



AI-Augmented Manufacturing: A CPMAI Lifecycle Approach to Enhancing Planning Accuracy, Scheduling Efficiency, and Decision Support

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ABSTRACT

The research examines the impact of the AI capabilities in terms of production planning and scheduling performance by their interaction with CPMAI-style lifecycle maturity in a manufacturing setting. The research design played a mixed method which combined survey data collected from 122 practitioners in Dubai UAE with semi-structured interviews to acquire numerical results and comprehensive contextual information. The research study evaluated four AI constructs which included predictive analytics capability and optimization, the decision support and real-time data integration, and explainability/user adoption. The survey measured four CPMAI constructs which included business understanding discipline and data governance and readiness and model lifecycle and MLOps and iterative phase adherence. The study was conducted using a multidimensional index to assess planning and scheduling performance. The results from the multiple regression analysis indicated that AI and CPMAI had over 97% combined explained variance for variance of performance and optimization and decision support and explainability and data governance and model lifecycle discipline emerged as the most significant factors. The qualitative results revealed that trustworthy data and clear problem definition and transparent decision support systems are key for the long-term use of AI tools in production environments. The research is of theoretical value due to its model of smart production planning as a socio-technical system which shows how technical and governance capabilities work together and it provides specific recommendations for manufacturers about their investment priorities. Limitations and directions for longitudinal, multi-site and more objective performance-based research are also identified.

1. INTRODUCTION

Modern factory operations depend on scheduling systems which handle volatility instead of running pre-defined plans. Research on reinforcement-learning (RL) rescheduling demonstrates that adaptive AI systems transform disruptions into major productivity increases through dynamic job-shop experiments which achieve makespan reductions of 22.12% to 53.87% when disturbances increase and peak performance exceeds 70% of the disrupted baseline values according to Saez et al. (2025) and Roblek et al.

(2024). The operational level scheduling problems require heuristic methods and learning systems because conventional methods fail to solve these problems (Fernandes et al., 2022; Sihag et al., 2024; Treacy et al., 2025; El Khatib et al., 2023). The European Manufacturing Survey shows AI systems for production management produce different results because 18.4% of companies use AI in their production areas but only 8.0% apply it to essential process management and 30.4% use it in advanced technology fields (Kovič et al., 2024; Waltersmann

et al.,2021). Manufacturers can boost their production rates and reduce environmental impact through the integration of AI with energy-aware scheduling and multi-objective optimization according to Fernandes et al. 2022; Li & Chen, 2023) while predictive maintenance helps maintain production stability (Debnath et al.,2023; AlMidfa et al., 2024; Naim et al., 2024; Khan et al., 2023). AI systems operating within a systematic lifecycle-based framework help manufacturers reach operational efficiency while maintaining production stability (Shwedeh et al., 2023; AlQassem, 2022; Kofinas et al., 2016).

1.2 Problem statement

The manufacturing sector is currently facing a major problem because the manufacturing schedules at the shop floor become rapidly outdated when the real-time operational interruptions like falling of equipment, any urgent order and inconsistent production time occur and then the traditional planning system continues with fixed plans once the production is started (Razmak et al., 2018; Murtaza et al., 2024; Yasir et al., 2024). Research studies using the reinforcement learning methods and search assisting methods are superior in term of makespan and tardiness performance in comparison to dispatching rules in the flexible job shops (Del Gallo et al., 2023; Alemão et al., 2021). The results of reliability studies shows that RL schedulers need validation and control systems in order to work properly as they become unreliable if used without the same (AlShawabkeh et al., 2016; AlKatheeri et al., 2025; Naim et al., 2025).

The current research meets two major barriers because the optimization of algorithms with basic synthetic benchmarks that do not solve real-world factory readiness and explainability and lifecycle management challenges (Alzoubi et al., 2024; El Khatib et al., 2023; Joghee et al., 2024). Scheduling research does not address the needs of the shop floor because most of the studies are conducted in a laboratory setting that does not resemble the actual industrial conditions (Alemão et al.,2021; Del Gallo et al. 2023). Manufacturing experts who champion parallel reviews believe that established governance systems are needed to ensure the transparency and robustness and accountability problems are implementable (Ahangar et al. 2025). Risk-based sector specific life cycle models yet these need experimental validation in real

production environments (Vyhmeister et al. 2023; Alshurideh et al., 2022; AlNajdawi et al., 2024; Ma'asor et al., 2023). This research combines the use of modern AI scheduling and forecasting systems and the CPMAI framework.

1.3 Research aim & objectives

1.3.1 Aim

The research investigates how the AI systems using CPMAI framework technology improve the production planning and scheduling results in manufacturing operation.

1.3.2 Objectives

1. To determine the main obstacles and operational problems that standard planning and scheduling systems face when they are operated in standard manufacturing situations.
2. To determine how AI forecasting and scheduling solutions can be utilized in manufacturing organizations.
3. To establish the ways in which the CPMAI framework supports the structured implementation of AI within production planning and scheduling processes.
4. To find out measurable improvements in efficiency and accuracy when AI technologies are implemented under the CPMAI framework.

1.4 Research Questions and Hypotheses

1.4.1 Research Questions

1. What are the main obstacles and operational problems that standard planning and scheduling systems face when they are operated in standard manufacturing situations?
2. How can AI forecasting and scheduling solutions be utilized in manufacturing organizations?
3. How does CPMAI framework support the structured implementation of AI within production planning and scheduling processes?
4. What are the measurable improvements in efficiency and accuracy when AI technologies are implemented under the CPMAI framework?

1.4.2 Hypotheses

1. H1: Artificial intelligence has a significant and positive effect on production planning and scheduling activities in manufacturing facilities

2. H2: The CPMAI framework is significantly and positively associated with on production planning and scheduling activities in manufacturing facilities

1.5 Scope and Significance of the Study

The research investigates how Artificial Intelligence (AI) capabilities work together with CPMAI lifecycle practices to boost manufacturing production planning and scheduling performance through four AI constructs and four CPMAI constructs (AlHamadi et al., 2024; El Khatib et al., 2023; Khan et al., 2024). The research investigates operational planning results through schedule adherence and flow efficiency and resource and changeover efficiency and plan stability data from 122 Dubai practitioners who handle planning and scheduling and AI-based practices (AlShawabkeh et al., 2017; Maydybura et al., 2024; Karthika et al., 2024). The research is significant in that it provides evidence that production planning success depends on both advanced algorithms and disciplined governance systems which manufacturers can use to determine their best operational investment points.

2. LITERATURE REVIEW

2.1 Theoretical & conceptual foundations

2.1.1 Artificial Intelligence

The manufacturing sector employs artificial intelligence through data-driven models which allow factories to detect their environment and develop control systems and dispatching protocols and make decisions regarding forecasting and resource management and production sequencing (Shwedeh & F., 2021; Shao et al., 2025; Kabiraj et al., 2009). The present research reveals that scheduling problems are still NP-hard when applied to real-world scenarios so factories now rely on learning-based metaheuristics and reinforcement learning in order to solve these problems in vast solution spaces with uncertain conditions (Plathottam et al., 2023; Kim et al., 2022). Industrial scheduling research has shown that particle swarm optimization, neural networks and reinforcement learning have become the leading methods in industrial scheduling research due to their better tardiness performance than traditional dispatching rules in actual and simulated test environments (Del Gallo et al., 2023). Mourtzis (2022) goes on to explain in more detail how AI, simulation and IIoT allow for

adaptive planning loops that respond to variability in demand and machine states at short intervals, rather than just at weekly horizons (Alzoubi et al., 2025; El Khatib et al., 2024; Kanwal et al., 2023). The basic idea demonstrates the key of AI systems to enhance planning operations by processing complex production data to produce rapid scheduling solutions following production constraints.

2.1.2 CPMAI

A lifecycle discipline needs to exist for making these models reliable and plant adoptable. In order for AI systems to facilitate this, Lahusen et al. (2024) suggest that these AI systems require governance frameworks that connect social responsibility with technical attributes using phase gated controls that travel from the beginning to the end of a project (Neyara Radwan et al., 2025; El Khatib et al., 2022; Joghee et al., 2020). Vyhmeister et al. (2023) present a risk-based manufacturing framework which introduces requirements capture and data readiness and validation and mitigation through FMEA tools in a defined project structure (Shwedeh et al., 2024; Khan et al., 2024; El Khatib et al., 2023). Ahangar et al., 2025 advocate for industrial toolkits for trustworthy AI systems. The study examines how three common failure modes such as poor data tracking and ambiguous models and weak monitoring systems lead to system failures when MLOps practices are not implemented (Alshurideh et al., 2025; Sihag et al., 2024; El Khatib et al., 2022).

2.1.3 Production Planning and Scheduling

The process of Production planning and scheduling (PPS) is the process of determination of production sequences by deciding what products are to be manufactured and when they are to be produced and what resources are to be used for execution of the production sequence (Joghee et al., 2018; Alzoubi et al., 2025; Som et al., 2023). The fundamental results of the methodological research in smart production planning and control are schedule adherence and flow efficiency (lead time, WIP, throughput) and resources and changeover efficiency and service level or plan stability (Kharbat et al., 2017; Anifa et al., 2024; Salloum et al., 2024). Oluyisola et al. (2022) developed a PPC system which brings together the IoT information and machine learning algorithms in order to perform factory level near-real time re-planning and performance monitoring through

environmental condition-based algorithm selection. Mourtzis (2022) explores adaptive scheduling architectures that bring together AI systems and simulation models with cloud-based connectivity for continuous system updates and reliable decisions in the face of disruptions in the system (Al-Qassem et al., 2024; Naim et al., 2024; AlKurdi et al., 2023). The research analyzes PPS results using performance metrics to determine whether the management of AI under lifecycle management results in better results of the factory.

2.2 Review of related studies

2.2.1 AI Effect on PPS performance

2.2.1.1 Predictive analytics capability/

A factory demonstrates its predictive analytics power with its capabilities of forecasting future demand and detecting the forthcoming shortage of resources and system limitations (Kumar et al., 2024; Ahmed et al., 2024; Alshurideh et al., 2024). The research having taken place in US manufacturing facilities indicate that forecasting models that are based on historical order data and market indicators help organizations reduce stockouts and excess inventory and reduce lead times because they help production planners match production capacity with material delivery times with the predicted demand rather than using general estimates according to Al Bashar et al. (2024) explain (Yas et al., 2024; El Khatib et al., 2024; Alblooshi et al., 2025). Through predictive modeling managers can find out what exactly the impact of human resources adjustment and sequencing and lot size changes will have on production output and delivery time, before making any operational decision (Al-Qassem et al., 2021; Rana et al., 2025; Halder et al., 2024). The application of smart PPC concepts help machine learning algorithms to predict failures of systems and delivery issues which leads to planned maintenance and deliverable times as per Oluyisola (2020) in his industrial examples. The system offers features in predictive analytics which are a basic performance improvement tool for operational planning and scheduling (Khatib et al., 2024; Hanaysha et al., 2021; AlNajdawi et al., 2024).

2.2.1.2 Optimization, decision support

The process of optimization and decision support systems takes the forecasted data and constraints and produces detailed and precise scheduling and capacity planning solutions (Kanwal et al., 2023;

AlMidfa et al., 2024; El Khatib et al., 2023). Meng et al. (2023) showed through their research that genetic-algorithm model for machine-part operations and flexible job shops can use metaheuristic optimization to find better machine assignments and operation sequences than rule-based planning methods which results in shorter makespan and higher machine utilization (Alzoubi et al., 2024; Pande et al., 2024; Al-Nakeeb et al., 2024). Park et al. (2021) report that he multi-objective reinforcement-learning schedulers function as decision support systems which develop dispatching policies to achieve better tardiness reduction and energy efficiency in flexible job shops than traditional heuristics according to Li & Chen (2023). Decision-support systems have these optimization engines which assist planners to consider throughput and overtime and changeover trade-offs prior to plan finalization so these algorithms can be integrated with human decision-making (Karthika et al., 2024; Naim et al., 2025; Murtaza et al., 2024). Decision support systems make direct links between organizational goals and operational scheduling activities at the operational level.

2.2.1.3 Real-time data integration

The integration of real-time data allows planning and scheduling systems to make quick modifications to the systems in the event that actual events do not match their forecasted values (Treacy et al., 2025; AlKatheeri et al., 2025; Shehab et al., 2023). Woschank et al. (2024) found that integrating real-time shop-floor information into planning rules via discrete event simulation in make-to-order environments results in better delivery reliability and WIP levels than do the traditional low frequency replanning techniques (AlShawabkeh et al., 2023; Shao et al., 2025; Ilyas et al., 2023). The Smart PPC framework helps to provide real-time streaming of the machine health and buffer levels and transport times from the IoT sensors and MES logs via cloud connectivity to analytics and scheduling modules as per Oluyisola (2022). Rahmani et al. (2018), in their study of smart PPC, concluded that real-time data needs are associated with system characteristics which include variability and routing flexibility as high volatility systems require continuous feedback to achieve their maximum potential (Khan et al., 2023; Rosmadi et al., 2025; Kukunuru et al., 2019). Real-time integration enables organizations to

develop a perpetual control system that exists outside the normal periodic planning systems (Joghee et al., 2024; AlShawabkeh et al., 2021; Joghee et al., 2021).

2.2.1.4.1 *Explicability and user adoption*

Explainability and user adoption influence whether or not sophisticated AI schedulers are trusted and used by production planners (Vij et al., 2025; Kharabsheh et al., 2024; Kabiraj et al., 2009). Research into AI production management reveals that operators build trust when they understand system recommendations and find them dependable and goal-oriented and explanation quality stands out as the primary factor that influences trust according to Saßmannshausen et al. (2021). The explainable manufacturing AI platform XMANAI shows with counterfactual explanations and feature importance views and constraint visualizations that planners can understand why a certain sequence is suggested and why other options are not as good from Agostinho et al. (2023) describe for several industrial use cases (Alzoubi et al., 2025; Ma'asor et al., 2023; Nuseir et al., 2021). Research studies about AI trustworthiness in manufacturing operations shows factory workers do not trust black box scheduling systems but experts suggest to use explainable systems with performance tracing and responsibility allocation methods as proposed by Ahangar et al. (2025) (AlQassem et al., 2022; Lee et al., 2024; Khadragy et al., 2022). AI enabled planning and scheduling requires decision support systems with explainable recommendations to achieve successful long-term implementation (AlShawabkeh et al., 2018; Joghee et al., 2023; Sun et al., 2016).

2.2.2 *CPMAI style framework on PPS Outcomes*

2.2.2.1 *Business Understanding Discipline*

AI implementation success in production planning and scheduling require organizations to have a good business foundation which supports operational needs of their factories. Lahusen et al. (2024) explain that AI governance requires organizations to outline specific roles and goals and create accountability systems throughout the AI development process because trust in AI systems is reliant on social and technical factors (Samer Hamadneh et al., 2023; Alshurideh et al., 2022; Tangri et al., 2023). In manufacturing, The TAI-PRM framework is planning to implement this

concept through risk register and FMEA-style analysis development for particular use-cases and operational hazards which will use KPIs as performance indicators (AlHamadi et al., 2024; El Khatib et al., 2023; Nuseir et al., 2019). The first step of smart PPC methodologies involves problem-definition and performance-metric identification which requires planners to define service level targets and WIP and changeover costs before selecting an algorithm as Oluyisola et al. (2022) illustrate (Tanveer et al., 2025; Kofinas et al., 2016; El Khatib et al., 2024). The CPMAI framework allows this discipline to validate AI planning and scheduling systems using business outcome measurements which will set specific criteria for subsequent data and modeling phases to be successful.

2.2.2.2 *Data governance and readiness*

The capability to achieve business objectives is dependent on data governance and preparedness as they set the conditions for AI models to learn from the signals (Yasir et al., 2024; AlKatheeri et al., 2025; Rana et al., 2025). Ahangar's et al. (2025) study indicates that manufacturing facilities face three key obstacles to credible AI deployment due to their poor data quality and lack of lineage and ambiguous access controls, which pose a risk to system robustness and accountability (Anifa et al., 2022; Al-Kassem & A. H., 2021; Kurdi et al., 2025). Smart PPC work emphasizes that integrated and high-quality streams from MES, IoT sensors, and ERP systems are the prerequisites for adaptive planning with Oluyisola et al (2022) divide their research methodology into two separate stages which include data acquisition and feature engineering and performance feedback (Alshurideh et al., 2024; Alblooshi et al., 2025; AlQassem et al., 2025). According to Paul and Sarkar (2022) MLOps needs industrial AI frameworks to implement simulation-based synthetic data and digital twins and structured data management systems in order to address data scarcity and concept drift problems (Maydybura et al., 2024; AlQassem & A. H., 2024; Khan et al., 2024). The CPMAI framework allows for disciplined data readiness that will link business requirements with model training using controlled production data (rather than random extracts) for scheduling algorithms (AlShawabkeh et al., 2021; El Khatib et al., 2023; Pande et al., 2024).

2.2.2.3 *Model Lifecycle and MLOps*

The deployment and maintenance of AI schedulers after laboratory testing is carried out according to MLOps standards and procedures of the model lifecycle (AlShawabkeh et al., 2014; Kanwal et al., 2023; Nazeer et al., 2025). Paul and Sarkar (2022) describe an industrial MLOps framework which covers data management and model development and testing and monitoring and governance with a focus on detecting drift and implementing sandboxed deployments for AI systems that control physical equipment (Alshurideh et al., 2025; Khatib et al., 2024; AlKurdi et al., 2025). Martinez-Arellano et al. (2024) state that shop-floor AI systems require semantic models which connect process context to data and models for achieving solution reuse and adaptation instead of starting from new development (AlNajdawi et al., 2024; AlShawabkeh et al., 2013; Yas et al., 2024). Research studies about MLOps adoption reveal that organization struggles with creating automated deployment pipeline and linking monitoring systems to retraining procedures. According to John et al. (2025), MLOps serves as organizational capability which exceeds the status of a collection of tools (Alzoubi et al., 2024; Razmak et al., 2018; El Khatib et al., 2022). The CPMAI-aligned PPS project ensures safety as well as accuracy of its forecasting and scheduling models with lifecycle discipline which prevents unexpected production pilot degradation (Al-Kassem et al., 2022; Kharbat et al., 2021; Shwedehe et al., 2024).

2.2.2.4 Iterative Phase Adherence

AI planning projects maintain ongoing improvement through lifecycle stages which enable continuous development through iterative patterns which prevent projects from becoming inflexible single-use deployments which cannot learn from their outcomes (Joghee et al., 2020; AlQassem, 2022; Karthika et al., 2024). Vyhmeister et al. (2025) recommends that manufacturers should perform risk assessments and periodic risk assessments of production AI systems, to develop flexible defensive plans for new security risks and regulatory changes (Som et al., 2023; El Khatib et al., 2023; Shwedehe & F., 2022). Rahmani et al. (2022) and other smart PPC authors depict production planning as a repetitive process which employs performance indicators to refresh rules and architectures rather than pursuing a static design (Alzoubi et al., 2024; Shwedehe, 2022;

Ahmed et al., 2024). Martinez-Arellano et al. (2024) apply this reasoning to industrial AI systems by stating that the continuous learning and deployment of models on the production floor is necessary for the management of concept drift and reconfigurable systems (Joghee et al., 2013; Habbal et al., 2019; Alshurideh et al., 2025). CPMAI requires organization to treat each production planning and scheduling cycle as an experimental process which generates data for better AI system development and organization process optimization (Alshurideh et al., 2022; Joghee et al., 2018; Kumar et al., 2024).

2.3 Research Gaps & Rationale

Research studies show AI technology improves forecasting and scheduling and factory response times but multiple critical issues remain for factory implementation of these capabilities (AlShawabkeh et al., 2023; Shwedehe et al., 2024; El Khatib et al., 2024). The research based on empirical data examines prediction and metaheuristic optimization with help of benchmark and simulation data, but does not examine the systems how different AI capability affects the operational schedule adherence and flow efficiency and service levels in real world operation environment (Del Gallo et al., 2023; Woschank et al., 2024; AlAmiri et al., 2024; Hanaysha et al., 2021; AlQassem et al., 2024). The research by Lahusen et al. (2022) indicates that governance and lifecycle papers develop risk frameworks and MLOps toolchains, but they do not assess the influence of business understanding and data readiness and iterative controls on the production planning and control outcomes of AI systems. Vyhmeister et al. (2024) and Ahangar et al. (2025) research on methodology-oriented smart-PPC have some successful case studies but require quantitative data for wider use and does not provide enough qualitative data on user's actions and choice behavior (Kabiraj et al., 2011; Joghee et al., 2021; Rosmadi et al., 2025). The research fills in the gaps in knowledge by its mixed-methods approach that examines AI and CPMAI constructs along with their quantitative and subjective effects on production planning and scheduling.

2.4 Conceptual Framework/Model

The conceptual framework in figure 1 shows the relationship between the capabilities of the AI and CPMAI lifecycle disciplines to influence production

planning and scheduling life-cycle performance in manufacturing. AI forecasting accuracy improvement depends on three main technical capabilities which include predictive analytics and optimization tools and real-time data integration and explainability. The CPMAI components strengthens these effects through the AI project development around business needs and use of high-quality data which follows governance rules

and follows a structured model lifecycle for continuous improvement (Alzoubi et al., 2024; Anifa et al., 2024; Shao et al., 2025). The two domains work together to determine essential planning and scheduling results which include schedule adherence and flow efficiency and changeover and resource utilization and plan stability.

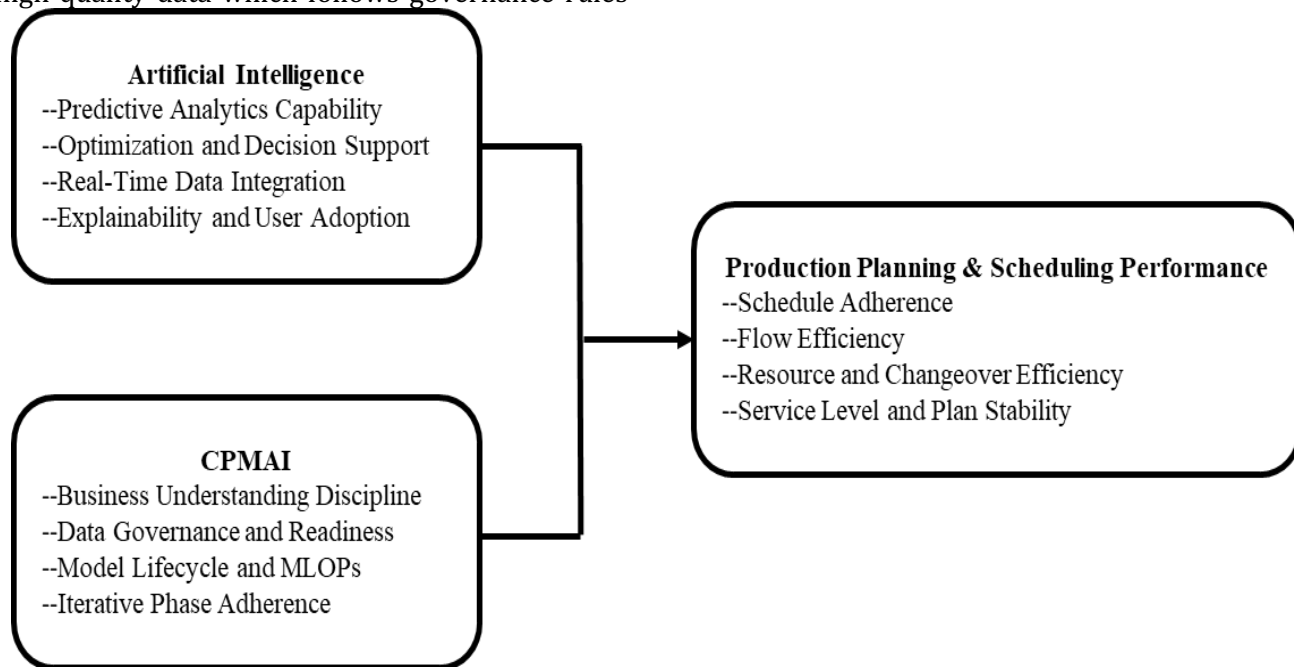


Figure 1: Conceptual Framework for the Study

3. RESEARCH METHODOLOGY

3.1 *Design and Rationale*

The research design employed a mixed method since it had to integrate quantitative data with qualitative findings, knowing the nature of this study. The quantitative section helped researchers to evaluate the connections between the studied variables and the qualitative section provided detailed descriptions about how the practitioners used these technologies and processes in their work. The research design that was used was mixed methods which allowed for sequential refinement as preliminary results from the survey informed the creation of interview questions to investigate the patterns and inconsistency that were discovered in greater detail. The two strands of data analysis were converged during the middle of the study to gather more valid results which increased the validity of the research findings through narrative explanations of the patterns of numbers based on Fetter (2019) who supports the use of both methods in technology-based organizational research. The research design provided assessment methods for all end results and operational systems which generated the results.

3.2 *Sampling and Participants*

The research selected 122 participants from Dubai UAE who worked directly with production planning, scheduling, and long AI-based practices. The research method used to validate the constructs studied was to apply survey participant and interviewee operational and decision-making knowledge. The research participants were planners and scheduling officers and process-improvement staff and digital-transformation professionals that demonstrated the capacity to analyze technological aspects as well as organizational factors of implementation. The survey gathered sufficient information for statistical analyses and the interview participants had varying experiences and worked in varying departments to obtain multiple perspectives. The recruitment strategy was based on research guides as the purposive sampling is best suited when the researcher wants to access specific expertise and not statistical data (Palinkas et al., 2015). The sampling approach allowed the research to obtain in-depth information with knowledgeable participants on their AI and CPMAI practices.

3.3 *Instruments and Data Collection*

The method of data collection followed by this research was structured survey and semi structured interviews to collect data on all the variables in the conceptual framework. The survey instrument used Likert-scaled items to measure predictive analytics capability and optimization support and real-time integration and explainability and business understanding discipline and data readiness and model lifecycle practices and iterative adherence to enable respondents in their assessment of their organization's level of maturity in these areas. The research team selected semi-structured interviews as it is a method in which the participants can respond within the set parameters, but the researchers can determine what new information emerges in the interview process (Jamshed, 2014). The researchers employed an integrated approach to collect different kinds of data which yielded both general information and accurate results from the evidence collected.

3.4 *Data Analysis Techniques*

The data analysis process was structured in a method that corresponded to the mixed-methods research design and the conceptual framework structure. The initial process in the quantitative analysis of survey data involved the use of descriptive statistics to display the central tendency and dispersion values for all the constructs and reliability tests to measure multi-item scales and correlation analyses to establish initial relationships. Multiple regression models were then estimated to determine the predictive effects of constructs on production planning and scheduling outcomes (AI and CPMAI) while controlling for organizational characteristics, following the emphasis on regression-based modelling in mixed-methods integration described by Guetterman et al. (2015). The researchers used thematic analysis to study qualitative interview data using open coding which led to higher order themes explaining implementation experience and aspects of the intervention as positive and negative.

3.5 *Ethical Considerations and Data Governance*

The research team developed ethical standards and data management protocols that will preserve the rights of the participants, while ensuring the reliability of the evidence. The participants were provided study information sheets containing information about the research goals and

voluntary participation rules and data handling procedures and research contact information before participating in the study. The research was done following the standards of digital record and organizational actor research by getting consent from the participants via current research protocols. The survey data were kept anonymous, and interviews were pseudonymized and encrypted for storage in research team-accessible drives with all identifying information removed from transcripts for the benefit of participants and organizations.

4. DATA ANALYSIS AND RESULTS

4.1 Descriptive Statistics

In the Table 1 below the central values and spread of data points in the descriptive statistics indicated the main characteristics of the three main constructs. The scores of AI evaluation showed average understanding towards the AI capabilities because the participants scored 3.24 on average while their answers were distributed across 2.33 points. The scores indicated that people saw the AI capabilities as average but their responses did not reveal great variations in their opinions. CPMAI has the highest mean of 3.77 and the greatest range of 2.92 which shows that CPMAI has the most advanced and varied knowledge of the lifecycle practices of AI. The results of the PPSP indicated a mean score of 3.41 with a range of 2.75 which showed the level of planning and scheduling performance to be stable and at the moderate level. Standard deviations across all variables remain below 1.0 which indicates that the responses grouped close to their corresponding means. The negative kurtosis values for each construct indicated that the distributions were flatter than normal as the participants had spread their responses onto multiple categories rather than just focusing on the average.

Table 1: Descriptive Statistics on Key Study Variables

Variable	N	Range	Mean	Std. Deviation	Kurtosis
AI	122	2.33	3.2425 (.05473)	0.60454	-0.659 (0.435)
CPMAI	122	2.92	3.7732 (.07375)	0.81454	-0.859 (0.435)
PPSP	122	2.75	3.4112 (.06205)	0.68532	-0.699 (0.435)

4.2 AI on Production Planning and Scheduling Performance

In the Table 2 below the regression model for the evaluation of AI constructs and production planning and scheduling performances revealed a very strong overall effect. With $N = 122$ and an $F(4, 117) = 622.39$, $p < .001$, the model was highly significant and an R^2 of some .96 (adjusted = .95) indicated that AI-related variables accounted for nearly all variance in PPSP. The dominant predictor among all factors was optimization and decision support which had a B value of 0.389 and a beta value of 0.499 and a P value less than .001 indicating that performance depended a lot on advanced scheduling and scenario tools. Explainability and user adoption also had a large impact ($B = 0.261$, $\beta = 0.317$, $p < .001$), which supports transparent, trusted AI recommendations for consistent use in planning decisions. The result found that real-time data integration had a moderate but significant effect ($B = 0.185$, $\beta = 0.221$, $p < .001$) and predictive analytics capability had a smaller but significant effect ($B = 0.115$, $\beta = 0.065$, $p = .001$) which supported the idea that the AI capability bundle improved PPSP.

Table 4. 2: Regression PPSP on AI

Key	Value
Dependent variable	PPSP (Production Planning & Scheduling Performance)
N	122
F statistic (model)	$F(4, 117) = 622.39$, $p < .001$
R^2 (Adjusted R^2)	≈ 0.96 (≈ 0.95)
Constant	$B = 0.074$ (SE = 0.085), $p = .390$
PAC	$B = 0.115$ (SE = 0.035), $\beta = 0.065$, $p = .001$
ODS	$B = 0.389$ (SE = 0.027), $\beta = 0.499$, $p < .001$
RDI	$B = 0.185$ (SE = 0.043), $\beta = 0.221$, $p < .001$
EUA	$B = 0.261$ (SE = 0.039), $\beta = 0.317$, $p < .001$

From the interviews, almost all respondents acknowledged that artificial intelligence has become an integral component in the planning of operations in their manufacturing facilities. Some comments stated "...AI is indispensable because of

its ability to predict future events with much ease...I do not think there is any serious production team that is yet to adopt artificial intelligence into their planning and scheduling activities, especially in this digital age..."

4.3 CPMAI on Production Planning and Scheduling Performance

In the Table 3 below the model that was used to assess CPMAI constructs in relation to production planning and scheduling performance exhibited a high level of explanatory strength. The result of the regression analysis with a sample size of 122 participants was $F(4, 117) = 722.29$ $p < .001$ and an R^2 of 0.961 (adjusted 0.960) which showed that maturity in CPMAI accounted for 96.1% of the total variance in PPSP scores. The most important factor that emerged for planning system success was data governance and readiness since organizations require stable data environments to have successful planning systems ($B = 0.468$, $\beta = 0.612$, $p < .001$). The results shows that Business understanding discipline has a positive effect on the outcome ($B = 0.193$, $p < .001$) which means that when the goals and metrics are well defined, the outcome is better. The combination of Model lifecycle and MLOps practices was a significant contribution ($B = 0.177$, $\beta = 0.218$, $p < .001$) in the process of continuous monitoring and controlled modifications. The results of the analysis showed that the adherence of Iterative phase results in a non-significant negative coefficient ($B = -0.042$, $\beta = -0.058$, $p = .124$) which showed the factor of iteration was not a significant predictor of PPSP alone.

Table 3: Regressing PPSP on CPMAI

Key	Value
Dependent variable	PPSP (Production Planning & Scheduling Performance)
N	122
F statistic (model)	$F(4, 117) = 722.29$, $p < .001$
R^2 (Adjusted R^2)	0.961 (0.960)
Constant	$B = 0.409$ (SE = 0.060), $p < .001$
BUD	$B = 0.193$ (SE = 0.026), $\beta = 0.261$, $p < .001$
DGR	$B = 0.468$ (SE = 0.040), $\beta = 0.612$, $p < .001$
MLM	$B = 0.177$ (SE = 0.036), $\beta = 0.218$, $p < .001$

Key	Value
IPA	$B = -0.042$ (SE = 0.027), $\beta = -0.058$, $p = .124$

The interviews compounded the narrative that CPMAI has a profound effect on production planning and scheduling. One respondent remarked "The [CPMAI] framework is fit for use in our situation and also easy to adapt regardless of the highly dynamic nature of our planning and scheduling operations..." These findings suggest that the framework is popular among planning and scheduling teams because of its effectiveness.

4.4 AI and CPMAI on Production Planning and Scheduling Performance

In the Table 4 below the combined regression model for AI and CPMAI against production planning and scheduling performance demonstrated an extremely high overall model fit. With $N = 122$ and $F(2, 119) = 2135.28$, $p < .001$, the model was highly significant and the R^2 of 0.973 (adjusted 0.972) indicated that the two predictors explained almost all the variance in PPSP. The two variables showed independent strength as predictors since AI got a B value of 0.596 (SE = 0.045) with a β of 0.526 and $p < .001$ and CPMAI got $B = 0.404$ (SE = 0.033) with a β of 0.480 and $p < .001$. The results showed that better planning and scheduling results occurred when participants scored better on one or the other dimension. The B value of -0.044 and p value of .442 indicated that PPSP levels were mainly affected by the combined effect of AI capabilities and CPMAI maturity because the combination of these two factors yielded a robust model to explain operational performance.

Table 4: Regressing PPSP on AI & CPMAI

Key	Value
Dependent variable	PPSP (Production Planning & Scheduling Performance)
N	122
F statistic (model)	$F(2, 119) = 2135.28$, $p < .001$
R^2 (Adjusted R^2)	0.973 (0.972)
Constant	$B = -0.044$ (SE = 0.057), $p = .442$
AI	$B = 0.596$ (SE = 0.045), $\beta = 0.526$, $p < .001$
CPMAI	$B = 0.404$ (SE = 0.033), $\beta = 0.480$, $p < .001$

Interview sessions also concurred that combining AI and CPMAI result in a tremendous positive effect on the effectiveness of production planning and scheduling operations. In one instance, a participant argued, "Both AI and CPMAI are important to us in planning and scheduling...they are even more effective when applied together." The quantitative and qualitative findings both indicate that the two work better jointly than when used separately.

5. DISCUSSION

The three regression models have shown that AI capabilities and CPMAI maturity independent of each other improve production planning and scheduling performance and when combined they achieve over 97% explanatory power. The AI bundle showed that optimization and decision support were its greatest individual driver followed by explainability and user adoption and real-time data integration and predictive analytics. The study indicates that the highest level of AI performance was achieved when AI was within scheduling tasks and was able to provide immediate data and explanations that workers on the production floor could understand. The CPMAI side showed that data governance and readiness together created the greatest impact on results but business understanding discipline and model lifecycle practices also made significant contributions to the results while iterative phase adherence did not produce any noticeable effect.

5.1 Comparison to Previous Studies

The optimization and decision support systems yield results that are commensurate with the results of metaheuristic and reinforcement learning research which indicates that flexible job shops benefit from major improvements in makespan and tardiness with the use of genetic algorithms or learning-based schedulers rather than the traditional dispatching rules according to Meng et al. (2023) Park et al. (2021), and Li and Chen (2023) each demonstrate. The study conducted by Al Bashar et al. confirms manufacturing research from the US which proves that accurate forecasting leads to improved inventory management and lead time performance when it is operated within a comprehensive planning framework. The study by Al Bashar et al. (2019) verifies U.S manufacturing research which proves that forecasting leads to better inventory

management and lead time performance but requires connection to broader planning systems for optimal results (2024) and by smart PPC case studies such as Oluyisola (2020). The research findings regarding data readiness and understanding of the business in the case of governance support the idea of the trustworthy industrial AI requires excellent data governance and precise use case definition instead of algorithmic excellence as stated by Ahangar et al. (2025), Lahusen et al. (2024) and Vyhmeister et al. (2025). The importance of model lifecycle practices falls under the MLOps principles which focus on monitoring and controlled deployment as key requirements for ensuring sustainable shop-floor AI according to Paul and Sarkar (2022) and according to Martínez-Arellano et al. (2024) which maintain.

5.2 Implications for Theory and Practice

The AI- CPMAI model indicates that smart production planning theories must shift their focus from algorithm-based methods to socio-technical frameworks which integrate optimization with explainability and real-time integration and governance and data quality and lifecycle capabilities. Rahmani et al. (2022) suggest that PPSP conceptual models should consider the AI capability constructs and the CPMAI constructs as connected elements instead of retaining them as separate layers. The method extends smart PPC and industrial AI theories which separate technical aspects and organizational aspects from each other. Findings by Lahusen et al. (2024) suggest that practitioners need to adopt a two-part strategy which includes implementing better scheduling and forecasting systems and establishing data governance programs and clear business definitions for AI projects and reliable MLOps systems. The implementation of AI projects entails operational set up that includes defining measurable PPSP results and securing data streams from MES and IoT systems and implementing continuous monitoring and retraining protocols into regular planning activities.

6. CONCLUSION AND RECOMMENDATIONS

The research shows that the capabilities of AI are independent of the CPMAI maturity levels to improve production planning and scheduling performance through optimization and decision support and explainability and data governance

and model lifecycle discipline. The research evidence supports the socio-technical approach to smart production planning because the algorithmic power and the real-time data and lifecycle governance are working as a unified system and not independent tools. AI operational components require direct links to governance-based constructs for PPSP to move forward in the future. Manufacturers who want to improve their performance need to spend money for not only sophisticated scheduling and forecasting systems but also reliable data connections and well-defined business objectives for AI projects and stable model operations using the MLOps practices. The research had several limitations because it used a single region purposive sample and self-reported measures and a cross-sectional design which limited both in generalizability and in the ability to establish cause and effect. Future research needs to overcome these limitations by implementing research that covers multiple time periods and multiple locations and using performance metrics and complete models of how AI impacts CPMAI constructs in various manufacturing settings.

REFERENCES

- Agostinho, C., Dikopoulou, Z., Lavasa, E., Perakis, K., Pitsios, S., Branco, R., Reji, S., Hetterich, J., Biliri, E., Lampathaki, F., Rodríguez Del Rey, S., & Gkolemis, V. (2023). Explainability as the key ingredient for AI adoption in Industry 5.0 settings: The XMANAI platform. *Frontiers in Artificial Intelligence*, 6. <https://doi.org/10.3389/frai.2023.1264372>
- Ahangar, M. N., Farhat, Z. A., & Sivanathan, A. (2025). AI Trustworthiness in Manufacturing: Challenges, Toolkits, and the Path to Industry 5.0. *Sensors*, 25(14), 4357. <https://doi.org/10.3390/s25144357>
- Al Bashar, M., Taher, M. A., & Johura, F. T. (2024). Utilizing predictive analytics for enhanced production planning and inventory control in the US manufacturing sector. *International Research Journal of Modernization in Engineering Technology and Science*, 6(5), 8332–8339. <https://doi.org/10.56726/IRJMETSS7936>
- Alemão, D., Rocha, A. D., & Barata, J. (2021). Smart Manufacturing Scheduling Approaches—Systematic Review and Future Directions. *Applied Sciences*, 11(5), 2186. <https://doi.org/10.3390/app11052186>
- Del Gallo, M., Mazzuto, G., Ciarapica, F. E., & Bevilacqua, M. (2023). Artificial Intelligence to Solve Production Scheduling Problems in Real Industrial Settings: Systematic Literature Review. *Electronics*, 12(23), 4732. <https://doi.org/10.3390/electronics12234732>
- Fernandes, J. M. R. C., Homayouni, S. M., & Fontes, D. B. M. M. (2022). Energy-Efficient Scheduling in Job Shop Manufacturing Systems: A Literature Review. *Sustainability*, 14(10), 6264. <https://doi.org/10.3390/su14106264>
- Fetters, M. D. (2019). The mixed methods research workbook: Activities for designing, implementing, and publishing projects. SAGE Publications
- Guetterman, T. C., Fetters, M. D., & Creswell, J. W. (2015). Integrating quantitative and qualitative results in health science mixed methods research through joint displays. *Annals of Family Medicine*, 13(6), 554–561. <https://doi.org/10.1370/afm.1865>
- Jamshed, S. (2014). Qualitative research method—Interviewing and observation. *Journal of Basic and Clinical Pharmacy*, 5(4), 87–88. <https://doi.org/10.4103/0976-0105.141942>
- John, M. M., Olsson, H. H., & Bosch, J. (2021). Towards MLOps: A framework and maturity model. In 47th Euromicro Conference on Software Engineering and Advanced Applications (SEAA) (pp. 1–8). IEEE. <https://doi.org/10.1109/SEAA53835.2021.00050>
- Kim, S. W., Kong, J. H., Lee, S. W., & Lee, S. (2022). Recent advances of artificial intelligence in manufacturing industrial sectors: A review. *International Journal of Precision Engineering and Manufacturing*, 23(1), 111–129. <https://doi.org/10.1007/s12541-021-00600-3>
- Kovič, K., Tominc, P., Prester, J., & Palčič, I. (2024). Artificial Intelligence Software Adoption in Manufacturing Companies. *Applied Sciences*, 14(16), 6959. <https://doi.org/10.3390/app14166959>
- Lahusen, C., Maggetti, M., & Slavkovik, M. (2024). Trust, trustworthiness and AI governance. *Scientific Reports*, 14, 20752. <https://doi.org/10.1038/s41598-024-71761-0>
- Li, Z., & Chen, Y. (2023). Minimizing the makespan and carbon emissions in the green flexible job shop scheduling problem with learning effects. *Scientific Reports*, 13, 6369. <https://doi.org/10.1038/s41598-023-33615-z>
- Luo, D., Thevenin, S., & Dolgui, A. (2023). A state-of-the-art on production planning in Industry 4.0. *International Journal of Production Research*, 61(19), 6602–6632. <https://doi.org/10.1080/00207543.2022.2122622>
- Martínez-Arellano, G., & Ratchev, S. (2025). Towards Frugal Industrial AI: A framework for the development of scalable and robust machine learning models in the shop floor. *The International Journal of Advanced Manufacturing Technology*, 138(1–2), 169–191. <https://doi.org/10.1007/s00170-024-14508-5>
- Meng, L., Zhang, C., Shao, X., et al. (2023). An improved genetic algorithm for solving the multi-AGV flexible job-shop scheduling problem. *Applied Sciences*, 13(22), 4700. <https://doi.org/10.3390/s23083815>
- Mourtzis, D., Panopoulos, N., & Angelopoulos, J. (2022). Production management guided by industrial IoT and adaptive scheduling in smart factories. In D. Mourtzis (Ed.), *Design and Operation of Production Networks for Mass Personalization in the Era of Cloud Technology* (pp. 215–234). Elsevier. <https://doi.org/10.1016/B978-0-12-823657-4.00014-2>

- Oluyisola, O. E., Bhalla, S., Sgarbossa, F., & Strandhagen, J. O. (2022). Designing and developing smart production planning and control systems in the Industry 4.0 era: A methodology and case study. *Journal of Intelligent Manufacturing*, 33(1), 311–332. <https://doi.org/10.1007/s10845-021-01808-w>
- Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and Policy in Mental Health*, 42(5), 533–544. <https://doi.org/10.1007/s10488-013-0528-y>
- Park, J.-S., Ng, H.-Y., Chua, T.-J., Ng, Y.-T., & Kim, J.-W. (2021). Unified genetic algorithm approach for solving flexible job-shop scheduling problem. *Applied Sciences*, 11(14), 6454. <https://doi.org/10.3390/app11146454>
- Paul, R. K., & Sarkar, B. (2022). Operationalizing AI in advanced manufacturing: A responsible MLOps framework. *International Journal of Artificial Intelligence in Manufacturing*, 1(1), 1–10. https://iaeme.com/Home/article_id/IJAIM_01_01_001
- Plathottam, S. J., Rzonca, A., Lakhnori, R., & Iloeje, C. O. (2023). A review of artificial intelligence applications in manufacturing operations. *Journal of Advanced Manufacturing and Processing*, 5(3), e10159. <https://doi.org/10.1002/amp2.10159>
- Rahmani, M., Sgarbossa, F., & Strandhagen, J. O. (2022). Towards smart production planning and control: A conceptual framework linking planning environment characteristics with the need for smart PPC. *Journal of Manufacturing Systems*, 62(1), 205–217. <https://doi.org/10.1016/j.jarcontrol.2022.03.008>
- Roblek, M., Kern, T., Andrašć, E. K., & Brezavšček, A. (2024). Comparative Analysis of Human and Artificial Intelligence Planning in Production Processes. *Processes*, 12(10), 2300. <https://doi.org/10.3390/pr12102300>
- Sáez, P., Rivera, J., Salas, P., & Parada, V. (2025). Rescheduling under disruption: A product-driven framework with reinforcement learning. *Management and Production Engineering Review*, 14(1), 5–17. <https://journals.pan.pl/dlibra/show-content?id=136719>
- Saßmannshausen, T., Burggräf, P., Wagner, J., Hassenzahl, M., Heupel, T., & Steinberg, F. (2021). Trust in artificial intelligence within production management: An exploration of antecedents. *Ergonomics*, 64(10), 1333–1350. <https://doi.org/10.1080/00140139.2021.1909755>
- Vyhmeister, E., & González-Castañé, G. (2025). TAI-PRM: Trustworthy AI—project risk management framework towards Industry 5.0. *AI and Ethics*, 5(2), 819–839. <https://doi.org/10.1007/s43681-023-00417-y>
- Waltersmann, L., Kiemel, S., Stuhlsatz, J., Sauer, A., & Mieke, R. (2021). Artificial intelligence applications for increasing resource efficiency in manufacturing companies—a comprehensive review. *Sustainability*, 13(12), 6689. <https://doi.org/10.3390/su13126689>
- Woschank, M., Pacher, C., Zunk, B. M., & Gruber, E. (2024). Potentials of using real-time data to increase the update frequency of production planning and control. *Flexible Services and Manufacturing Journal*. 36, 760–779. <https://doi.org/10.1007/s10696-024-09550-0>
- Anifa, M., Ramakrishnan, S., Joghee, S., Kabiraj, S., & Bishnoi, M. M. (2022). Fintech Innovations in the Financial Service Industry, *Journal of Risk and Financial Management*, 15(7), 287. MDPI AG <http://dx.doi.org/10.3390/jrfm15070287>
- El Khatib, M., Mahmood, A., Al Azizi, A., Al Marzooqi, A., Al Abdooli, K., Al Marzooqi, S., ... & Alshurideh, M. (2023). A trial to improve program management in government bodies through focusing on program resource management: Cases from UAE. In *The effect of information technology on business and marketing intelligence systems* (pp. 1315–1340). Cham: Springer International Publishing.
- Alshurideh MT, Al Kurdi B, Alzoubi HM, et al. Factors affecting customer-supplier electronic relationship (ER): A customers' perspective. *International Journal of Engineering Business Management*. 2023;15. doi:10.1177/18479790231188242
- Neyara Radwan Halder, B., Ahmed, M. F., Refadah, S. S., Khan, M. Y. A., Scholz, M., Sammen, S. S., & Pande, C. B. (2025). Seasonal precipitation and anomaly analysis in Middle East Asian countries using Google Earth Engine. *Water*, 17(10), 1475. <https://www.mdpi.com/2073-4441/17/10/1475>
- AlShawabkeh, A., Kharbat, F, Abu Daabes, A., and Woolsey, L. (2023), "Technology- based Learning and the Digital Divide for Deaf/hearing Students during Covid-19: Academic Justice lens in Higher Education", *Educational Technology & Society*, 26(4).
- Alshurideh, M., Tariq, E., Al Kurdi, B., Al-Ahmed, H., Al-Sulaiti, K., Alzoubi, H. M., Alzboun, N., Ahmed, G., Allozi, Y., & Alshaketheep, K. (2025). How the company interrelated factors increase business with existing customers with customer hotel experience as a moderator variable: Empirical study in the hotels. *Uncertain Supply Chain Management*, 13(2), 447–454.
- Samer Hamadneh, Muhammad Turki Alshurideh, Haitha M. Alzoubi, Iman Akoure, Barween Al Kurdi and Shanmugan Joghee (2023). Factors affecting e-supply chain management systems adoption in Jordan: An empirical study, *Uncertain Supply Chain Management*, 11(2023), 411–422. doi: 10.5267/j.uscm.2023.3.008
- Tanveer, A., Iram, Saleem, S., & Neyara Radwan (2025). Peristaltic rotating motion of couple stress nanofluid affected by Soret and Dufour effects: An application to nanotechnology. *ZAMM - Journal of Applied Mathematics and Mechanics*, 105(5). <https://doi.org/10.1002/zamm.70047>
- Khatib, M. E., Angelova, Y., & Kazim, H. (2024). Digital transformation significance on quality of SMART services: Innovation, mobility, adaptability, analytical ability and trust. In *2024 2nd International Conference on Cyber Resilience (ICCR)* (pp. 1–4). IEEE.
- Som, A. P. M., Shariffuddin, N. S. M., Zain, W. M. A. W. M., & Al-

- Qassem, A. (2023). The influence of socio-cultural and economic impact on tourism support: A mediating role of community value. *Planning Malaysia*, 21.
- Kharbat, F., AlShawabkeh, A., Sharairi, M. (2024), "A research-based ontology for collaborative innovation: a methodology leveraging ai and domain expert knowledge", *Jordanian Journal of Computers and Information Technology*, 10(3), pp. 265 – 280.
- Kabiraj, S., & Shanmugan, J. (2009). Indigenous Customer Relationship Management Practices in Indian Automobile Companies: Strategic Implications. *International Journal of Management Perspectives*, 1(4) 1-11.
- Kharabsheh, A. A. E. A., Alnuaimi, M. A., & Alzoubi, H. M. (2024). The Impact of Employee Empowerment and Organizational Citizenship Behavior with Mediating Role of Job Satisfaction at Amman Private Hospitals. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 483-500). Cham: Springer Nature Switzerland.
- Rosmadi, H. S., Ahmed, M. F., Neyara Radwan Chen Kim Lim, M. B. M., Halder, B., Scholz, M., & Pande, C. (2025). Flood management framework for local government at Shah Alam, Malaysia. *Water*, 17(4), 513. <https://doi.org/10.3390/w17040513>
- Naim, H., Rani, L., Omair, A., Aziz, T., Ahmed, G., & Rafiuddin, A. (2024). Ownership concentration impact on the firm performance: Evidence from the manufacturing and services industrial sector. *Corporate Ownership & Control*, 21(4), 28–40.
- Joghee, S., Kalra, D., Ramakrishnan, S., Nair, K., & Alzoubi, A. A. (2023). Digital entrepreneurial marketing strategy: An empirical analysis using resource based theory. In *2023 International Conference on Business Analytics for Technology and Security (ICBATS)* (pp. 1–5). IEEE. <https://doi.org/10.1109/ICBATS57792.2023.10111356>
- Alkathheeri, S., Hilmi, M. F., Ahmed, G., & Abudaqa, A. (2025). Impact of strategic outsourcing on operational performance: A moderating role of information sharing in the healthcare industry of UAE, under the influence of predominantly oil economy. *Journal of Mines, Metals and Fuels*, 73(7), 1–14.
- Haitham, M. A., & Gouher, A. (2024). Factors affecting attitude to use metaverse technology application. *International Journal of Data and Network Science*.
- Joghee, S., & Kabiraj, S. (2013) 'Innovation in product promotions: A Case of Intended Use of Characters in the Chinese Market' *European Journal of Business Management*, 5 (1)120-131.
- Tangri, K., Joghee, S., Kalra, D., Shameem, B., & Agarwal, R. (2023). Assessment of perception of usage of mobile social media on online business model through Technological Acceptance Model (TAM) and Structural Equation Modeling (SEM). In *2023 International Conference on Business Analytics for Technology and Security (ICBATS)* (pp. 1–6). IEEE.
- Yas, H., Dafri, W., Sarhan, M. I., Albayati, Y., & Shwede, F. (2024). Universities Faculty's Perception of E-learning Tools: Filling the Gaps for Enhanced Effectiveness. In *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 573-588). Cham: Springer Nature Switzerland.
- Shao, Y., Arshad, Z., Neyara Radwan Shah, Z., Raja, M. A. Z., Almohammadi, S. M., & Khan, W. A. (2025). Investigating the radiative heat transfer analysis of magnetized Cross fluid flow capturing variable properties around paraboloid surface using artificial intelligence stochastic approach. *Chaos, Solitons & Fractals*, 191. <https://doi.org/10.1016/j.chaos.2024.115887>
- Shwede, F., Salloum, S. S., Aburayya, A., Fatin, B., Elbadawi, M. A., Al Ghurabli, Z., ... & Ismail, B. (2024). Prediction of Retailer's Intention to Use Chat-GPT in Educating Retailers: A Case Study in the UAE. In *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 389-402). Cham: Springer Nature Switzerland.
- Alzoubi, A. A., & Alzoubi, H. M. (2024). Implementing Machine Learning for the Analysis of Data. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 211-221). Cham: Springer Nature Switzerland.
- Alhashmi, M., Hilmi, M. F., Ahmed, G., & Abudaqa, A. (2025). Impact of green HRM on sustainable performance: Moderating role of green employee motivation among the resources industry based public entities in UAE. *Journal of Mines, Metals and Fuels*, 73(7), 1–13.
- Shehab, E., Som, A. P. M., & Al-Qassem, A. (2023). Destination image and tourist retention in Jerusalem. *Planning Malaysia*, 21.
- Alzoubi, A. A., Almarzooqi, I. A., & Alzoubi, H. M. (2024). Investigating Benefits of Digitalized in Home Systems. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 381-389). Cham: Springer Nature Switzerland.
- Neyara Radwan, Rana, B., Halder, B., Pramanik, M., Ahmed, K. O., Alshehri, F., & Pande, C. B. (2025). Impact assessment of climate variables using Google Earth Engine in semi-arid and tropical environments. *Acta Geophysica*, 73, 5095–5116. <https://doi.org/10.1007/s11600-025-01661-y>
- Alshurideh, M., Al Kurdi, B., Hamadneh, S., Chatra, K., Snoussic, T., Alzoubi, H. M., Alzoubi, N., and Ahmed, G. (2024) 'Utilizing Artificial Intelligence (AI) in enhancing customer-supplier relationship: An exploratory study in the banking industry' *Uncertain Supply Chain Management*, 12 (2024) 1-12. [doi:10.5267/j.uscm.2024.5.005](https://doi.org/10.5267/j.uscm.2024.5.005)
- Alzoubi, H. M., Alshurideh, M. T., Al-Gharaibeh, S. M., Al-Shyaab, K. O. M., Al Kurdi, B., Al-Sulaiti, I., Ahmed, G., Bataineh, A. Q., Alquqa, E. K. (2025). Assessing Economic and Infrastructure Constraints on Electric Vehicle Purchase Decisions: A Demographic-Moderated Analysis in Emerging Markets. *International Journal of Energy Economics and Policy*, 15(3), 471–485.
- Al-Qasem, A. (2021). Impact of pandemic Coronavirus Disease

- (COVID-19) on United Arab Emirates tourism industry. *PalArch's Journal of Archaeology of Egypt/Egyptology*, 18(7), 2556-2570.
- Nazeer, M., Saleem, S., Fatima, N., Imran, M., & Neyara Radwan (2025). Role of zeta potential and slip boundary conditions to improve the heat transfer analysis of hybrid nanofluid. *Journal of Radiation Research and Applied Sciences*, 18(3). <https://doi.org/10.1016/j.jrras.2025.101702>
- Kukunuru, S., Pillai, M. R., & Kassem, A. A. (2019). Creating happiness at workplace: Work team contributions and concerns. *Journal of Computational and Theoretical Nanoscience*, 16(12), 5313-5326.
- Ilyas, A., Akbar, S. S., Wajid, S. H., Joghee, S., Fatima, A., & Mago, B. (2023). The growing importance of modern technology in education. 2023 International Conference on Business Analytics for Technology and Security (ICBATS), 1-4. <https://doi.org/10.1109/ICBATS57792.2023.10111128>
- Alqassem, A. H., & Panwar, N. S. (2022). Efficacy of accessible tourism dimensions for individuals with disabilities at the National Museum. *resmilitaris*, 12(4), 2449-2459.
- Sakkthivel, A. M., Ahmed, G., Moovendhan, V., & Ramu, N. (2025). A cross-sectional study of mall shopping behaviour of women consumers in United Arab Emirates and India: An empirical study. *International Journal of Business Excellence*, 36(2), 225-249.
- Al Kurdi, B., Nawaiseh, A., Alshurideh, M., Al-Ahmed, H., Al-Sulaiti, K., Allozi, Y., AlZoubi, M., Ahmed, G., Alshaketheep, K. (2024). Investigating the Main Factors Affecting Doing More Business with Existing Customers in Light of Customer Experience: An Empirical Study in the Malls. *International Review of Management and Marketing*, 14(6), 301-306.
- Nuseir, M., AlShawabkeh, A., Leibfried, L. (2021), "Factors affecting the use of social networks as a customer relationship management tool", *International Journal of Business Information Systems*, 38(2), pp. 179-199.
- Rana, B., Halder, B., Neyara Radwan, Pramanik, M., Ahmed, M. F., Alshehri, F., & Pande, C. B. (2025). Remote sensing-based impact analysis of artificial lighting on land surface temperature using Google Earth Engine. *Theoretical and Applied Climatology*, 156, 394. <https://doi.org/10.1007/s00704-025-05625-6>
- Karthika, D., Ramya, E., Farouk, M., & Alzoubi, H. M. (2024). An Effect of Big Data Analytics on Pandemic Prevention. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 183-196). Cham: Springer Nature Switzerland.
- Yas, N., Dafri, W., Yas, H., & Shwedehe, F. (2024). Effect of e-Learning on Servicing Education in Dubai. In *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 623-639). https://link.springer.com/chapter/10.1007/978-3-031-52280-2_40
- El Khatib, M., Al Abdooli, K., Alhammedi, R., Alshamsi, F., Abdulla, N., Al Hammadi, A., ... & Alshurideh, M. (2023). The Role of Distance Learning Technology in Mitigating Unknown-Unknown Risks: Case of Covid-19. In *The Effect of Information Technology on Business and Marketing Intelligence Systems* (pp. 551-567). Cham: Springer International Publishing.
- Khan, M. F., Farooq, M. S., & Joghee, S. (2023). Increase the degree of accuracy by employing a more accurate classification approach. 2023 International Conference on Business Analytics for Technology and Security (ICBATS), 1-7. <https://doi.org/10.1109/ICBATS57792.2023.10111398>
- Rana, B., Halder, B., Neyara Radwan, N., Hazra, M., Alshehri, F., Pande, C. B., Shafik, S. S., & Yaseen, Z. M. (2025). Two decadal monthly forest ecological challenges and climate variability analysis in Cambodia. *Acta Geophysica*. <https://doi.org/10.1007/s11600-025-01621-6>
- Treacy, S., Brandt, T., Al-Kharusi, S., Bakhadirov, M., Ahmed, G., Militaru, A. M. G., Bakker, D., & Dubickis, M. (2025). Cultural Differences of Needed Qualities Towards Entrepreneurship. *Journal of Entrepreneurship, Business and Economics*, 12 (2) 69-108.
- Shwedehe, F., Yas, N., Abdijabar, Z., Flayyih, N., Fadli, A., Yas, H., & Allouzi, A. S. (2024). The impact of intellectual property rights and the level of information sensitivity on information security in the United Arab Emirates. *Journal of Infrastructure, Policy and Development*, 8(8), 6303. <https://doi.org/https://doi.org/10.24294/jipd.v8i8.6303>
- Almidfa, J. F., Alnawayseh, S. E., Al-Sit, W. T., & Alzoubi, H. M. (2024). Developing Rescue Mobile Application. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 501-513). Cham: Springer Nature Switzerland.
- Zeeshan, Mahmoud, E., Khan, W., Saleem, S., Kallel, M., & Neyara Radwan. (2025). Stability analysis of Casson hybrid nanofluid in a rocket engine nozzle with Cattaneo-Christov heat flux and velocity slip effects. *ZAMM - Journal of Applied Mathematics and Mechanics*, 105(5). <https://doi.org/10.1002/zamm.70103>
- Al-Nakeeb, A., El Khatib, M., & Zitar, R. A. (2024). From PMO to PMOCoe: How Manage Project Knowledge Process Improves Quality of Organization Knowledge Management Assets Cases from UAE. *International Journal for Computers & Their Applications*, 31(1).
- Al-Shawabkeh, A., Kofinas, A., and Sharp, M., (2011), "Developing an Innovative Knowledge Management Implementation Approach", Published in the proceedings the 12th European Conference on Knowledge Management, Passau, Germany.
- Hanaysha, J. R., Al-Shaikh, M. E., Joghee, S., & Alzoubi, H. M. (2021). Impact of Innovation Capabilities on Business Sustainability in Small and Medium Enterprises. *FIIB Business Review*. <https://doi.org/10.1177/23197145211042232>
- Al-Shawabkeh, A., Romanova, A., and Lim, A., (2016), "Developing an Open Source Knowledge Sharing System for Sustainable Hospitality Industry", University of Greenwich Conference.

- Kabiraj, S., & Shanmugan, J. (2011). Development of a conceptual framework for brand loyalty: A euro-mediterranean perspective. *Journal of Brand Management*, 18(4-5), 285-299 doi: <http://dx.doi.org/10.1057/bm.2010.42>
- Nazeer, M., Almohammadi, S. M., Neyara Radwan, N., & Ahmad, W. (2025). Heat transfer analysis in hydromagnetic two-phase Williamson fluid through tilted channel: Applications of gold and silver nanoparticles in solar thermal energy. *ZAMM - Journal of Applied Mathematics and Mechanics*. <https://doi.org/10.1002/zamm.202400397>
- AlShawabkeh, A., Razmak, J., Qasim, A., Kharbat, F., (2018), "Enhancing internal communication in organisations using enterprise social networking", *International Journal of Economics and Business Research*, 15(1), pp. 72-86.
- Al-Shawabkeh, A., Kanungo, R., (2013), "Risk of Default Loans in Jordanian Banks under Credit Risk Classification Models", *Banking, Finance, Money and Institutions: The Post Crisis Era* Conference held at University of Surrey.
- Al Najdawi, M. H., Zainab, A. A., Shwede, F., & Yehia, B. F. (2024). The Role of Legal Laws and Intellectual Property Rules in the Era of using Artificial Intelligence in Scientific Publications.
- Al-Qassem, A., & Al-Shamaila, M. (2021). Sustainable tourism development: Case study of Aqaba, Jordan. *The International Journal of Hospitality and Tourism Research*, 15(2), 51-76.
- Alzoubi, A. A., AlSuwaidi, A., & Alzoubi, H. M. (2024). Analyzing the Approaches for Discovering Privacy and Security Breaches in Iomt. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 345-355). Cham: Springer Nature Switzerland.
- Alzoubi, H. M., Al Kurdi, B., & Nuseir, M. T. (2024). Empowering Supply Chain Management System with Machine Learning. *Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges*, 117, 335.
- El Khatib, M., Beshwari, F., Beshwari, M., Beshwari, A., Alzoubi, H. M., & Alshurideh, M. (2023). Can Better Capabilities Lead to Better Project and Program Governance? Cases from Dubai. In *The effect of information technology on business and marketing intelligence systems* (pp. 1295-1313). Cham: Springer International Publishing.
- El Khatib, M., Al Khayat, A., Al Mansoori, S., Alzaabi, A., & Ankit, A. (2023, March). Metaverse skills for executives and senior managers: The pros and cons. In *2023 International Conference on Business Analytics for Technology and Security (ICBATS)* (pp. 1-7). IEEE.
- Al-Qassem, A. H. (2024). The mediating role of tourist satisfaction in the relationship between destination authenticity and destination loyalty: The case of Machu Picchu. *The International Journal of Learner Diversity and Identities (IJLDI)*, 31(1), 601-613.
- El Khatib, M., Al-Shalabi, A., Alamim, A., Alblooshi, H., Alhosani, S., Al-Kaabi, E., ... & Alshurideh, M. (2023). How Drones Can Mitigate Unknown-Unknown Risks Case of Covid-19. In *The Effect of Information Technology on Business and Marketing Intelligence Systems* (pp. 717-732). Cham: Springer International Publishing.
- Alhashmi, M., Hilmi, M. F., Ahmed, G., & Abudaqa, A. (2025). Moderating role of green employee behaviour on the relationship between green HRM practices, green leadership and sustainable performance in the resources economy based public firms of UAE. *Journal of Mines, Metals and Fuels*, 73(7)14
- Ahmed, G., Al Amiri, N., & Abudaqa, A. (2024). Strategic leadership and economic transformation: The United Arab Emirates (UAE) model. *Journal of Global Business Research and Practice*, 1(1), 60-77.
- Al-Qassem, A. H., Tharwat, A., & Sahawneh, N. (2025). Work addiction as an effective factor for employee's performance in the banking industry in Egypt. *Journal of International Business Policy*. Advance online publication.
- Alblooshi, M., Hilmi, M. F., Ahmed, G., & Abudaqa, A. (2025). Investigating the role of critical risk factors on the construction project success in the oil and gas industry. *Journal of Mines, Metals and Fuels*, 73(7), 1-10.
- Yas, H., Dafri, W., Sarhan, M. I., Albayati, Y., & Shwede, F. (2024). Universities Faculty's Perception of E-learning Tools: Filling the Gaps for Enhanced Effectiveness. In *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 573-588). https://link.springer.com/chapter/10.1007/978-3-031-52280-2_36
- Anifa, M., Ramakrishnan, S., Kabiraj, S., & Joghee, S. (2024). Systematic Review of Literature on Agile Approach. *NMIMS Management Review*, 32(2), 84-105.
- Razmak, J., AlShawabkeh, A., Qasim, A., & Kharbat, F. (2018). Examining the factors affecting the adoption of e-health innovative technology. *International Journal of Economics and Business Research*, 16(2), 196-209.
- Shwede, F., Aldabbagh, T., Aburayya, A., & Uppilappatta, H. (2023). The impact of harnessing total quality management studies on the performance of smart applications: A study in public and private sectors in the UAE. *Migration Letters*, 20(S12), 83-108.
- Habbal, F., AlShawabkeh, A., Al Nuaimi, A., Safi, A., (2019), "Using virtual reality simulation for optimizing traffic modes toward service level enhancements", *Proceedings of the 36th International Symposium on Automation and Robotics in Construction, ISARC 2019*, pp. 831-837.
- Ma'asor, M. A., Som, A. P. M., Yusof, Y., & Al-Qassem, A. (2023). Level of Islamic attributes practices by Muslim-friendly hotels in Malaysia. *Planning Malaysia*, 21.
- Maydybura, A., Chang, A. G., Channa, K. A., Pan, S. H., Alzoubi, H. M., & Chang, B. H. (2024). Carbon emissions and the rising effect of foreign direct investment and trade openness: Evidence from panel data countries. *Advances in Decision Sciences*, 28(4), 1-22.
- Joghee, S., Kabiraj, S., Ramakrishnan, S., M. Alzoub, H., & Turki Alshurideh, M. (2023). Empirical study to understand marketing influence of environmental

- impact assessment on end users in UAE. *Digital Economy and Sustainable Development*, 1–12. <https://doi.org/https://doi.org/10.1007/s44265-023-00012-3>
- Al Kurdi, B., Alquqa, E. K., Al-gharaibeh, S. M., Alhyasat, K. M. K., Alzoubi, H. M., Alshurideh, M. T., Al-Oran, O., Ahmed, G., & Al-Sulaiti, G. (2025). Determinants influencing consumer adoption of energy-efficient home appliances in Jordan: An empirical analysis. *International Journal of Energy Economics and Policy*, 15(4), 780–788.
- Razmak, J., AlShawabkeh, A., Qasim, A., & Kharbat, F. (2018). Examining the factors affecting the adoption of e-health innovative technology. *International Journal of Economics and Business Research*, 16(2), 196–209.
- Al Hamadi, H., Alzoubi, H. M., Alyafei, M., Almokahel, A., Alyafei, M., Al-Sit, W. T., & Alnawayseh, S. E. (2024). Evaluation of Purchasers Mentalities When Buying IoT Home Security Devices. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 239-258). Cham: Springer Nature Switzerland.
- El Khatib, M., Alzoubi, H. M., Alshurideh, M., & Alzoubi, A. A. (2023). Project Quality Management in the United Arab Emirates Mining and Construction Sector: A Literature Review. The Effect of Information Technology on Business and Marketing Intelligence Systems, 1341-1353.
- Al Najdawi, M. H., Shwede, F., Abdelmoghies, M. M., Kitana, A., & Ali, A. (2024). Applying artificial intelligence in predicting educational excellence in higher education institutions: A case study in Jordanian universities. *Edelweiss Appl Sci Technol*, 8(6), 7273-7289.
- Shwede, F. (2024b). The Integration of Artificial Intelligence (AI) Into Decision Support Systems Within Higher Education Institutions. *Nanotechnology Perceptions*, 20(S5), 331–357. <https://doi.org/https://doi.org/10.62441/nano-ntp.v20iS5.26>
- Naim, H., Rani, L., Yattoo, T. A., Anas, M., Nizamuddin, M., & Ahmed, G. (2025). Does audit committee quality enhance firm performance within a new corporate law? *Corporate Law & Governance Review*, 7(2), 112–126.
- Sun, J., Garibaldi, M., and Al-Shawabkeh, A., (2016), "A Novel Hybridisation Strategy Based Memetic Algorithm for Constrained Optimisation", *Journal of Information Sciences*, Volume 340-341, pp. 175-190
- Nuseir, M., AlShawabkeh, A., (2019), "Marketing communication in the digital age: Exploring the cultural historical activity theory in examining Facebook's advertising platform", *International Journal of Electronic Customer Relationship Management*, 12(2), pp. 97-107.
- Pande, C. B., Neyara Radwan, N., Salim, H., Ahmed, K. O., Alshehri, F., Pal, S. C., & Pramanik, M. (2024). Forecasting of monthly air quality index and understanding of the air pollution in the Delhi city, India based on machine learning models and k-fold cross-validation. *Journal of Atmospheric Chemistry*, 82(1). <https://doi.org/10.1007/s10874-024-09466-x>
- Khatib, M. E., Harmoodi, S. A., & Angelova, Y. (2024). Virtual reality as a hub for innovation – Correlations and interdependencies. In *2024 2nd International Conference on Cyber Resilience (ICCR)* (pp. 1–5). IEEE.
- Kharbat, F.F., AlShawabkeh, A. and Woolsey, M.L. (2021), "Identifying gaps in using artificial intelligence to support students with intellectual disabilities from education and health perspectives", *Aslib Journal of Information Management*, 73(1), pp. 101-128.
- Al-Kassem, A. H. (2022). Accreditation of academic programs: Implications on quality governance and administration of Taguig City University. *Journal of Positive School Psychology*, 6(4), 3908-3923.
- El Khatib, M., El Baradie, M., & Alrashedi, M. B. (2024). AI capable emotional robot teacher as a new economical trend in education. In *2024 2nd International Conference on Cyber Resilience (ICCR)* (pp. 1–5). IEEE.
- Al-Qassem, A., Agha, K., Mendoza, S., & El-Farra, E. (2022). Emergency management and its implications for the hospitality industry during the Coronavirus Disease 2019 (COVID-19) outbreak. *Journal of Positive School Psychology*, 6(2), 1824-1839.
- Khan, W. A., Hussain, Z., Neyara Radwan, N., Ali, M., & Jamal, N. (2024). Characterizing non-similar analysis for chemically reactive magnetized Sutter by bidirectional fluid flow capturing features of non-linear thermal radiation. *Journal of Radiation Research and Applied Sciences*, 17(4). <https://doi.org/10.1016/j.jrras.2024.101152>
- AlShawabkeh, A., Nuseir, M.T., Urabi, S. (2023), "The Impact of Social Media Usage on Companies' Customer Relationship Management (CRM)", *Studies in Computational Intelligence*, Vol. 1056, pp. 147-172
- Alzoubi, A. A., Alhammadi, M. K., Alhammadi, K. A., Alhammadi, A., & Alzoubi, H. M. (2024). Investigating Impact of Ethical Considerations on IoMT Medical Devices of UAE Healthcare System. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 391-402). Cham: Springer Nature Switzerland.
- AlNaoimi, B., AlRaesi, R., AlKaboory, O., Aziz Alrasasi, A., Al-Sit, W. T., Alnawayseh, S. E., & Alzoubi, H. M. (2024). Data Warehousing for Assisting the Decision Makers. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 197-209). Cham: Springer Nature Switzerland.
- Al-Qassem, A. H., Singh, N., Chopra, A., & Haddad, A. M. (2024). Impact of coronavirus crisis (COVID-19) on the sentiments of travelers in UAE. *The International Journal of Learner Diversity and Identities (IJLDI)*, 31(1), 601-613.
- Alshurideh, M., Al Kurdi, B., Okleh, I., Chatra, K., Al Omari, T.G.B., Alzoubi, H.M., Alzboun, N., Ahmed, G. and Abduljabbar, O.J. (2024) 'Factor affecting internet information credibility: The moderating effect of

- gender' International Journal of Data and Network Science, 8 (2024) 1-8. doi:10.5267/j.ijdns.2024.5.011
- Alzoubi, A. A., ALKaabi, R., ALAmeri, S., & Alzoubi, H. M. (2024). Contemporary Security Concerns in IoT-Based Devices with Healthcare System. In Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation (pp. 423-436). Cham: Springer Nature Switzerland.
- Alblooshi, M., Hilmi, M. F., Ahmed, G., & Abudaqa, A. (2025). The moderating effect of risk management on the relationship between critical risk factors and project success: A case of construction projects in the oil and gas industry of the UAE. *Journal of Mines, Metals and Fuels*, 73(7), 1–13.
- Ismail, M., Neyara Radwan, Khan, W. A., Hussain, Z., & Hussain, I. (2024). Analyzing numerical insights of entropy generation and existence of chemotactic microorganisms for magnetized radiative Carreau nanofluid flow subjected to stratified medium via viscous dissipation. *Journal of Radiation Research and Applied Sciences*, 17(4). <https://doi.org/10.1016/j.jrras.2024.101197>
- AlShawabkeh, A., Woolsey, L., Kharbat, F. (2021), "Using online information technology for deaf students during COVID-19: A closer look from experience", *Heliyon*, 7(5), e06915.
- Alshurideh, M. T., Al Kurdi, B., Alzoubi, H. M., Ghazal, T. M., Said, R. A., AlHamad, A. Q., ... & Al-Kassem, A. H. (2022). Fuzzy assisted human resource management for supply chain management issues. *Annals of Operations Research*, 1-19.
- Joghee, S., Kabiraj, S., Ramakrishnan, S., & Alzoubi, H. M. (2024). Consumer Decision-Making Study Regarding the SUV Market in the Indian Context. *Indian Journal of Marketing*, 54(11), 8-25.
- Alzoubi, A. A., Al Neyadli, A., & Alzoubi, H. M. (2024). Security Flaws in Medical Wearables Devices Used in Health Care Systems. In Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation (pp. 291-299). Cham: Springer Nature Switzerland.
- Aldawsari, S. H., Tan, W. S., Elsherazy, T. A., Chang, B. H., Alzoubi, H. M., & Ognjanović, I. (2024). A Quantile Dependence among Exchange Rate, Stock Prices and Oil Prices: An Empirical Evidence from India. *Annals of Financial Economics*, 19(03), 2450010.
- Alzoubi, A. A., Shammas, S., & Alzoubi, H. M. (2024). Investigating E-Supply Chain Challenges in The Internet of Medical Things (IoMT). In Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation (pp. 357-367). Cham: Springer Nature Switzerland.
- El Khatib, M. M., Abidi, N., Al-Nakeeb, A., Alshurideh, M., & Ahmed, G. (2023). Dubai smart city as a knowledge based economy. In The effect of information technology on business and marketing intelligence systems (pp. 1657-1672). Cham: Springer International Publishing.
- Yas, H., Aburayya, A., & Shwede, F. (2024). Education quality and standards in the public school and the private school-case study in Saudi Arabia. In artificial intelligence in education: The power and dangers of ChatGPT in the classroom (pp. 563-572). Cham: Springer Nature Switzerland.
- Halder, B., Chatterjee, P., Rana, B., Bandyopadhyay, J., Pande, C. B., Ahmed, K. O., Elkhachy, I., & Neyara Radwan. (2024). Delineating the climate change impacts on urban environment along with heat stress in the Indian tropical city. *Physics and Chemistry of the Earth*, 136. <https://doi.org/10.1016/j.pce.2024.103745>
- Som, A. P. M., & Al-Qassem, A. (2023). The influence of social and economic inequalities on support for tourism in developing communities: An intervening effect of tourism resources. *Planning Malaysia*, 21.
- Alshurideh, M. T., Alzoubi, H. M., Al Kurdi, B., Hamadneh, S., Ahmed, G., Al-Sulaiti, K., Bataineh, A. Q., Alquqa, E. K., Ozturk, I. (2025). Consumer and Economic Influences on Electric Vehicle Adoption: The Mediating Role of Attitudes and the Moderating Effect of Demographics. *International Journal of Energy Economics and Policy*, 15(3), 214–229.
- Lee, K. L., Amin, A. J., Alzoubi, H. M., Alshurideh, M., El Khatib, M., Joghee, S., & Nair, K. (2024). Investigating the factors affecting e-procurement adoption in supply chain performance: An empirical study on Malaysia manufacturing industry. *Uncertain Supply Chain Management*, 12(2), 615-632.
- Kofinas, A., Al-Shawabkeh, A., and Lim, A., (2016), "Critical Success Factors of Using Social Media in Higher Education", chapter in a book titled Analysing the Strategic Role of Social Networking in Firm Growth.
- Kanwal, N., Irtaza, G., Joghee, S., Ateeq, K., & Khadim, A. (2023). A safe and reliable method for data exchange in the cloud. 2023 International Conference on Business Analytics for Technology and Security (ICBATS), 1–7. <https://doi.org/10.1109/ICBATS57792.2023.10111401>
- Al-Shawabkeh, A., Lim, A., (2014), "The Use of Social Media in Higher Education Learning", European Conference on Social Media ECSM 2014.
- Al-Kassem, A. H., & Marwaha, S. (2022). Employee satisfaction and its impact on faculty members' performance at Al Ain University of Science and Technology in the UAE. *NeuroQuantology*, 20(2), 272-287.
- Pande, C. B., Sidek, L. M., Varade, A. M., Elkhachy, I., Neyara Radwan Tolche, A. D., & Elbeltagi, A. (2024). Forecasting of meteorological drought using ensemble and machine learning models. *Environmental Sciences Europe*, 36, 160. <https://doi.org/10.1186/s12302-024-00975-w>
- Al Kurdi, B., Alshurideh, M. T., Akour, I., Alzoubi, H. M., Obeidat, Z. M., Hamadneh, S., & Joghee, S. (2023). Factors affecting team social networking and performance: The moderation effect of team size and tenure. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(2), 100047.
- Al-Kassem, A. H. (2021). Significance of human resources training and development on organizational achievement. *PalArch's Journal of Archaeology of Egypt/Egyptology*, 18(7), 693-707.
- Salloum, S. A., Almarzouqi, A., Aburayya, A., Shwede, F., Fatin,

- B., Al Ghurabli, Z., ... & Alfaisal, R. (2024). Redefining Educational Terrain: The Integration Journey of ChatGPT. In *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 157-169). Cham: Springer Nature Switzerland.
- Salloum, S. A., Almarzouqi, A., Aburayya, A., Shwede, F., Fatin, B., Al Ghurabli, Z., ... & Alfaisal, R. (2024). Embracing ChatGPT: Ushering in a Revolutionary Phase in Educational Platforms. In *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 171-183). Cham: Springer Nature Switzerland.
- AlShawabkeh, A., Nuseir, M.T., and Aljumah, A. (2021), "Impacts of social media on the buying intention of the consumers in Edinburgh, UK", *International Journal of Procurement Management*, 14(4), pp. 470-486.
- Tanveer, A., Jarra, S., Al-Zubaidi, A., Saleem, S., & Neyara Radwan. (2024). The varying viscosity impact in an inclined peristaltic channel with diffusion-thermo and thermo-diffusion. *ZAMM - Journal of Applied Mathematics and Mechanics*, 104(5). <https://doi.org/10.1002/zamm.202300794>
107. Joghee, S., Alzoubi, H. & Dubey, A. (2020) "Decisions Effectiveness of FDI Investment Biases at Real Estate Industry: Empirical Evidence from Dubai Smart City Projects", *International Journal of Scientific & Technology Research*, 9(3):3499-3503
- Alzoubi, A. A., Alzarooni, M. Y., & Alzoubi, H. M. (2024). Privacy Violation and Information Misuse in the Internet of Medical Things (IoMT). In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 323-332). Cham: Springer Nature Switzerland.
- Alzoubi, H. M., Alshurideh, M., El Khatib, M., Shamot, M. D., Joghee, S., Nair, K., & Al-Gharaibeh, S. M. (2024). Optimizing supply chain excellence: Unravelling the synergies between IT proficiencies, smart supply chain practices, and organizational culture. *Uncertain Supply Chain Management*, 12(3), 1855-1866.
- Kurdi, B. Al, Alzoubi, H. M., Tan, C. L., El Khatib, M., Yanamandra, R., Ozturk, I., & Shwede, F. (2025). Internet of Things-Driven Information Sharing: A Strategic Approach to Mitigating Supply Chain Risks. *International Review of Management and Marketing*, 15(3), 325-332. <https://doi.org/https://doi.org/10.32479/irmm.19474>
- Al Amiri, N., Ahmed, G., Al Qawasmeh, K. and Afana, H. (2024) 'Effect of crises on the healthcare marketing mix and customer satisfaction: evidence from the UAE during the COVID-19 pandemic', *Middle East Journal of Management*, 11(5) 471-495.
- Al-Nakeeb, A., El Khatib, M., Zitar, R. A., Alhosani, A., & Alhosani, I. (2023). Project Manager's role in manage Project knowledge process: An approach to enhance Project quality. *International Journal for Computers & Their Applications*, 30(4).
- Alzoubi, A. A., Nikoo, S. A., & Alzoubi, H. M. (2024). Investigating Contemporary Ethical Issues of Using Blockchain in E-Supply Chain in Internet of Medical Things (IoMT). In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 437-452). Cham: Springer Nature Switzerland.
- Khadragy, S., Elshaeer, M., Mouzaek, T., Shammass, D., Shwede, F., Aburayya, A., ... & Aljismi, S. (2022). Predicting diabetes in United Arab Emirates healthcare: artificial intelligence and data mining case study. *South East. Eur. J. Public Heal*, 5.
- Al Najdawi, M. H., Shwede, F., Mokhtar Abdelmoghies, M., Kitana, A., & Ali, A. (2024). Applying artificial intelligence in predicting educational excellence in higher education institutions: A case study in Jordanian universities. *Edelweiss Applied Science and Technology*, 8(6), 7273-7289. <https://doi.org/10.55214/25768484.v8i6.3579>
- Alkatheeri, S., Hilmi, M. F., Ahmed, G., & Abudaga, A. (2025). Examining the nexus between strategic outsourcing and operational performance: A case of the health care industry of the UAE under the resource-based economy. *Journal of Mines, Metals and Fuels*, 73(7), 1-13.
- Kumar, P., Neyara Radwan., Vij, M., & Vij, A. (2024). The role of robotics in enhancing service quality, efficiency, and customer satisfaction in the hospitality industry. *IEEE Xplore*. <https://doi.org/10.1109/ICCR61006.2024.10532969>
- Vij, M., Vij, A., Kumar, P., Masoud, E. Y., Al Kurdi, B., & Alzoubi, H. M. (2025). Artificial Intelligence in Digital Marketing Strategies in the UAE: The Mediating Role of Predictive Analytics in Enhancing Customer Conversion. *International Review of Management and Marketing*, 15(4), 380.
- Kharbat, F., Razmak, J., AlShawabkeh, A., (2017), "Proposing UAE-patient portal: A new direction in the health services", 2017 Medical Technologies National Conference, TIPTEKNO 2017.
- Alzoubi, A. A., Mubarak, S. O., Sultan, M. K., Ali, A. O., & Alzoubi, H. M. (2024). Investigating the Impact of Ethical Concerns on the Security and Privacy of Medical Devices in the UAE. In *Technology Innovation for Business Intelligence and Analytics (TIBIA) Techniques and Practices for Business Intelligence Innovation* (pp. 465-479). Cham: Springer Nature Switzerland.
- AlShawabkeh, A., Kharbat, F., Razmak, J. (2023), "Knowledge Management Role in Enhancing Customer Relationship Management in Hotels Industry in the UK", 2022 9th International Conference on Social Networks Analysis, Management and Security, SNAMS 2022.
- Al-Shawabkeh, A., Kanungo, R., (2017), "Credit risk estimate using internal explicit knowledge ", *Investment Management and Financial Innovation*, 14(1), pp. 55-66.
- Joghee, S., Dubey, A., & Sonia. S (2021) "Investigation of Green Marketing Practices of UAE Hypermarkets", *International Journal of Enterprise Network Management*.

- <https://doi.org/10.1504/IJENM.2021.10043386>
- Joghee, S., & Dubey, A. (2018) 'Performance Measurement in Entrepreneurial Marketing' *The Journal of Human Resource and Adult Learning*, 14 (1) 78-84.
- El Khatib, M., AlQurashi, M., AlHashemi, S., AlKetbi, M., & AlHarmoodi, S. (2023, March). Digital Platforms' Influence on Project Management. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-7). IEEE.
- El Khatib, M., Al-Nakeeb, A., Alketbi, A., Al Hashemi, A., Mustafawi, F., Almansoori, R., ... & Alshurideh, M. (2023). Impact of Remote Work on Project Risks Management: Focus on Unknown Risks. In *The Effect of Information Technology on Business and Marketing Intelligence Systems* (pp. 747-766). Cham: Springer International Publishing.
- Joghee, S., Al Kurdi, B., Alshurideh, M., Alzoubi, H.M., Anu V., Murali M., & Samer H., (2021). Expats impulse buying behaviour in UAE: A customer perspective. *Journal of Management Information and Decision Sciences*, 24(S1), 1-24.
- Alzoubi, H. M., Alshurideh, M. T., El Khatib, M., Shamout, M. D., Yanamandra, R., Nair, K., & Al-Gharaibeh, S. M. (2024). Exploring the nexus between innovation orientation, green supply chain management, and organizational performance in e-retailing industry. *Uncertain Supply Chain Management*, 12(3), 1923-1934.
- Shwede, F. (2021). The Impact Of Smart City Policy Timeliness And Technology Readiness On Smart City Performance In Dubai: The Moderating Effect Of Financial Availability.
- Al-Qassem, A. H. (2024). Performance: The mediating role of job satisfaction and pro-environmental behavior. *Taylor & Francis Cogent Business & Management*, 11(1).
<https://doi.org/10.1080/23311975.2024.2328316>
- Yasir, M., Saleem, S., Khan, M., & Neyara Radwan (2024). Dynamics of magnetized viscous dissipative material of hybrid nanofluid with irregular thermal generation/absorption. *Case Studies in Thermal Engineering*, 58.
<https://doi.org/10.1016/j.csite.2024.104359>
- Khatib, M. M. E., & Ahmed, G. (2024). Achieving excellence in business practices through artificial intelligence: a case study of the Dubai public sector. *International Journal of Public Sector Performance Management*, 14(2), 262-277.
- El Khatib, M., Ankit, A., Al Ameeri, I., Al Zaabi, H., Al Marqab, R., Alzoubi, H. M., & Alshurideh, M. (2023). The Role and Impact of Big Data in Organizational Risk Management. In *The Effect of Information Technology on Business and Marketing Intelligence Systems* (pp. 2139-2153). Cham: Springer International Publishing.
- Al-Qassem, A. H. (2022). Efficiency and effectiveness of human resource development in the tourism industry of the United Arab Emirates. *Journal of Positive School Psychology*, 6(2), 1811-1823.
- Shwede, F., Nour, M. A., & Akour, I. (2024). Optimizing augmented reality adoption in higher education: A comprehensive analysis of factors impacting data management efficiency. *Journal of Infrastructure, Policy and Development*, 8(9), 6232.
<https://doi.org/https://doi.org/10.24294/jipd.v8i9.6232>
- Shwede, F. (2024a). Designing Delight: Exploring the Nexus of Interactive Design, User Experience, and Psychological Theory in Banking Chatbot. *Nanotechnology Perceptions*, 20(S4), 378-398.
<https://doi.org/https://doi.org/10.62441/nano-ntp.vi.650>
- Shwede, F., Salloum, S. S., Aburayya, A., Fatin, B., Elbadawi, M. A., Al Ghurabli, Z., ... & Akkass, M. A. (2024). The impact of educating managers in adopting AI applications on decision making development: a case study in the UAE. In *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 591-603). Cham: Springer Nature Switzerland.
- Martinez, E. B., Al-Kassem, A. H., & Aгуenza, B. B. (2022). Operationalization of Negosyo Center as an entrepreneurial strategy to selected micro, small, and medium enterprises in Taguig City. *Global Business & Management Research*, 14.
- Khatib, M. E., Al-Nakeeb, A., Binkhadim, S., & Shehata, O. (2024). Modern digitization, technical integration, and social sustainability: Together toward better quality of life. 2024 2nd International Conference on Cyber Resilience (ICCR), 1-5. IEEE.
- Al-Qassem, A. H., Tharwat, A., & Marwaha, S. (2024). The impact of digital transformation readiness towards the new normalcy in the education system. *The International Journal of Learner Diversity and Identities (IJLDI)*, 31(1), 601-613.
- Sihag, P., Mehta, T., Sammen, S. S., Pande, C. B., Puri, D., & Neyara Radwan (2024). Predictive modelling of nitrogen dioxide using soft computing techniques in Agra, Uttar Pradesh, India. *Physics and Chemistry of the Earth*, 134.
<https://doi.org/10.1016/j.pce.2024.103589>
- Murtaza, A., Rehman, A., Malik, S. U. R., Ahmed, G., Abbas, A., & Khan, M. A. (2024). A model-based approach to enhance the communication between the participants of collaborative business processes. *IEEE Access*, 12, 121780 – 121791 3450690.
- Alzoubi, H. M., Tan, C. L., El Khatib, M., Alshurideh, M. T., Shwede, F., Yanamandra, R., & Lee, K. L. (2025). Smart Government Initiatives: Transforming Global Supply Chains through Digital Change. *International Review of Management and Marketing*, 15(3), 209-217.
<https://doi.org/https://doi.org/10.32479/irmm.18962>