line learning module and (2) a Q-learning-based RL module. According to various performance criteria over a long period, the proposed approach performs better than the previously proposed MDRs method, the machine learning-based RTS using the SDR approach, and heuristic individual dispatching rules.

In addition, according to Wang, J., & Gao, R. X. (2022), smart manufacturing refers to an advanced mode of manufacturing, which incorporates computer-integrated manufacturing (CIM) and artificial intelligence (AI) for data-enabled adaptability throughout the production cycle, from product design over process scheduling, control, and optimization to product quality assurance. Enabling this mode of manufacturing are two essential techniques: smart scheduling and predictive maintenance. For Industry 4.0 (I4.0)-based manufacturing systems, all resources (e.g., machines, robots, vehicles, materials, etc.) in a smart factory are represented as cyber-physical systems (CPS), i.e., physical entities equipped with digital identification such as RFIDs, sensors, edge computing electronics, etc. Supported by AI, this new manufacturing paradigm provides new opportunities for scheduling production resources and predictive maintenance. This chapter focuses on describing cutting-edge tools, technologies, and infrastructure that enable the transition from traditional production scheduling and time-based maintenance to smart scheduling and predictive maintenance, which ultimately enable smart manufacturing.

Furthermore the study by Alemão, D., Rocha, A. D., & Barata, J. (2021). The recent advances in technology and the demand for highly customized products have been forcing manufacturing companies to adapt and develop new solutions in order to become more dynamic and flexible to face the changing markets. Manufacturing scheduling plays a core role in this adaptation since it is crucial to ensure that all operations and processes are running on time in the factory. However,

to develop robust scheduling solutions it is necessary to consider different requirements from the shopfloor, but it is not clear which constraints should be analyzed and most research studies end up considering very few of them. In this review article, several papers published in recent years were analyzed to understand how many and which requirements they consider when developing scheduling solutions for manufacturing systems. It is possible to understand that the majority of them are not able to be adapted to real systems since some core constraints are not even considered. Consequently, it is important to consider how manufacturing scheduling solutions can be structured to be adapted effortlessly for different manufacturing scenarios.

Gao, H., Wang, L., Liu, J., & Wei, Z. (2018). Day-ahead scheduling has played a significant role in the operation of distribution systems, aiming at minimizing the total operation cost. With the excessive integration of information and communication technologies and intelligent electronic devices, distribution system operators may seek to optimally control the active management elements to increase the economic and technical performance of future smart distribution systems. This paper focuses on an integrated day-ahead scheduling scheme that is formulated as a mixed integer second-order cone programming problem to obtain the optimal solution by means of the relaxed power flow model (RPFM). The detailed technical constraints for all the elements are accommodated based on the RPFM-based optimization method. Meanwhile, active management cost and punishment cost of wind power curtailed and customer energy not supplied are also considered in the design objectives of this paper. In order to address the uncertainties, a stochastic robust optimization method is first introduced to decide the active management elements (including capacitor bank, electrical storage system, controllable load, and switch) as the robust decision scheme. Afterwards, the column-and-constraint generation algorithm is applied to solve the proposed stochastic robust two-stage optimization model.

Numerical results based on the IEEE 33-bus, PG&E 69-bus, and practical 152-bus systems are obtained to verify the effectiveness of the proposed method.

The study by Rossit, D. A., Tohmé, F., & Frutos, M. (2019). Traditional methods of scheduling are mostly based on the use of pieces of information directly related to the performance of schedules, as for instance processing times, delivery dates, etc., assuming that the production system is operating normally. In the case of malfunctions, the literature concentrates on the ensuing corrective operations, like scheduling with machine breakdowns or under remanufacturing considerations. These event-driven approaches are mainly used in dynamic scheduling or rescheduling systems. Unlike those, Smart Manufacturing and Industry 4.0 production environments integrate the physical and decision-making aspects of manufacturing processes in order to achieve their decentralization and autonomy. On these grounds we propose a data-driven architecture for scheduling, in which the system has real time access to data. Then, scheduling decisions can be made ahead of time, on the basis of more information. This promising approach is based on the architecture of cyber-physical systems, with a data-driven engine that uses, in particular, Big Data techniques to extract vital information for Industry 4.0 systems.

On the other hand Yang, S., & Xu, Z. (2022). To realise the intelligent decision-making of dynamic scheduling and reconfiguration, we studied the intelligent scheduling and reconfiguration with dynamic job arrival for a reconfigurable flow line (RFL) using deep reinforcement learning (DRL), for the first time. The system architecture of intelligent scheduling and reconfiguration in smart manufacturing is proposed, and the mathematical model is established to minimise total tardiness cost. In addition, a DRL system of scheduling and

reconfiguration is proposed by designing state features, actions, and rewards for scheduling and reconfiguration agents. Moreover, the advantage actor-critic (A2C) is adapted to solve the studied problem. The training curve shows the A2C-based agents have effectively learned to generate better solutions for unseen instances. The test results show that the A2C-based approach outperforms two traditional meta-heuristics, iterated greedy (IG) and genetic algorithm (GA), in solution quality and CPU times by a large margin. Specifically, the A2C-based approach outperforms IG and GA by 57.43% and 88.30%, using only 0.46‰ and 2.20‰ CPU times of IG and GA. The trained model can generate a scheduling or reconfiguration decision within 1.47 *ms*, which is almost instantaneous and can satisfy real-time optimisation. Our work shows a promising prospect of using DRL for intelligent scheduling and reconfiguration.

Workload Allocation

Abbasi, M., Mohammadi-Pasand, E., & Khosravi, M. R. (2021). Because of the tremendous growth in the number of smart vehicular devices and 5G mobile technologies, the Internet of Things (IoT) has experienced rapid expansion. This has led to a considerable increase in the volume of sensory data produced from, but not limited to, monitoring devices, traffic congestion in cities, safety, and pollution control. Cloud computing can deal with the corresponding workload by providing virtually unlimited computational resources. But, given the importance of the quality of service and security in delay-sensitive requests, other solutions like fog computing have also been introduced to speed up processing and management of sensory data in real scenarios like smart grid and IoT. Processing workloads at the network edge reduces the delay in mobile edge computing, but it highly increases the consuming power. Therefore, there is an urgent need for the improvement of the energy model of fog devices at the network edge. This paper is an attempt to modify this model using the green energy concept and reduce

both delay and power consumption in multi-sensorial frameworks in secure IoT systems. In the proposed method, a Genetic Algorithm (GA) is used for handling a large number of requests and the corresponding quality and security limitations. Simulation results show that the proposed method can simultaneously reduce the delay and the power consumption of edge devices compared to a baseline strategy.

The study by Saif, F. A., Latip, R., Hanapi, Z. M., Alrshah, M. A., & Kamarudin, S. (2023). The Internet of Things (IoT) generates massive data from smart devices that demand responses from cloud servers. However, sending tasks to the cloud reduces the power consumed by the users' devices, but increases the transmission delay of the tasks. In contrast, sending tasks to the fog server reduces the transmission delay due to the shorter distance between the user and the server. However, this occurs at the user end's expense of higher energy consumption. Thus, this study proposes a mathematical framework for workload allocation to model the power consumption and delay functions for both fog and clouds. After that, a Modified Least Laxity First (MLLF) algorithm was proposed to reduce the maximum delay threshold. Furthermore, a new multi-objective approach, namely the Non-dominated Particle Swarm Optimization (NPSO), is proposed to reduce energy consumption and delay compared to the state-of-the-art algorithms. The simulation results show that NPSO outperforms the state-of-the-art algorithm in reducing energy consumption, while NGSA-II proves its effectiveness in reducing transmission delay compared to the other algorithms in the experimental simulation. In addition, the MLLF algorithm reduces the maximum delay threshold by approximately 11% compared with other related algorithms. Moreover, the results prove that metaheuristics are more appropriate for distributed computing.

According to Zhou, Y., Ye, Q., & Huang, H. (2024). Machine learning (ML) has been widely applied to successfully address a variety of different problems across diverse domains, such as robotics, healthcare, and finance. However, high-complexity ML algorithms often require overlong computation time, which significantly impacts their feasibility. Distributed ML (DML) has been used to tackle the slow computation problem with high-complexity ML algorithms. Nevertheless, with DML, the computation results from all participating computing devices need to be collected in order to complete an ML task. When part of the participating devices, known as the stragglers, cannot return their results in time, the overall computation time will be extended. Distributed coded ML (DCML) is a promising solution to mitigate the negative impact of the stragglers. With DCML, redundancy is injected into an ML task so that only a subset of the results from participating devices are required to finish the ML task. In DCML, how to select proper participating devices, referred to as workers, and how to allocate appropriate workloads to the selected workers are two challenging problems. In this article, we consider a DCML scenario where numerous computing devices are available for an ML task. These devices are willing to offer their computation capacity in exchange for compensation. To encourage the computing devices to participate in the distributed computation, a reverse auction-based incentive mechanism is employed. With the objective of minimizing both the completion time of the ML task and the compensation for participating devices, we propose a deep-reinforcement-learning-based workload allocation and worker selection scheme for DCML, DAS. To our knowledge, this is the first attempt to simultaneously tackle both the workload allocation and worker selection issues in DCML. Our experimental results indicate that DAS outperforms the state-of-the-art schemes in terms of completion time and compensation.

Fan, Q., & Ansari, N. (2018) argue that empowered by computing resources at the network edge, data sensed from Internet of Things (IoT) devices can be processed and stored in their nearby cloudlets to reduce the traffic load in the core network, while various IoT applications can be run in cloudlets to reduce the response time between IoT users (e.g., user equipment in mobile networks) and cloudlets. Considering the spatial and temporal dynamics of each application's workloads among cloudlets, the workload allocation among cloudlets for each IoT application affects the response time of the application's requests. While assigning IoT users' requests to their nearby cloudlets can minimize the network delay, the computing delay of a type of requests may be unbearable if the corresponding virtual machine of the application in a cloudlet is overloaded. To solve this problem, they design an application aware workload allocation scheme for edge computing-based IoT to minimize the response time of IoT application requests by deciding the destination cloudlets for each IoT user's different types of requests and the amount of computing resources allocated for each application in each cloudlet. In this scheme, both the network delay and computing delay are taken into account, i.e., IoT users' requests are more likely assigned to closer and lightly loaded cloudlets. Meanwhile, the scheme will dynamically adjust computing resources of different applications in each cloudlet based on their workloads, thus reducing the computing delay of all requests in the cloudlet. The performance of the proposed scheme has been validated by extensive simulations.

In addition to that, Hung, Y. W., Chen, Y. C., Lo, C., So, A. G., & Chang, S. C. (2021) claims that artificial intelligence models implemented in power-efficient Internet-of-Things (IoT) devices have accuracy degradation due to limited power consumption. To mitigate the accuracy loss on IoT devices, an edge-server joint inference system is introduced. On the edge-server inference system, allocate more workloads to the server end can mitigate accuracy

loss, but data transmission contributes to the power consumption of the edge device. Thus, in this article, the authors present a novel two-stage method to allocate workloads to the server or the edge to maximize inference accuracy under a power constraint. In the first stage, they present a clusterwise threshold-based method for estimating the trustworthiness of a prediction made at the edge. In the second stage, they further determine the workload allocation of a trustworthy image based on the probability of the top 1 prediction and the power constraint. In addition, the authors propose a fine-tuning process to the pretrained model at the edge for achieving better accuracy. In the experiments, they apply the proposed method to several well-known deep neural network models. The results show that the proposed method can improve inference accuracy up to 3.93% under a specific power constraint compared to previous methods.

Moreover, the study by Boncori, I., Bizjak, D., & Sicca, L. (2020) highlighted that academic ‘labour’ within the Higher Education landscape is changing as universities are increasingly managed as business organisations. In the contemporary neoliberal academic context, departments and individuals are required to develop forms of accountability based on quantitative metrics regarding performance, budgets, human resource management and income generation. Drawing from Foucauldian theories of power, this article explores the contentious implementation of workload allocation models in the UK Higher Education sector not only as an illustration of a superimposed managerial tool of control but also as an instrument of resistance. This article suggests that in order to counteract the systematic failure of neoliberal academia at the individual and collective level, these performance management tools can be used as forms of empowerment and resistance. Further, it is recommended that these instruments are designed in a collaborative way to ensure fair and transparent allocations of tasks and responsibilities, and to avoid unmanageable workloads.

According to Rafea, S. A., & Jasim, A. D. (2023). Edge computing is used with cloud computing as an extension to increase the performance of delay-sensitive applications such as autonomous vehicles, healthcare systems, video surveillance systems, ..etc. The fast increase in the Internet of Things (IoT) devices increases the amount of data transferred in the network. IoT devices are resource-constrained in terms of energy consumption and computation capability. Data processing near IoT devices enabled by edge devices. Hence reduces the transmission power of sending data to the cloud and causes delays due to the cloud being placed far away from the devices. Most real-time applications depend on artificial intelligence (AI) techniques, increasing the computations on IoT-edge devices. Conversely, if this AI workload is executed on the cloud, the delay increase causes degradation in application performance. How to decide where the computation is done in an IoT, edge and cloud network is an important issue. The purpose of optimizing the workload allocation decision is to increase the application performance in terms of Quality of Experience (QoE) and Quality of Service (QoS); hence, the major goal is to reduce the delay time while maintaining the accuracy of the AI systems. As presented in this review, many researchers focus on proposing a workload allocation decision based on AI techniques. In contrast, other research focuses on the AI workload, hence presenting a method for partitioning the AI model to increase the system's accuracy in the resource constraint devices (end device and edge server). Many other researches also used the AI model for resource allocation and provisioning between edge servers and the cloud. In this review, the integration between AI and edge–cloud environment is investigated, the AI workload allocation methods are presented and analyzed, a brief overview of the application of deep learning in edge-cloud computing is also presented, and many challenges that need to be addressed for the

AI application are discussed. Many issues and challenges are also presented for optimizing the edge.

According to Fan, Q., & Ansari, N. (2018), edge cloudlets are promising to mitigate the high network delay incurred by the remote cloud in executing workloads offloaded from a user equipment (UE). However, the response time of a task request consists of both the network delay and computing delay. Considering the spatial and temporal dynamics of workloads among cloudlets, if the workload of an edge cloudlet is heavy, the computing delay in the cloudlet may be unbearable. In this letter, they design a hierarchical cloudlet network and propose a workload allocation scheme to minimize the average response time of UEs' requests by deciding which cloudlet a UE is assigned to and how much computing resource is provisioned to serve it. The performance of the proposed scheme is validated by extensive simulations.

Similarly, Guo, M., Li, L., & Guan, Q. (2019) emphasized that edge computing has recently emerged as an extension to cloud computing for quality of service (QoS) provisioning particularly delay guarantee for delay-sensitive applications. By offloading the computationally intensive workloads to edge servers, the quality of computation experience, e.g., network transmission delay and transmission energy consumption, could be improved greatly. However, the computation resource of an edge server is so scarce that it cannot respond quickly to the bursting computation requirements. Accordingly, queuing delay is un-negligible in a computationally intensive environment, e.g., a computing environment consists of the Internet of Things (IoT) applications. In addition, the computation energy consumption in edge servers may be higher than that in clouds when the workload is heavy. To provide QoS for end users while achieving green computing for computing systems, the cooperation between edge servers and the cloud is significantly important. In this paper, the energy-efficient and delay-guaranteed

workload allocation problem in an IoT-edge-cloud computing system are investigated. They formulate a delay-based workload allocation problem which suggests the optimal workload allocations among local edge server, neighbor edge servers, and cloud toward the minimal energy consumption as well as the delay guarantee. The problem is then tackled using a delay-base workload allocation (DBWA) algorithm based on Lyapunov drift-plus-penalty theory. The theoretical analysis and simulation results have been conducted to demonstrate the efficiency of the proposal for energy efficiency and delay guarantee in an IoT-edge-cloud system.

Furthermore, the study by Abbasi, M., Mohammadi Pasand, E., & Khosravi, M. R. (2020) showed that with the rapid growth of Internet-of-Things (IoT) applications, data volumes have been considerably increased. The processing resources of IoT nodes cannot cope with such huge workloads. Processing parts of the workload in clouds could solve this problem, but the quality of services for end-users will be decreased. Given the latency reduction for end-users, the concept of processing in the fog devices, which are at the edge of the network has been evolved. Optimizing the energy consumption of fog devices in comparison with cloud devices is a significant challenge. On the other hand, providing the expected-quality of service in processing the requested workloads is highly dependent on the propagation delay between fog devices and clouds, which due to the nature of the distribution of clouds with the different workloads, is highly variable. To date, none of the proposed solutions has solved the problem of workload allocation given the criteria of minimizing the energy and delay of fog devices and clouds, simultaneously. This paper presents a processing model for the problem in which a trade-off between energy consumption and delay in processing workloads in fog is formulated. This multi-objective model of the problem is solved using NSGAI algorithm. The numerical results show that by using the proposed algorithm for workload allocation in a fog-cloud scenario, both

of energy-consumption and delay can be improved. Also, by allocating 25% of the IoT workloads to fog devices, the energy consumption and delay are both minimized.

Objective Task Allocation

Cheng, Y., Sun, F., Zhang, Y., & Tao, F. (2019). Task allocation (TA) problem is of critical importance in manufacturing industry, and determines the effectiveness and efficiency of advanced manufacturing systems. A proper TA approach can give an optimized arrangement of existing resources, enable manufacturing system's flexibility, thus improve both economic performance and social benefits. However, there is still no uniform analysis on TA to date, while it has been paid more attention from the view of manufacturing resource allocation. With the application of advanced information and manufacturing technologies, the TA process improved with intelligence or even smartness could respond to demand changes rapidly and maintain a good balance for supply-demand matching issues. In this paper, TA and its intelligent improvements are picked and investigated. The general workflow of TA is divided into six stages: *task description and modelling*, *analysis and modelling of TA process*, algorithm design and selection for TA, *decision-making of TA*, *simulation*, and *task execution*. Each stage is separately analyzed at first. In particular, the decision-making process of TA consists of two approaches: the traditional way of *system-oriented process* (SoP), and the *task-oriented process* (ToP). Researches show that the latter one can better suit current systems and their manufacturing environment. At last, future directions of TA are pointed out to make systems achieve much more intelligence.

Furthermore, the study by Weikert, D., Steup, C., & Mostaghim, S. (2020, December). This paper proposes a Multi-Objective Optimization Algorithm, which is designed for dynamic task allocation in the context of Internet of Things (IoT) and especially Wireless Sensor Networks (WSN). The resulting algorithm enables the WSN to optimize network metrics and mitigate changes in network topology through node failures by providing re-allocation of tasks based on continuous optimization of the task allocation. The approach is evaluated using a simulation of multiple WSNs with different topologies and task configurations measuring the network lifetime and latency. Comparing with existing single-objective algorithms, the approach shows comparable performance regarding network lifetime while improving the latency of the network.

The study by Mishra and Varshney (2024) titled “Comprehensive analysis of human and AI task allocation in the education sector: Defining futuristic roles and responsibilities” examines the integration of AI chatbots in higher education, focusing on their impact on teaching practices, learning outcomes, and student engagement. Utilizing frameworks such as Technological Pedagogical Content Knowledge (TPACK), the Technology Acceptance Model (TAM), and Constructivist Learning Theory (CLT), the research assesses how educators incorporate AI tools and how these tools support interactive, student-centered learning. The findings indicate that AI chatbots can significantly reduce administrative burdens on educators, provide personalized learning experiences, and enhance real-time feedback. The study emphasizes the importance of teacher training and ethical considerations in AI integration, advocating for a balanced synergy between human educators and technological tools to enhance educational practices.

Additionally, Filho et al.(2018) evaluate the literature in a systematic manner and look at several multicriteria models for job allocation in distributed software development (DSD) projects. They stress how crucial qualitative decision-making techniques are for efficiently

allocating work in remote teams, especially ones that take cognitive validity into account. The paper highlights methodologies considered psychologically viable for resolving the complexity inherent in work allocation choices in dispersed settings, and it reveals numerous important features and classifications that might help researchers concentrating on qualitative multicriteria methods.

Also, a thorough assessment of the literature on work distribution and performance management strategies in cloud data centers was carried out by Chauhan et al. in 2024. The study divides research into three main categories: scheduling, load balancing, and resource allocation. Additionally, it lists seven performance management techniques, such as resource usage optimization, power and energy management, and monitoring and control. The authors point out current research gaps and offer creative solutions to enhance performance management and work distribution in cloud computing settings.

In their comprehensive analysis of the literature, Simão Filho et al. (2018) look at several methods for allocating tasks in distributed software development (DSD) projects. The study outlines eleven different approaches that each address different DSD difficulties. These approaches include models, frameworks, and tools. The fact that just two approaches use qualitative multicriteria decision-making methodologies and none make use of verbal decision analysis frameworks is a significant discovery. With regard to the use of qualitative multicriteria techniques in job allocation for DSD, the authors point out a gap in the literature and offer potential avenues for further study. The authors identify a vacuum in the literature on the use of qualitative multicriteria approaches in DSD task allocation and offer future research prospects in this field.

On the other hand, Zhang et al. (2023) consider the wider ramifications of their findings in the discussion. As IoT devices continue to increase, the research recognizes the increasing requirement for work allocation systems to be scalable and adaptable. The authors contend that a potential direction for further study is represented by hybrid models, which blend machine learning and optimization methods. They further stress that, especially in large sensor networks, energy-efficient job allocation is still a major difficulty.

The absence of systems that can manage diverse jobs and dynamically shifting network circumstances is another important research need, according to the authors. The shortcomings of existing methods are also discussed, including their low real-time performance and the overhead expenses associated with computation-intensive optimization models. The study ends by suggesting more investigation into edge computing-based task allocation and adaptive scheduling techniques, where job processing may be shifted closer to the data source to lower latency and energy consumption.

Wang, C., Mei, D., Wang, Y., Yu, X., Sun, W., Wang, D., & Chen, J. (2022). Systematization, and clustering, as the next key direction for AUVs to perform their functions, is becoming an area of enthusiasm among related researchers. And this must be inseparable from task allocation. Task allocation, as we all know, is the implementation of an AUV subtask allocation based on the position, attitude, and status of each AUV in the region after the multi-AUV system is assigned the overall task. Due to the different forms of tasks, AUVs with the same function may be required to perform a certain task, and there is also the possibility that a complex task requires heterogeneous AUV clusters to cooperate to accomplish it. To flexibly cope with different situations, corresponding allocation algorithms have been designed by predecessors. The purpose of this paper is to analyze the existing literature on the models and algorithms of task allocation

for multi-AUV system and to provide a macroscopic impression for researchers in this field to improve their algorithms more comprehensively. The paper roughly classifies the algorithms into centralized and distributed. Also, it covers the enumeration of key algorithms, the analysis of the principles, the application situations, and the comparison of advantages and disadvantages; finally, we look forward to the future directions worthy of further research in this field and provides references.

In contrast, Joo, Jun, and Shin's (2022) study examines work allocation in human-machine production systems, with a focus on incorporating human operator attributes, including task preferences and skills, into the allocation procedure. The authors suggest a deep reinforcement learning (DRL) method to improve job assignments in light of the implicit character of these human elements and the inherent unpredictability in industrial environments. In their discussion of the need to include human aspects in task allocation schemes, the authors point out that conventional approaches frequently ignore the dynamic states of human operators, such as the buildup of weariness and differing degrees of competence. By taking operator well-being into account, the DRL-based method not only improves operational efficiency but also advances sustainable manufacturing practices. The paper notes the difficulties in simulating latent human traits and recommends that future work concentrate on improving the DRL model to more accurately represent these subtleties. The authors further suggest investigating the use of this strategy in several industrial contexts to confirm its efficacy and generalizability.

In connection, Pratama et al. (2023) offer an integrated system intended to improve project management efficiency in order to overcome the difficulties associated with resource and task allocation in information technology (IT) firms. They create the Resource Allocation and Task Allocation Optimization System (RATAOS), which integrates optimization methods using a

random forest model and natural language processing (NLP) with a Project Management Information System (PMIS). By optimizing work distribution and resource use, this integration seeks to enhance project performance as a whole. In order to handle the intricacies of resource and task allocation in IT projects, the study emphasizes the significance of combining cutting-edge optimization approaches with current PMIS. RATAOS was designed using enterprise architecture, which guarantees that the system is in line with business objectives and procedures. Although it may appear contradictory, the authors admit that the longer project completion time is a result of more thoughtful and strategic preparation, which eventually improves project outcomes.

Historical Data and Equitable Task Allocation

Historical data refers to information generated within an organization, either manually or automatically, from various sources such as press releases, log files, financial reports, project and product documentation, emails, and other communications. In a business setting, historical data plays a crucial role in shaping strategic decisions for both the present and future. Managers utilize it to assess organizational performance over time, pinpoint areas that require improvement, and forecast upcoming trends. Patsias, Vasilios & Amanatidis, Petros & Karampatzakis, Dimitris & Lagkas, Thomas & Michalakopoulou, Kalliopi & Nikitas, Alexandros. (2023). Task allocation in edge computing refers to the process of distributing tasks among the various nodes in an edge computing network. The main challenges in task allocation include determining the optimal location for each task based on the requirements such as processing power, storage, and network bandwidth, and adapting to the dynamic nature of the network. Different approaches for task allocation include centralized, decentralized, hybrid, and machine learning algorithms. Each approach has its strengths and weaknesses and the choice of

approach will depend on the specific requirements of the application. In more detail, the selection of the most optimal task allocation methods depends on the edge computing architecture and configuration type, like mobile edge computing (MEC), cloud-edge, fog computing, peer-to-peer edge computing, etc. Thus, task allocation in edge computing is a complex, diverse, and challenging problem that requires a balance of trade-offs between multiple conflicting objectives such as energy efficiency, data privacy, security, latency, and quality of service (QoS). Recently, an increased number of research studies have emerged regarding the performance evaluation and optimization of task allocation on edge devices. While several survey articles have described the current state-of-the-art task allocation methods, this work focuses on comparing and contrasting different task allocation methods, optimization algorithms, as well as the network types that are most frequently used in edge computing systems.

Additionally, emphasizing the importance of collecting and disaggregating data with an equity focus to better understand and address disparities in educational outcomes can be employed (Taylor et al., 2023). Here, the authors proposed methodologies for data collection that are sensitive to the unique challenges faced by these nations, including socio- economic disparities, resource limitations, and diverse cultural contexts. By implementing equity-minded data practices, the article suggests that educational institutions can develop more targeted interventions to improve learning environments and outcomes for all students, thereby fostering greater educational equity and social justice.

Wu et al., (2024) examined an actual industry project on task allocation at call centers. The existing self-selection-based system has led to conflicts among employees. To enhance job satisfaction and improve team morale, the call center must implement an allocation model that employees perceive as fair. Organizations can implement fairness by establishing clear allocation

frameworks, leveraging technology for automation, training managers on unbiased decision-making, and conducting periodic reviews. Moreover, allowing employees some control over their assignments can boost morale, while ensuring tasks match their skills enhances productivity. Transparency in task allocation also builds trust, reducing perceptions of favoritism, and incorporating feedback mechanisms helps refine the process over time. By prioritizing these elements, workplaces can create a more just and efficient system that benefits both employees and the organization.

The integration of artificial intelligence (AI) into performance management analytics is transforming human resource practices by enabling more precise analysis of employee performance data. AI algorithms and machine learning techniques can identify patterns in metrics such as productivity, engagement, and skill development, facilitating tailored development programs and equitable reward distributions. For instance, machine learning models can process metrics related to productivity, engagement, and skill development to uncover insights that inform tailored development programs and equitable rewards distribution. This data-driven approach promotes a meritocratic culture and enhances employee satisfaction. However, challenges like data privacy concerns, potential biases in AI algorithms, and the integration of AI tools into existing HR systems necessitate careful ethical considerations and transparent practices. Overall, AI-driven performance management analytics hold significant potential to revolutionize employee development and rewards programs, leading to a more engaged and productive workforce (Oladele, 2024).

In the field of Human Resources and Management (HRM), AI is revolutionizing HRM by improving the efficiency and effectiveness of essential processes, including recruitment, performance evaluation, and employee engagement. According to El-Ghoul et al., (2024), AI can

analyze vast amounts of data to identify potential candidates who match specific job criteria, thereby accelerating the hiring process and expanding the talent pool. Additionally, AI can personalize learning and development programs and predict turnover, aiding HR managers in retaining top talent. However, the integration of AI in HRM also presents challenges, including data privacy concerns and the risk of over-reliance on automated systems.

Ramachandran et al., (2022) also explored how AI and machine learning technologies can enhance organizational efficiency and employee performance. The authors discuss the application of predictive analytics to forecast employee performance and identify potential areas for improvement. They also examine the use of AI-driven tools for personalized training and development programs, which can adapt to individual learning styles and needs. The authors emphasized the importance of integrating these technologies ethically and responsibly, considering factors such as data privacy and the potential for algorithmic bias.

Organizations can leverage big data analytics to enhance human resource functions. By analyzing vast and diverse datasets—including text, images, videos, and social media posts—businesses can uncover patterns and trends that traditional methods might miss. This data-driven approach enables companies to proactively identify skill gaps within their workforce and develop targeted training programs to address these deficiencies. The integration of big data into HR practices not only optimizes talent management but also fosters a culture of continuous learning and development, ultimately contributing to organizational success.

Al-Fraihat et al., (2024) discussed the transformative role of artificial intelligence (AI) in modernizing performance management systems. It highlights how AI algorithms can process extensive datasets to identify patterns and trends in employee performance metrics, such as

productivity, engagement, and skill development. A significant application of AI in performance management is predictive analytics. By analyzing historical performance data, AI models can forecast future employee performance and identify potential high performers or those at risk of underperformance. For instance, machine learning algorithms can assess various factors—such as past project outcomes, peer reviews, and engagement levels—to predict an employee's future performance trajectory. This predictive capability allows organizations to proactively implement interventions, such as targeted training or mentorship programs, to support employees in reaching their full potential. Moreover, predictive analytics can inform succession planning by identifying employees with the potential to fill critical leadership roles in the future.

On the other hand, Kushwaha et al., (2021) explored the impact of big data in transforming various management fields. In marketing, big data analytics enables companies to perform sentiment analysis on social media platforms, allowing them to gauge consumer opinions and tailor their strategies accordingly. In operations management, big data facilitates supply chain optimization by providing real-time insights into inventory levels and demand forecasting. Additionally, in human resource management, big data assists in talent acquisition by analyzing large datasets to identify potential candidates who best fit organizational needs. The authors emphasize that the integration of big data across these disciplines not only enhances decision-making processes but also offers a competitive advantage in today's data-driven business environment.

In the fast-changing business environment, predictive analytics plays a crucial role in achieving a competitive edge. It utilizes statistical methods, machine learning models, and data mining techniques to examine both current and past data, allowing organizations to generate well-informed forecasts about future trends and events. According to Adesina et al., (2024), the

historical evolution of predictive analytics and emphasize technological enablers like big data platforms, cloud computing, and artificial intelligence. Big data platforms enable businesses to collect, store, and process vast amounts of structured and unstructured data, uncovering valuable insights that inform strategic decision-making. Cloud computing enhances this capability by providing scalable, on-demand computing resources that facilitate real-time data analysis and collaboration without the need for extensive on-premises infrastructure. Additionally, AI, particularly machine learning, significantly improves predictive analytics by allowing models to learn from data, detect intricate patterns, and refine predictions over time. The integration of these technologies empowers organizations to transform raw data into actionable insights, ultimately driving efficiency, profitability, and competitive advantage. However, the article also underscores the importance of addressing potential challenges, such as data privacy concerns and ethical considerations, to ensure responsible and effective implementation of predictive analytics in business strategy.

By effectively integrating predictive analytics, businesses can anticipate market trends, optimize operations, and gain a competitive edge. They also addressed emerging trends, including advancements in AI, the Internet of Things (IoT), and real-time analytics, while considering associated risks like data privacy and ethical considerations. The authors conclude that adopting predictive analytics is essential for sustainable growth and maintaining competitiveness in today's data-driven business environment.

Panda et al., (2021) also outlined the essential stages of predictive analytics, beginning with the clear articulation of the problem statement, followed by data collection and preparation, model development and tuning, and concluding with deployment. The authors emphasized the

importance of selecting appropriate algorithms, ranging from simple regressions to complex ensemble methods, and the iterative nature of model optimization.

Reporting and Feedback Mechanisms

The incorporation of Artificial Intelligence (AI) into project management systems marks a major advancement in enhancing resource distribution, risk management, and decision-making within intricate project settings. Nabeel (2024) examined the impact of AI-driven systems, emphasizing the use of big data analytics to forecast project results, monitor real-time performance, and streamline decision-making in large-scale projects. One good example of using AI to leverage project management is resource allocation optimization. Here, AI systems analyze both historical and real-time project data to identify patterns and predict future resource requirements. This predictive capability allows for dynamic adjustments in resource distribution, ensuring that materials, personnel, and equipment are allocated efficiently. Such optimization minimizes delays, prevents resource bottlenecks, and helps avoid cost overruns. For instance, in construction projects, AI can forecast the need for specific materials at different stages, enabling timely procurement and allocation. Additionally, the author added that predictive analytics can be used to mitigate risks by continuously monitoring project performance metrics and analyzing trends to detect early warning signs of potential issues. Machine learning algorithms process vast amounts of unstructured data from sources like financial reports and communication logs to identify correlations indicative of risk factors. This proactive approach allows project managers to address risks before they escalate, ensuring smoother project execution. For example, AI can alert managers to emerging financial discrepancies that could signal budgetary risks. In terms of improving decision making, Ai can help predict project outcomes with high accuracy, enabling

informed decision-making. It automates routine tasks and workflows, freeing project managers to focus on strategic activities.

On the other hand, the field of financial reporting is experiencing a significant shift driven by advancements in AI technologies. Consequently, Antwi et al., (2024) reported that AI technologies, including machine learning and natural language processing, enable organizations to automate repetitive tasks such as data collection, validation, and analysis. This automation reduces manual errors and enhances the overall quality of financial reports. Along with this, machine learning algorithms can identify patterns and detect irregularities in financial data that may escape human analysts. Timeliness in the reporting can also be observed by automating time-consuming tasks like data entry to ensure financial information is delivered promptly.

As feedback tools continue to evolve, various artificial intelligence technologies are transforming how businesses collect and interpret input. A notable example is natural language processing (NLP), which allows companies such as Google and Microsoft to analyze large volumes of unstructured text data efficiently.

In the manufacturing process, AI revolutionized quality control and process optimization. Okuyelu et al., (2024) reported the use of AI-driven real-time quality monitoring in automobile manufacturing. Companies like Tesla, BMW, and Toyota leverage AI-driven computer vision systems and machine learning algorithms to detect defects in vehicle components during the production process. Additionally, by adopting AI-driven real-time quality monitoring and process optimization, manufacturers can achieve significant improvements in performance metrics, including reduced downtime, enhanced product quality, and optimized resource

utilization. This approach not only addresses current operational challenges but also positions manufacturers to meet future demands in a competitive market.

On the other hand, along with monitoring and feedback integration for task management, authors also thought of unified AI approach to dynamic work pattern monitoring and real-time burnout prevention in the IT sectors. The proposed AI system collects data from various sources, including productivity metrics, time-tracking tools, and employee feedback systems. Machine learning techniques analyze this data to identify patterns indicative of potential burnout, such as prolonged work hours, decreased productivity, or negative sentiment in communications. Additionally, upon detecting early signs of burnout, the system can initiate interventions tailored to individual needs. These interventions may include workload adjustments, recommendations for breaks, or prompts for managers to engage in supportive conversations with affected employees. Natural Language Processing (NLP) algorithms can also evaluate the sentiment of employees' communications, such as emails and chat messages, to gauge emotional well-being. A consistent negative sentiment may trigger alerts for potential burnout, prompting preemptive support measures. However, implementing such systems requires careful consideration of data privacy, ethical implications, and the need to maintain employee trust. (Hassan, 2023).

Artificial Intelligence (AI) is widely seen as the next general-purpose technology, characterized by its rapid adoption and extensive impact across various industries. A key attribute of such technology is its ability to introduce innovative production methods that can enhance overall productivity.

Czarnitzki et al., (2023) examined the multifaceted relationship between artificial intelligence (AI) and economic growth. The authors delve into theoretical frameworks, empirical

evidence, and potential future trajectories to understand how AI influences productivity, labor markets, and overall economic expansion. In the manufacturing sector, the implementation of AI-driven predictive maintenance systems in factories reported a reduction in equipment downtime by up to 20%, leading to increased operational efficiency and cost savings. In the healthcare industry, the utilization of AI algorithms for diagnostic imaging helped enhanced accuracy in disease detection, leading to improved patient outcomes and potential reductions in healthcare costs. Additionally, the application of AI in financial services, specifically for fraud detection in banking transactions resulted in a decrease in fraudulent activities, safeguarding assets and increasing consumer trust. The authors emphasized the importance of regulatory frameworks to ensure ethical AI deployment and to mitigate potential negative societal impacts and calls for a balanced approach that leverages AI's benefits while addressing its potential drawbacks through informed policy-making and strategic planning.

Another study by Gao and Feng (2022) found out that every 1% increase in artificial intelligence penetration can lead to a 14.2% increase in total factor productivity. They highlighted that artificial intelligence enhances productivity mainly through value-added improvements, skill-biased advancements, and technological upgrades. Moreover, the authors revealed that the impact of AI on productivity differs based on property rights and industry concentration. Additionally, the composition of factor endowments within firms can influence the productivity benefits derived from AI. This research provides strong evidence of AI's role in promoting economic sustainability within the Industry 4.0 framework.

In the context of increasing company performance, Rozman et al., (2019) developed a multidimensional model of AI-supported employee workload reduction. Multidimensional constructs of the model include several aspects of artificial intelligence related to human

resource management: AI-supported organizational culture, AI-supported leadership, AI-supported appropriate training and development of employees, employees' perceived reduction of their workload by AI, employee engagement, and company's performance. Here, the models demonstrated that AI implementation leads to significant reductions in employee workload by automating routine tasks and optimizing processes. This reduction in workload was associated with increased job satisfaction and productivity among employees. Furthermore, the models indicated that companies leveraging AI technologies experienced improvements in overall performance metrics, including efficiency, adaptability, and profitability. The study concludes that integrating AI into organizational workflows is a viable strategy for enhancing performance in today's dynamic business landscape.

Artificial Intelligence techniques are progressively enhancing decision support by optimizing data coordination, analyzing trends, generating forecasts, ensuring data consistency, quantifying uncertainty, predicting user data requirements, presenting information in the most suitable formats, and recommending appropriate actions.

In the healthcare sector, AI algorithms analyze patient data to assist in diagnosing diseases, predicting patient outcomes, and personalizing treatment plans. In finance, I systems detect fraudulent activities by analyzing transaction patterns and provide investment recommendations based on market data analysis. Additionally, AI optimizes logistics by forecasting demand, managing inventory levels, and selecting efficient shipping routes in the supply chain management. AI can also be applied in marketing field as it AI analyzes consumer behavior to personalize marketing campaigns, predict customer preferences, and improve customer engagement strategies.

The impact of AI in decision making can also be seen in a review written by Balbaa and Abdurashidova (2024). Here, governments are integrating AI to enhance decision-making processes, improving efficiency and service delivery. However, challenges such as bias, transparency, and accountability need to be addressed. In the education sector, AI is being adopted to personalize learning experiences and administrative decision-making. Nonetheless, concerns regarding over-reliance on AI, potential laziness, and privacy issues have been identified among students. The authors also emphasized the importance of human-AI collaboration to optimize decision outcomes while ensuring responsible implementation. They conclude that while AI significantly benefits decision-making, addressing its social, economic, and ethical implications is crucial for sustainable adoption.

Another thing to point out in the application of AI for decision making is presented by a review by Ahmad et al., (2024). The authors examined the transformative role of artificial intelligence (AI) in business decision-making processes and highlighted AI's capacity to enhance efficiency, problem-solving, and automation, thereby providing businesses with a competitive edge. They emphasize that integrating AI into business strategies can lead to more effective marketing, improved audience engagement, and innovative organizational restructuring. The study involved 204 professionals across various fields to assess factors influencing AI's role in business intelligence and decision-making. Here, they found out that AI contributes significantly to productivity growth, efficient problem resolution, and informed decision-making. The authors conclude that, in the context of rapid technological advancements and the challenges posed by events like the COVID-19 pandemic, AI serves as a crucial tool for businesses aiming to adapt and thrive in evolving market dynamics.

Fostering a Fair Workplace Culture

In a review written by Balasubramaniam et al., (2023), the integration of artificial intelligence (AI) in project management has the potential to enhance transparency and fairness, but it also presents challenges that must be carefully managed. AI systems can inadvertently perpetuate biases present in their training data, leading to unfair outcomes. For instance, in recruitment processes, AI tools have been found to discriminate against certain groups if not properly designed and monitored. Ensuring fairness requires the implementation of robust frameworks that address bias throughout the AI project lifecycle. This includes careful consideration during data collection, model development, and deployment phases. Additionally, transparency in AI systems is crucial for building trust and accountability. Transparent AI allows stakeholders to understand how decisions are made, which is essential for identifying and correcting biases. However, achieving transparency can be challenging due to the complexity of AI models and proprietary constraints. Efforts to enhance transparency include developing explainable AI techniques and establishing clear documentation practices. In project management, applying these principles ensures that AI tools support equitable and understandable decision-making processes. By prioritizing fairness and transparency, organizations can leverage AI to improve project outcomes while maintaining ethical standards.

On the other hand, Shamim (2024) reviewed the integration of artificial intelligence in project management practices to improve efficiency and decision-making processes. Here, the author pointed out the impact of AI in various aspects of project management including planning, scheduling, resource allocation, risk management and stakeholder communication. For instance, AI systems can analyze vast amounts of data to provide objective insights, reducing reliance on subjective judgment and minimizing personal biases. This leads to more transparent

and fair decision-making processes. Another good example is how AI allows resource allocation by assessing team members' skills and workloads, AI can recommend equitable task assignments, ensuring a fair distribution of work and preventing favoritism. Shamim (2024) also reiterated the improved performance evaluation where AI can monitor project metrics impartially, providing transparent evaluations of team performance based on data rather than subjective opinions. Bias detection is also possible as Advanced AI algorithms can identify patterns that may indicate biases in project processes or team interactions, allowing managers to address these issues proactively. However, while AI offers promising tools to enhance transparency and fairness in project management, its effectiveness depends on mindful implementation and ongoing oversight to mitigate potential biases and ethical concerns.

By thoughtfully integrating AI with a focus on ethical considerations and equitable practices, organizations can harness its capabilities to reduce workplace inequalities and foster a more inclusive environment. Farahani et al., (2024) delved into the dual nature of AI and how it influences societal disparities. The authors noted that the use of AI can promote equity in the workplace through several avenues such as in mitigating bias in recruitment, assessing performance, personalizing professional development and even monitoring workplace dynamics. AI can help identify and reduce biases in hiring processes by standardizing candidate evaluations and focusing on skills and qualifications rather than subjective criteria. However, it's crucial to ensure that the AI systems themselves are free from inherent biases. Another thing to take note of is how AI can analyze individual employee data to recommend tailored training and development programs, ensuring equitable access to growth opportunities within the organization. But, to effectively leverage AI in a workplace, it is necessary to ensure that the data used to train AI systems is representative of the diverse workforce to avoid perpetuation of

existing biases. Additionally, establishing an ethical framework and adhering to it would help prioritize fairness, accountability and respect for employee rights.

The American Psychological Association also addressed the potentially mitigating human biases with the use of AI. It emphasizes that while both algorithms and humans can introduce bias into AI systems, there is an opportunity for AI to correct or reverse these inequities. For instance, AI can identify discriminatory hiring practices and suggest adjustments to promote fairness. In the healthcare sector, AI holds promise for improving health systems and outcomes. However, ethical considerations are paramount to prevent potential harms, especially to vulnerable populations. The Carnegie Council's Artificial Intelligence C Equality Initiative (AIEI) seeks to understand how AI impacts equality and aims to promote its deployment in a just and inclusive manner. This initiative reflects a broader recognition of the need for ethical frameworks guiding AI development and implementation. (Abrams, 2024).

In a review written by Varsha (2023), types of biases were discussed along with the emphasis on the importance of responsible AI in firms to reduce risks. According to the author, AI biases and weaknesses observed across various industries contribute to gender disparities and racial discrimination. One notable example discussed is the presence of gender bias in AI-based decision-making systems. An AI recruitment tool trained on resumes from a male-dominated workforce might favor male candidates, thereby reinforcing gender disparities in hiring practices. To address such issues, the author suggested data diversification to ensure that training datasets are diverse and represent the entire population, bias detection and correction which may include statistical methods and adjustments, as well as continuous monitoring to help identify emerging biases.

Hanna et al., (2024) discussed ethical concerns and biases in AI/ML applications. According to the authors, bias in AI arises from multiple sources, including biased training data, algorithmic discrimination, and systemic inequalities in society. Literature on bias mitigation techniques includes data pre-processing such as oversampling underrepresented groups, algorithmic fairness adjustments or the fairness constraints in ML models, as well as post-processing corrections or adjustments of outputs for fairness. Several frameworks, such as the EU's Ethics Guidelines for Trustworthy AI, emphasize principles like fairness, transparency, and accountability.

As AI continues to expand in education, concerns about its ethical implications have emerged. Due to its ability to rapidly analyze datasets and generate new models for higher education programming, teaching, and learning, there is a risk that education could be influenced by flawed human reasoning or AI's trial-and-error processes. It is essential to examine how the principles of Fairness, Accountability, Transparency, and Ethics (FATE) have been recognized in existing research on AI in higher education. Memarian and Doleck (2023) provide a systematic review of AI in higher education through the lens of Fairness, Accountability, Transparency, and Ethics (FATE), offering valuable insights into ethical challenges. One key issue in the study is the ethical implications of AI-driven decision-making in higher education. It highlights concerns such as bias in AI algorithms, which can lead to unfair treatment of students, lack of accountability in AI-generated assessments, and the need for transparency in how AI models operate. The study emphasizes that without proper ethical guidelines, AI could reinforce existing inequalities in education rather than promoting fairness and inclusivity.

Meanwhile, AI and machine learning (ML) are transforming healthcare by providing innovative ways to improve patient care, streamline clinical processes, and drive medical

research forward. However, their integration into healthcare systems presents important ethical challenges that must be thoughtfully managed to ensure fair and responsible implementation. Tilala et al., (2024) explored the multifaceted ethical considerations of using AI in healthcare which includes privacy and data security, algorithmic bias, transparency, clinical validation and professional responsibility. Consider an AI system designed to allocate nursing staff across various hospital departments based on predicted patient admission rates. If the training data used by the AI reflects historical understaffing in departments that predominantly serve minority communities, the AI might continue to allocate fewer resources to these departments. This could perpetuate existing disparities in care quality, highlighting the ethical imperative to ensure that AI systems are trained on representative and unbiased data. Additionally, according to the authors, AI algorithms often operate as "black boxes," making it challenging for healthcare professionals to understand the decision-making processes. This can hinder trust and accountability, especially if the AI's task allocations are questioned. Bias and discrimination may also exist if past data reflects disparities in treatment across different demographic groups, as an AI system might recommend resource allocations that favor certain populations over others, leading to unequal care.

The rise of Artificial Intelligence (AI) has significantly transformed the workplace, reshaping industries, redefining job roles, and changing traditional work processes. As AI technologies rapidly evolve, their integration into various work environments has become inevitable. While these advancements promise enhanced efficiency and productivity, they also introduce complex challenges, particularly concerning employees' digital well-being. In an era of constant connectivity and growing reliance on digital tools, it is essential to explore how AI's

presence in the workplace impacts the well-being of the individuals who drive these organizations forward.

A study by Babu et al. (2024) delves into various AI applications, including automation, machine learning, and natural language processing, highlighting their potential to streamline routine tasks and enable employees to focus on more strategic and creative endeavors. For instance, AI-driven tools can handle data entry, scheduling, and basic customer service inquiries, which streamlines operations and enhances productivity. However, the study also highlights challenges such as ethical considerations and the need for workforce adaptation to these new technologies. This comprehensive analysis contributes to the ongoing dialogue on harnessing AI's potential to create adaptive, efficient, and collaborative workplaces in the digital era.

Synthesis

Project management systems, or PMS, are now essential tools for contemporary businesses, facilitating effective project planning, execution, monitoring, and completion. Project management has undergone a paradigm shift as a result of the incorporation of artificial intelligence (AI), which automates processes, improves decision-making, and optimizes resource allocation. By enhancing predictive analytics, reducing human error, and encouraging data-driven decision-making, AI-driven solutions optimize operations. These technologies give businesses the flexibility and reactivity they need to succeed in ever-changing business settings, in addition to increasing efficiency. Project managers may concentrate on more strategic and innovative activities by using AI to automate monotonous chores, which greatly increases overall productivity.

The capacity of AI to optimize job distribution is a crucial component of project management. AI systems are able to evaluate team members' abilities, workloads, and performance indicators in order to suggest efficient and fair job distributions. Because it guarantees a balanced allocation of duties and avoids favoritism, this capacity is essential for creating a fair work environment. Additionally, AI's predictive analytics can automate work scheduling, estimate resource demands, and even offer real-time performance ratings, which facilitates the early detection and resolution of possible problems.

In addition to that, the use of AI in project management is especially noticeable in intelligent scheduling. AI-driven scheduling solutions increase efficiency in sectors like manufacturing by dynamically allocating resources according to real-time data. These systems use cutting-edge technology, such as cyber-physical systems and digital twins, to minimize delays, cut waste, and maximize resource use. In addition to manufacturing, smart scheduling is revolutionizing industries like cloud computing and mobile apps, where artificial intelligence (AI) is essential for allocating workloads and maximizing system efficiency. AI makes sure that resources are used effectively by anticipating changes in workload and modifying task distribution accordingly, which promotes sustainability and performance resilience.

AI is being used in a number of fields, including as cloud computing, healthcare, and education, to distribute tasks fairly. AI systems in academia can help with workload imbalances, which frequently cause academic members to get burned out and unhappy. AI assists in ensuring task distribution is transparent and equitable through the use of structured workload models. Similar to this, AI aids in resource allocation among servers and edge devices in cloud and edge computing, maximizing system dependability and energy usage while enhancing user experience. Workload management driven by AI makes sure that assignments are distributed

according to engagement and performance rather than arbitrary assessments, producing more equitable and efficient results.

Even though AI has many benefits for assigning tasks, there are drawbacks to take into account. It is necessary to address ethical issues including algorithmic biases and the possibility of escalating already-existing imbalances. If AI systems are trained on inaccurate or unrepresentative data, they may unintentionally reinforce prejudices and provide unjust results. For example, if AI-driven tools are not calibrated correctly, they may favor some demographics over others in the hiring process. Fairness, accountability, and transparency should be given top priority in AI model design at every level, from data collecting to model deployment, in order to reduce such dangers.

Moreover, the way businesses manage resources and evaluate performance is changing as a result of the incorporation of AI into reporting and feedback systems. Managers may make better decisions thanks to AI-driven analytics, which offer greater insights into team dynamics, resource allocation, and project progress. Predictive models can automate financial reporting, predict resource demands, and guarantee equitable work distribution. But these developments also bring up issues with algorithmic transparency, data privacy, and regulatory compliance. For AI-driven systems to reach their full potential, ethical norms must be followed.

AI-driven project management's future depends on improving models to handle new issues including scalability, computing costs, and system flexibility. Even though AI has a lot of potential to maximize workload distribution and enhance organizational performance, its effective use depends on continual supervision, ethical concerns, and advancements in AI

frameworks. Organizations may use AI to build more agile, efficient, and egalitarian workplaces by striking a balance between automation and human knowledge.

In summary, there are a lot of chances to improve job distribution and maximize organizational performance with AI-driven project management. With data-driven decision-making, better scheduling, and equitable labor allocation, artificial intelligence (AI) has the ability to completely transform businesses and guarantee the efficient and just use of resources. However, resolving ethical issues, reducing biases, and promoting openness across the AI lifecycle are essential to the success of AI in project management. Organizations may optimize AI's potential while maintaining moral principles and advancing equity throughout their operations by putting strong frameworks in place and continuously improving AI models.

The review of related literature and studies highlights the evolving role of AI-driven project management systems in enhancing task allocation, resource optimization, and decision-making processes. In addition to discussing possible drawbacks including biases, ethical issues, and the requirement for ongoing monitoring, it highlights the advantages of AI, such as increased efficiency, transparency, and justice. The literature emphasizes how crucial it is to carefully integrate AI in order to guarantee fair and efficient project management results across a range of sectors.

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