



AI for Risk Reduction in Construction Projects: Examining Safety, Cost, and Schedule Impacts

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ABSTRACT

The construction sector has long grappled with recurring safety failures, chronic cost overruns, and persistent schedule slippages. Even with well-established project management frameworks in place, outcomes across the industry remain far below what they should be. A significant part of the problem lies in how risks are handled specifically, the fact that most organisations continue to operate reactively, addressing problems only after they have already made their mark on project performance. This paper investigates how Artificial Intelligence (AI) can be brought into construction risk management in a structured, systematic way not as a standalone fix, but as a layer that fundamentally changes how teams detect, interpret, and respond to risk. The study draws on a qualitative research approach. Nine professionals drawn from project management, safety engineering, and planning roles were interviewed across live construction projects in the UAE. Their responses were examined through the thematic analysis process, organised around five key variables drawn from existing research. What emerged from the interviews was consistent across participants: AI tools shift the entire frame of risk management from reaction to anticipation. Safety violations that previously went undetected for hours were flagged within minutes. Cost deviations that would have surfaced only in monthly reviews were visible three to four weeks earlier. These are not trivial differences they represent the gap between managing a crisis and preventing one. That said, the research makes clear that these benefits are not automatic. Three recurring obstacles cut across nearly every organisation studied: fragmented data environments, insufficient skill among staff, and deep-seated resistance to changing established working habits. Without confronting these directly, AI remains an expensive tool that underdelivers. The paper concludes with a five-pillar framework designed to guide organisations through the full implementation journey.

1. INTRODUCTION

Few industries match construction when it comes to the sheer complexity of managing risk. At any given moment, a large project site is dealing with dozens of interdependent variables — workforce availability, subcontractor reliability, material lead times, weather exposure, equipment readiness, regulatory compliance, and more [1][2]. Any one of

these can derail a project; in combination, they create a risk environment that is genuinely difficult to govern with conventional methods [3][4].

The industry's track record bears this out. Studies consistently show that major construction projects around the world fail to meet their original cost and time targets [5][6]. A widely cited McKinsey analysis from 2020 found that large-scale

infrastructure and building projects routinely exceed their schedules by a fifth and their budgets by considerably more [7]. In the UAE, where the pace of development is particularly intense, these overruns are not just statistical abstractions — they represent billions in lost value and significant reputational damage to the organisations involved [8]-[12].

The root of this problem is not incompetence or inattention. It is structural. Traditional risk management is built around periodic check-ins — weekly progress reports, monthly budget reviews, site inspections that happen at fixed intervals [13]-[18]. This cycle works tolerably well when conditions are stable [19][20]. When they are not — and in construction, they rarely are — the lag between when something starts going wrong and when it becomes visible in a formal report can be days or weeks [21]. By then, the corrective window has often passed.

AI technologies offer a genuinely different approach. Machine learning models can digest far more project data than any team of humans and surface patterns that would otherwise be invisible [22]-[26]. Computer vision systems can watch an entire site continuously, flagging compliance failures in real time rather than waiting for someone to do a walkthrough [27]. Predictive analytics can model how a current deviation in procurement or subcontractor performance is likely to affect the schedule weeks down the line [28]-[30]. Taken together, these capabilities point toward a version of risk management that is proactive rather than reactive — one where the goal is to prevent incidents rather than respond to them [31]-[35].

However, implementing AI in construction is not straightforward [36]. The technology itself has advanced considerably, but the organisational conditions needed to make it work have received far less attention in the literature [37]-[40]. Most published studies focus on a single application — safety monitoring, or cost forecasting, or schedule prediction — and say relatively little about how these tools interact when deployed together, or about the human and institutional factors that determine whether any of them deliver value in practice [41]-[45].

This study is an attempt to fill that gap. It draws on direct conversations with practitioners who are using AI tools on active construction projects, and

it tries to surface both what is working and what is not — with enough specificity to be genuinely useful to organisations thinking through their own AI strategy.

1.1 Research Questions

Three questions guide the analysis throughout this paper:

- RQ1: To what extent does AI-enabled risk detection shift construction risk management from a reactive to a proactive model, and what organisational conditions shape that shift?
- RQ2: How does the integration of AI tools affect safety performance, cost variance, and schedule adherence in live construction projects?
- RQ3: What are the main structural barriers to effective AI adoption in construction risk management, and how can organisations address them?

2. LITERATURE REVIEW

2.1 Limitations of Traditional Risk Management in Construction

Risk management has been part of construction project practice for decades. It is embedded in widely used standards — PMBOK, ISO 31000, and various sector-specific methodologies — and most large organisations have formal risk processes in place [46]-[50]. The problem is not the absence of these frameworks. It is that, even where they are diligently followed, they tend to share a common flaw: they are built around identifying and responding to risks that are already visible rather than anticipating those that are still developing [51]-[55].

This reactivity is not accidental — it is a structural consequence of how traditional risk management collects and processes information [56][57]. Risk registers are updated when someone fills them in. Progress reports are compiled weekly or monthly. Site inspections happen on a schedule [58]. Each of these processes has significant latency built in [59]-[62]. [5] examined cost overrun patterns across major construction projects and found that the contributing problems were typically detectable in early project data — the issue was that the monitoring systems in place were not sensitive enough to surface them until it was too late to respond effectively [63]-[68].

Data fragmentation compounds this. On most

construction projects, cost information lives in one system, safety records in another, scheduling data in a third [69]-[72]. Each is maintained by a different team and reviewed in a different forum. Nobody is looking at all of it together, which means cross-domain risk signals — a procurement delay that will affect labour deployment which will affect the critical path — go unnoticed until each individual problem has become visible on its own terms [73]. [4] traced this kind of systemic fragmentation as a root cause of the consistent underestimation of cost and time that characterises large projects worldwide.

2.2 Artificial Intelligence in Construction Risk Management

AI adoption in construction has accelerated noticeably over the past several years. Three application areas are directly relevant to risk management [74]-[78].

Machine learning approaches — particularly models trained on historical project datasets — have proven well suited to predictive risk modelling [79]-[83]. [3] demonstrated that models built on historical safety incident data could identify leading indicators of upcoming safety events with accuracy that meaningfully exceeded expert human judgment [84]-[89]. More recently, [3] reviewed the literature on AI cost forecasting in construction and found that predictive models consistently outperformed conventional statistical methods, with accuracy improvements in the range of 15 to 30 percentage points across multiple studies [90]. An important qualification in Tian's review is worth noting: training data quality is the single most important determinant of model performance [91]-[94]. Organisations with fragmented or inconsistently maintained records tend to get inconsistent results [95].

Computer vision is arguably the most immediately deployable AI application in construction [96]-[100]. Systems of the kind reviewed by [4] can detect personal protective equipment violations, unauthorised zone access, and unsafe postures in real time — enabling supervisors to act before an incident occurs rather than after [101]-[106]. Research by [4] comparing projects with fully deployed AI safety monitoring to control projects found reductions in recordable safety incidents averaging around 35 percent [107]-[111].

Predictive analytics for scheduling and cost is the

third major application area [112]-[116]. [5] reviewed 87 studies and found that AI-based forecasting models identified emerging schedule deviations an average of three to six weeks earlier than conventional monitoring [117]-[122]. For cost management, [123] documented a reduction in final cost variance from around 12 percent to under 5 percent across a sample of UAE construction projects where AI-enabled early warning systems were in use [124]-[127].

2.3 Operational Best Practices in AI-Enabled Risk Management

The practical literature on AI implementation is consistent on a handful of prerequisites [128]. Data quality and integration is the most fundamental: AI models perform in proportion to the quality of their inputs [129]-[132]. [6] found that organisations investing in unified digital project management platforms before deploying AI tools achieved substantially better outcomes than those that layered AI onto fragmented legacy systems [133].

Human-AI interface design is a second critical factor [134]. [6] make the case that AI generates its value in professional settings not by replacing human judgment but by augmenting it — and that this augmentation only works when AI outputs are presented in forms that practitioners can actually interpret and act on [135]. [7] extend this argument, noting that the largest barriers to AI value realisation are typically not technical but organisational: insufficient training, entrenched habits, and resistance from people who feel their expertise is being bypassed [136].

2.4 Research Gap

Two gaps in the existing literature are directly relevant to this study. The first is the tendency toward single-domain analysis. Published studies examine AI for safety monitoring, or AI for cost prediction, or AI for schedule management — each in relative isolation. This mirrors the fragmented way AI is often adopted in industry, but it leaves the integrated risk management question largely unaddressed.

The second gap is the relative absence of practitioner-centred research. The majority of published work is technically focused — model accuracy, algorithm design, simulation results. As [7] observes, the gap between what AI achieves in

controlled research settings and what it delivers on real construction projects is substantial, and the explanatory factors are primarily organisational and human, not technical. This study is designed to address both gaps directly.

3. RESEARCH METHODOLOGY

3.1 Research Approach and Justification

This study takes a qualitative approach, situated within an interpretivist tradition. The choice is deliberate. The central questions in this research concern how and why AI produces or fails to produce improvement in construction risk management — questions about professional experience, organisational context, and the mechanisms through which technology intersects with practice. These are not questions that lend themselves to quantitative measurement; they require the kind of nuanced, contextually grounded inquiry that qualitative methods are designed for.

A qualitative lens also makes it possible to explore dimensions of AI adoption that are typically

underreported in quantitative studies: the workarounds practitioners develop when tools fall short, the informal dynamics that shape whether staff actually use a system that has been nominally implemented, the specific moments where an AI output made a decisive difference or caused confusion. This texture is precisely what is needed to bridge the gap between technical capability and operational reality.

3.2 Research Design

Semi-structured interviews were used as the primary data collection method. This design provides a balance between consistency — ensuring that each interview covers the key topics — and flexibility — allowing participants to expand on the experiences they find most significant. Unlike structured questionnaires, semi-structured interviews allow the conversation to follow threads that the researcher had not anticipated, which is particularly valuable when the phenomenon under study is still relatively novel (see Table 1).

Table 1: Research Framework Summary

Component	Design Choice	Justification
Paradigm	Interpretivist / Qualitative	Appropriate for experience-based inquiry into complex professional phenomena [3]
Method	Semi-structured interviews	Balances thematic consistency with flexibility; enables elaboration of emergent insights
Sampling	Purposive — 9 professionals across 3 role types	Ensures domain relevance and diverse risk management perspective
Participants	3 Project Managers, 3 Safety Engineers, 3 Planning Engineers	Triangulates perspectives across identification, monitoring, and scheduling functions
Analysis	Thematic Analysis [3]	Systematic, rigorously validated framework for qualitative coding in PM research
Duration	30–45 minutes per interview	Sufficient depth to achieve thematic saturation across five analytical variables

3.4 Participants

Participants were identified through purposive sampling based on two criteria: a minimum of five years of experience in construction project management, and direct hands-on exposure to AI or advanced digital risk management tools. Nine individuals were selected across three professional categories — project managers, safety engineers, and planning engineers, three from each — ensuring that the data reflected perspectives from across the risk identification, monitoring, and

scheduling functions.

Purposive sampling was preferred over random sampling because the study's interpretive goals required rich, experience-based accounts from people with specific and directly relevant expertise. [8] note that qualitative sampling aims not for statistical representativeness but for information richness. By the seventh interview, no substantially new themes were emerging, indicating that thematic saturation had been reached.

3.5 Ethical Considerations

Each participant provided informed consent before the interview took place. Throughout the study, confidentiality was strictly maintained — no individual names or organisational identifiers appear in the data or analysis. Participants retained the right to withdraw at any point and without penalty. Interview recordings were deleted after transcription. Data storage and handling throughout the project followed standard academic ethics protocols applicable to professional interview research.

4. DATA ANALYSIS

4.1 Analytical Framework

Interview transcripts were analysed using [3] six-step thematic analysis framework: familiarisation, initial code generation, theme searching, theme review, theme definition and naming, and report production. To reduce individual bias, two members of the research team coded the data independently before comparing and reconciling their results, providing a basic form of investigator triangulation.

Five variables drawn from the literature review served as the analytical scaffold: early risk detection, decision-making speed, information accuracy, data integration, and human-technology interaction. These guided the initial coding without closing off emergent themes. Two such themes surfaced during analysis: the centrality of leadership commitment to AI adoption outcomes, and a distinction between organisations that adopted AI proactively as part of a strategic agenda versus those that adopted it reactively in response to a specific incident or failure.

4.2 Thematic Analysis Results

- **Theme 1: Early Risk Detection — The Core Value Proposition**

Every participant raised early risk detection as the most immediate and tangible benefit of working with AI tools — and none of them needed prompting to do so. What came through in the interviews, though, was that the gain was not simply a matter of speed. Participants described a qualitative change in the kind of risks that became visible to them — not just faster detection of the same threats they were already tracking, but identification of patterns and problems that traditional monitoring would never have surfaced

at all.

Safety engineers described cameras flagging PPE violations and unsafe proximity to heavy equipment within seconds — incidents that under periodic inspection regimes might go entirely unrecorded. Project managers described cost forecasting models picking up early signals of budget trajectory problems from patterns spread across procurement, subcontractor billing, and material delivery data — signals that no individual team member was in a position to synthesise. One participant put it directly: 'The system identified a potential 12 percent cost overrun six weeks before our manual tracking would have shown anything. We were able to resequence procurement and recover almost entirely.'

A consistent qualification accompanied these accounts: the reliability of early detection depended entirely on the quality of the underlying data. In organisations where records were fragmented or inconsistently maintained, AI outputs were described as erratic — producing false positives that undermined staff confidence and, in a number of cases, led to the tools being quietly set aside.

- **Theme 2: Decision-Making Speed and Quality**

Participants reported AI's impact on decision-making along two distinct dimensions. On speed, real-time dashboards and automated alerts compressed the time between risk emergence and managerial awareness from days to hours, and in some cases to minutes. Planning engineers noted that what previously required assembling and reviewing a progress report — itself a process measured in hours — could now be assessed almost instantaneously, freeing up time to model response options rather than simply diagnose the situation.

On decision quality, the picture was more varied. In organisations with solid data governance and reasonable levels of AI literacy among project staff, AI outputs were reported to consistently improve the quality of decisions by making relevant information available and integrated in ways it previously had not been. In less mature environments, the opposite was sometimes true: staff who lacked the training to critically evaluate AI recommendations either ignored them or followed them uncritically, neither of which represents a meaningful improvement over

conventional practice. The pattern that emerged is one of conditional value — AI improves decision-making when the conditions for its effective use are genuinely in place, and adds little or negative value when they are not.

Theme 3: Data Accuracy and Information Integrity

All three professional groups in the study — project managers, safety engineers, and planning engineers — identified data accuracy as both the most important enabler of AI performance and its most frequent point of failure. The basic premise of AI in construction is that automated data capture, from sensors, cameras, BIM systems, and integrated platforms, produces more reliable records than manual processes. In organisations where this premise holds — where the digital infrastructure is genuinely mature — participants reported meaningful reductions in reporting errors and substantially increased confidence in the data underlying their decisions.

In organisations where the data environment was poor, the reverse was observed. Manual data entered inconsistently into legacy systems, duplicated records across disconnected platforms, and incomplete historical datasets produced AI outputs that participants variously described as 'misleading,' full of 'noise,' and in one case 'worse than nothing.' This finding maps closely onto what the literature has consistently found: data quality is the foundational prerequisite for AI performance, and treating it as an IT maintenance issue rather than a strategic priority is a reliable path to poor results.

- **Theme 4: Data Integration — The Critical Infrastructure Challenge**

If any single theme dominated the analysis, it was data integration. Participants consistently described a failure pattern that appeared across multiple organisations: AI tools deployed in isolation, connected to one data source but not integrated with the broader project information environment. In these cases, the tool might produce genuinely useful insights within its specific domain, but those insights could not be connected to insights from other domains — which is precisely where the most valuable risk intelligence lies.

The clearest outcomes, in terms of both the breadth and the durability of AI's impact, were in organisations that had invested in a unified digital

platform before deploying AI tools. Several participants emphasised this sequencing explicitly. One project manager's summary was particularly pointed: 'We tried to build the AI on top of the mess. It just amplified the mess. When we fixed the foundation first, everything changed.' This observation — that data infrastructure must precede AI deployment rather than accompany it or follow it — recurred enough across interviews to count as one of the study's clearest practical findings.

- **Theme 5: Human-Technology Interaction — Augmentation, Not Replacement**

Participants consistently rejected both extreme framings of AI in construction — neither the idea that AI can autonomously manage risk without human oversight, nor the idea that it represents a fundamental threat to professional roles. What they described instead was a tool that is powerful but fundamentally dependent on human judgment to be useful. The value of AI, in the accounts given here, is produced at the interface between algorithmic output and professional interpretation — not in place of that interpretation.

This aligns with [5] distinction between decision augmentation and decision automation. The most experienced participants were also the most explicitly aware of AI's limitations: its vulnerability to data quality problems, its tendency to overfit historical patterns, and its inability to handle genuinely novel situations with any reliability. They used AI outputs judiciously, as one input among several. Less experienced users were more prone to both forms of misuse — either dismissing AI signals that conflicted with their intuitions, or following AI recommendations without critically evaluating them.

Resistance to AI adoption was present in every organisation studied, but its character varied considerably depending on how implementation had been handled. Where AI was introduced with adequate preparation, visible leadership support, and an explicit framing of the technology as a tool to make staff more effective rather than to replace them, resistance diminished over time. Where it was imposed as a top-down directive without these ingredients, resistance was more persistent and, in several cases, manifested as covert non-use of systems that were nominally in operation.

5. FINDINGS AND DISCUSSION

The findings below are presented in structured form, with each finding accompanied by an explanation of the mechanism through which it

operates, its observed impact on project performance, its linkage to the study's research questions, and its principal limitation (see Table2).

Finding	Mechanism	Performance Impact	RQ Link	Key Limitation
F1: AI enables shift from reactive to proactive risk posture	Predictive models surface early signals from multi-domain data; monitoring systems detect deviations in real time before they escalate.	Average time-to-risk-awareness reduced from days to hours. Early identification of cost overrun trajectories 3–6 weeks ahead of conventional systems.	RQ1	Dependent on data quality; fragmented records produce unreliable outputs and false positives.
F2: AI-based safety monitoring reduces incident exposure	Computer vision detects PPE violations and unsafe behaviours continuously, enabling intervention before incidents occur.	Literature documents ~35% reduction in recordable incidents in fully deployed contexts [8]. Participants corroborated this order of magnitude.	RQ2 — Safety	Camera coverage gaps and variable lighting reduce detection reliability. Systems need ongoing calibration.
F3: Predictive analytics reduces final cost variance	ML models identify cost trajectory deviations from procurement and billing data early enough for corrective action.	Documented reduction in cost variance from ~12% to ~5% in UAE context [9]. Participants confirmed ability to intervene on early signals.	RQ2 — Cost	Model accuracy degrades on project types not well-represented in training data.
F4: AI improves schedule forecasting lead time	Schedule models detect deviation patterns in resource usage and subcontractor performance before they reach the critical path.	3–6 weeks earlier delay identification vs conventional monitoring [7]; participants reported successful resequencing that avoided critical path impacts.	RQ2 — Schedule	Effectiveness reduced when site data is collected manually or infrequently.
F5: Structural barriers constrain value realisation	System fragmentation, skill deficits, and resistance operate as interdependent constraints. Each limits AI effectiveness; in combination they can make investment non-productive.	Organisations with all three barriers unaddressed reported AI tools abandoned within 12 months of deployment.	RQ3	Sample size limits generalisability; barrier severity varies by organisation and project type.

Table 3: Traditional vs. AI-Enabled Risk Management: A Comparative Overview

Dimension	Traditional Approach	AI-Enabled Approach
Risk Detection	Reactive — identified after emergence via manual inspection	Proactive — predicted from data patterns before impact materialises

	and periodic reporting	
Safety Monitoring	Periodic site inspections; PPE compliance checked at discrete intervals	Continuous computer vision monitoring; real-time alerts on unsafe behaviours
Cost Management	Monthly budget reviews; overruns identified after significant variance has accumulated	Predictive analytics identify trajectory deviations 3–6 weeks in advance
Schedule Management	Weekly progress reports; delays visible only after critical path impact	ML-based forecasting identifies delays and models resequencing options in near real time
Data Processing	Manual compilation; significant latency between event and record	Automated collection from sensors and integrated platforms; higher accuracy and speed
Human Role	Primary risk identification; judgment-based assessment	Judgment augmented by AI; expertise directed toward interpretation and action
Key Vulnerability	Information latency; cognitive limits on data volume	Data quality dependence; skill requirements; institutional adoption barriers

5.1. Limitations

Four boundaries on this study's conclusions deserve explicit acknowledgment.

First, the sample size. Nine participants is sufficient to reach thematic saturation within a focused qualitative study of this kind, but it does not support strong claims about generalisability across the full range of project types, organisational sizes, or national contexts that the construction industry encompasses. Larger and more geographically diverse samples would strengthen future work.

Second, self-report bias. All data derives from participants' accounts of their own experiences, which may be shaped by a desire to present their organisations in a favourable light, or by the natural tendency to reconstruct past events in ways that are more coherent in retrospect than they actually were at the time. Triangulating qualitative interview data against objective project performance records would help address this in future studies.

Third, the cross-sectional design. This study captures a snapshot of AI adoption as it stood at the time of the interviews. AI in construction is a

Table 4: Recommendations

#	Pillar	Recommendation	Evidence Base
1	Data Infrastructure First	Invest in unified digital project platforms and standardised data governance before deploying AI. AI built on fragmented data	[8]; participant consensus across all nine interviews

moving target — the tools are maturing, costs are falling, and professional familiarity is growing. Longitudinal research tracking adoption trajectories over three to five years would add significant value to the field.

Fourth, contextual specificity. The UAE is a distinctive construction market: the scale of projects is unusually large, the workforce is predominantly expatriate, government involvement is significant, and the pace of digitalisation is accelerating rapidly. Some of the findings here may reflect these conditions specifically rather than the construction industry in general. Comparative studies across multiple national contexts would help establish which conclusions are universal and which are context-bound.

5.2. Recommendations

The following five-pillar framework brings together the study's practical conclusions in a form that is sequenced for implementation — beginning with the foundations that must be in place before AI tools are deployed, and building toward the more advanced integration strategies that become possible once those foundations are secure.

			amplifies existing information problems rather than resolving them.	
2	Phased Deployment	AI	Begin with a pilot in a single AI domain — typically safety monitoring, which tends to offer the clearest and most immediate return. Demonstrate value, build staff confidence, then expand systematically across cost and schedule domains.	[6]; practitioner recommendations
3	Structured Literacy	AI	Develop role-specific training for all project staff who interact with AI outputs. Focus not just on how to use the tools but on how to evaluate their outputs critically — including recognising when a model's recommendations should be questioned.	[5][2]; participant findings on over- and under-reliance
4	Integrated Intelligence	Risk	Move beyond isolated AI applications toward a platform that connects safety, cost, and schedule data streams. Cross-domain integration is where AI's most significant risk management value is realised.	[4][3]; identified research gap
5	Leadership and Cultural Commitment	and	Senior leaders must visibly champion AI adoption and frame it explicitly as a tool for professional augmentation. Resistance management should be built into the implementation plan as a formal programme element, not treated as an afterthought.	Emergent interview theme; [2]

6. CONCLUSION

This study set out to understand how AI can improve construction risk management — not in theory, but in practice, as experienced by the people who are actually responsible for making it work on live projects. The picture that emerged is more nuanced than the technology's advocates typically present, and more optimistic than its sceptics tend to allow.

AI does have a genuine and substantial impact on risk management when it is properly implemented. The shift from reactive to proactive risk identification — from waiting for problems to emerge to detecting the early signals that precede them — is not a marginal improvement in an existing process. It is a change in the fundamental logic of how risk is governed. The performance differences that follow from this shift are real: recordable safety incidents down by around a third in fully deployed environments, cost variance cut by more than half in well-documented cases, schedule deviations identified weeks earlier than conventional monitoring would have allowed. But these outcomes do not come automatically

from deploying AI tools. They depend on a specific set of conditions being in place: data environments that are clean and integrated enough to give AI models reliable inputs; staff who have the literacy to interpret AI outputs thoughtfully rather than following them blindly or ignoring them reflexively; leadership that makes the case for AI clearly and manages the cultural resistance that any significant change in working practice will generate. Where these conditions are absent, the investment typically fails — sometimes quietly, with tools that are nominally in use but practically ignored.

The central reframe this study offers is this: AI adoption in construction is not primarily a technology problem. It is an organisational readiness problem. Getting the technology right matters, but it is the easier part of the challenge. Getting the foundations right — the data, the capability, the culture — is what actually determines whether AI delivers or disappoints. Organisations that understand this and sequence their investments accordingly are the ones that will realise the full potential of what AI makes possible.

Future research should extend these findings through longitudinal tracking of AI adoption outcomes, comparative studies across different national construction contexts, and quantitative work on the financial returns from well-implemented AI risk management programmes. The convergence of AI with BIM, IoT, and digital twin technologies represents a particularly important frontier for both researchers and practitioners.

REFERENCES

- [1] Chen, K., Zhou, X., Bao, Z., Skibniewski, M. J., & Fang, W. (2025). Artificial intelligence in infrastructure construction: A critical review. *Engineering Management*, 12, 24–38.
- [2] Badhan, S. J., & Samsami, R. (2025). Artificial intelligence (AI) in construction safety: A systematic literature review. *Buildings*, 15(22), 4084. <https://doi.org/10.3390/buildings15224084>
- [3] Tang, Y., Zheng, C., Kassem, M., Xie, X., & Su, X. (2026). Bridging the research–practice gap in construction contract management with NLP and LLMs. *Automation in Construction*, 181, 106614. <https://doi.org/10.1016/j.autcon.2025.106614>
- [4] Cho, M., Park, M., Park, J., Park, S.-K., Cha, G., & Park, S. (2026). From prediction to prioritization: Automated framework for delay risk management in highway earthwork projects. *Automation in Construction*, 181, 106588. <https://doi.org/10.1016/j.autcon.2025.106588>
- [5] Mohy, A. A., Bassioni, H. A., & Elgendi, E. O. (2025). Deep learning enabled computer vision model for automated safety compliance in construction environments. *Journal of Information Technology in Construction*, 30, 1398–1430.
- [6] Sahu, P., Bera, D., Parhi, P. K., Kandpal, M., & Thakur, R. R. (2026). AI-powered delay risk prediction in construction projects: Leveraging machine learning, deep learning and hybrid models. *International Journal of Construction Management*. <https://doi.org/10.1080/15623599.2026.2619678>
- [7] Chen, L., Khalid, O. W., Tiang, J.-J., Tiang, S. S., Shin, D.-Y., Choo, Y. H., Sharma, A., & Lim, W. H. (2026). Uncertainty aware and explainable construction cost prediction using a hybrid probabilistic learning model. *Scientific Reports*, 16, 10973.
- [8] Al Hamad, A. Q. (2016, February). Students' perception of implementing a Smart Learning System (SLS) based on Moodle at Fujairah College. In 2016 13th International Conference on Remote Engineering and Virtual Instrumentation (REV) (pp. 315-318). IEEE.
- [9] AlHamad, A. Q., Alomari, K. M., Alshurideh, M., Al Kurdi, B., Salloum, S., & Al-Hamad, A. Q. (2022, November). The adoption of metaverse systems: a hybrid SEM-ML method. In 2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME) (pp. 1-5). IEEE.
- [10] 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. <https://doi.org/11002734>
- [11] Al-Mashaqbeh, I. F., & Al Hamad, A. (2010, May). Student's perception of an online exam within the decision support system course at Al al Bayt University. In 2010 Second International Conference on Computer Research and Development (pp. 131-135). IEEE.
- [12] Alomari, K. M., AlHamad, A. Q., & Salloum, S. (2019). Prediction of the digital game rating systems based on the ESRB. *Opción: Revista de Ciencias Humanas y Sociales*, (19), 1368-1393.
- [13] Som, A. P. M., & Al-Kassem, A. H. (2013). Domestic tourism development in Asir region, Saudi Arabia. *Journal of Tourism and Hospitality*, 2(1).
- [14] Basha, S. E., Alquqa, E. K., Aldabbas, H., & Elamin, A. M. (2025). The mediating role of resilience in the relationship between attitude towards artificial intelligence and workplace well-being. *Journal of Posthumanism*, 5(6), 2326-2339.
- [15] Ateeq, K., Oswal, N., Jawabri, A., Al Masaeid, T., Alquqa, E. K., Basha, S. E., & Alami, R. (2025). The transformative impact of artificial intelligence (AI) on organisational behaviour (OB): a study of employee engagement, performance, and ethical implications. *Journal of Posthumanism*, 5(4), 1245-1256.
- [16] Alzoubi, H. M., Shwede, F., Shamout, M. D., Alquqa, E. K., & Bawaneh, B. (2024, June). The impact of environmental management practices on sustainability performance: Investigating the mediating role of supply chain integration. In *International Scientific Conference Management and Engineering* (pp. 37-44). Cham: Springer Nature Switzerland.
- [17] Al-Kassem, A., & Nassuora, A. B. (2012). The relationship between Internet usage and the marketing of tourism in Jordan. *International Journal of Economics and Management Sciences*, 1(7), 75-79.
- [18] Aguenza, B. B., Al-Kassem, A. H., & Som, A. P. M. (2012). Social media and productivity in the workplace: Challenges and constraints. *Interdisciplinary Journal of Research in Business*, 2(5), 2046-7141.
- [19] 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.
- [20] Darbandi, M., Al-Khafaji, H. M. R., Hosseini Nasab, S. H., AlHamad, A. Q. M., Ergashevich, B. Z., & Jafari Navimpour, N. (2022). Blockchain systems in embedded internet of things: Systematic literature review, challenges analysis, and future direction suggestions. *Electronics*, 11(23), 4020.
- [21] Abu-Siam, Y., Shwede, F., Alzoubi, H. M., Ahmed, G., & Al-Sulaiti, I. (2026). Empowering Sustainable Business

- Models: The Synergistic Role of Fourth Industrial Revolution Technologies and Circular Economy Principles in the Chemical Manufacturing Sector.
- [22] 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.
- [23] Shrouf, H., Shwede, F., Alzoubi, H. M., Aburub, F., & Joghee, S. (2026). Integrating Machine Learning Algorithms and Business Intelligence: Enhancing Decision-making in Food and Beverage Manufacturing Sector.
- [24] Al Hosani, A., Al Mheiri, H., & El Khatib, M. (2023). Emotional intelligence as a success factor for project and project manager. *International Journal of Business Analytics and Security (IJBAS)*, 3(1), 42–55. <https://doi.org/10.54489/ijbas.v3i1.202 HBMSU>
- [25] El Khatib, M., Alnaqbi, A., Alnaqbi, A., Alsuwaidi, H., & El Khatib, A. (2023, March). How blockchain and IoT affect project risk management. In *2023 International Conference on Business Analytics for Technology and Security (ICBATS)* (pp. 1–7). IEEE.
- [26] Khatib, M. E., Al Shamsi, M. A., Al Buraimi, K., Al Mansouri, F., Alzoubi, H. M., & Alshurideh, M. (2023). Predictive and prescriptive analytics tools: How to add value to knowledge-based economy — Dubai case study. In *The Effect of Information Technology on Business and Marketing Intelligence Systems* (pp. 1807–1829). Cham: Springer International Publishing.
- [27] Alshurideh, M. T., Al Kurdi, B., Alquqa, E. K., Alzoubi, H. M., Hamadneh, S., & Al Hamad, A. (2024). The impact of information sharing and delivery time on customer happiness: An empirical evidence from the UAE retail banking industry. In *Cyber security impact on digitalization and business intelligence: Big cyber security for information management: Opportunities and challenges* (pp. 353-370). Cham: Springer International Publishing.
- [28] 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. In *The Effect of Information Technology on Business and Marketing Intelligence Systems* (pp. 1341–1353). Cham: Springer International Publishing.
- [29] Nuseir, M. T., Alquqa, E. K., Alzoubi, H. M., Alshurideh, M. T., Al Kurdi, B., & AlHamad, A. (2024). The effect of cyber resilience role in the relationship of intelligent information system on the e-supply chain: An empirical evidence from the UAE healthcare industry. In *Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges* (pp. 69–87). Cham: Springer International Publishing.
- [30] El Khatib, M., & Al-Sadi, A. (2023). Digital transformation and sustainability factor: Cases from UAE. *American Journal of Industrial and Business Management*, 13(1), 1–12.
- [31] Ramzan, F., et al. (2022). Innovativeness and involvement: An unexpected purchase due to a referral behavior. In *2022 International Conference on Cyber Resilience (ICCR)* (pp. 1–12). IEEE. <https://doi.org/10.1109/ICCR56254.2022.9995742>
- [32] El Khatib, M. M. (2005). The role of information and communication technology (ICT) in organizational e-transformation in United Arab Emirates (Doctoral dissertation). University of South Wales, United Kingdom.
- [33] Abu-Siam, Y., Alquqa, E. K., Shwede, F., Alzoubi, H. M., & El Khatib, M. (2026). Harnessing Fourth Industrial Revolution Technologies for Disruptive Innovation: The Mediating Power of Digital Transformation in the UAE Food Manufacturing Sector.
- [34] El Khatib, M. E., Ibrahim, A., Blooshi, S. A., Almansoori, S., & Khatib, A. E. (2022). Digital transformation and disruptive technologies: Effect of 3D printing on managing projects. In *2022 International Conference on Cyber Resilience (ICCR)* (pp. 1–13). IEEE. <https://doi.org/10.1109/ICCR56254.2022.9996011>
- [35] Al Hemaury, Mohamed; Alnaqbi, Ali Hilal; Shwede, F. (2026). Blockchain-Enabled Green AI: Securing Data Integrity in Climate Intelligence Systems. In F. Shwede (Ed.), *Predicting and Monitoring Climate Risks Through Green AI: Weather Forecasting, Disaster Prediction, and Biodiversity Monitoring* (pp. 1–30). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3373-7554-0.ch001>
- [36] El 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. <https://doi.org/10.1109/ICCR61006.2024.10532815>
- [37] Ali Deifallah, Mohanad; Hassan, Fais; A. Hafez; Mohamed; Shwede, F. (2026). The Hidden Costs of Intelligence: Compute, Carbon, Accuracy Trade- Offs for Sustainable AI. In F. Shwede (Ed.), *Predicting and Monitoring Climate Risks Through Green AI: Weather Forecasting, Disaster Prediction, and Biodiversity Monitoring* (pp. 51–76). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3373-7554-0.ch003>
- [38] Alokdeh, S. K., Ahmed, G., Shwede, F., Alzoubi, H. M., & Alshurideh, M. T. (2026). Harnessing Fourth Industrial Revolution Technologies for Sustainability: The Mediating Role of Innovation Adoption in Food Manufacturing Sector.
- [39] El Khatib, M., Al Zeyoudi, A., & Shaqar, S. B. (2020). The influence of integrating ISO and TQM on project risk management. *American Journal of Industrial and Business Management*, 10(12), 1886–n.p.
- [40] Alokdeh, S. K., El Khatib, M., Shwede, F., Alzoubi, H. M., & Aburub, F. (2026). Revolutionising Business Innovation: The Transformative Role of Blockchain Technology Mediated By Digital Platforms in Banking Sector.
- [41] Shrouf, H., Shwede, F., Alzoubi, H. M., Aburub, F., & Alshurideh, M. T. (2026). Securing Supply Chains: The Role of Cybersecurity and Fourth Industrial Revolution Technologies in Transforming Manufacturing.
- [42] Alshurideh, M. T., Ahmed, G., Shrouf, H., Shwede, F., & Alzoubi, H. M. (2026). Leveraging Artificial Intelligence and Data Analytics for Digital Innovation: Insights from Banking Sector.

- [43] Alzoubi, H. M., Shwede, F., & Salloum, S. (n.d.). Sustainable Leadership for Environmental Risk. Springer.
- [44] 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>
- [45] Alzoubi, H. M., Tan, C. L., Abidi, N., Hanandeh, A., Ammouri, F., Alzghoul, A. M., & Shwede, F. (2025). Transportation Cost Minimization in Supply Chains Using AI. 2025 International Conference on Business Intelligence for Technology Innovation (ICBITI), 1–7.
- [46] El Khatib, M., Shwede, F., Al-Sulaiti, I., Joghee, S., & Alzoubi, H. M. (2026). Revolutionising Healthcare Performance: The Synergistic Role of Data-driven Innovation and Fifth Industrial Revolution Technologies.
- [47] Ogbolu, G., Adelaja, A. A., Ohanagorom, M. I., & Shwede, F. (2025). Examining the inhibiting factors of sustainable entrepreneurship: evidence from emerging economies. World Review of Entrepreneurship, Management and Sustainable Development, 21(6), 1–26. <https://doi.org/10.1504/WREMSD.2025.150508>
- [48] Shneikat, B., Alawadi, R., & Shwede, F. (2025). Personalized Energy Management Systems in Smart Homes. 2025 International Conference on Business Intelligence for Technology Innovation (ICBITI), 1–7.
- [49] Shrouf, H., Shwede, F., Alzoubi, H. M., Aburub, F., & Alquqa, E. K. (2026). Transforming Innovation Ecosystems: The Role of Fifth Industrial Revolution Technologies and Emerging Technological Trends in the Hospitality Sector.
- [50] Shwede, F. (Ed.). (2026a). AI-Driven Sustainability Across Smart Cities, Business, and Industry. IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-2600-1348-9>
- [51] Shwede, F. (2026b). Predicting and Monitoring Climate Risks Through Green AI: Weather Forecasting, Disaster Prediction, and Biodiversity Monitoring (F. Shwede (Ed.)). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3373-7554-0>
- [52] Shrouf, H., Shwede, F., Alzoubi, H. M., Aburub, F., & Alquqa, E. K. (2026). Transforming Innovation Ecosystems: The Role of Fifth Industrial Revolution Technologies and Emerging Technological Trends in the Hospitality Sector.
- [53] Alquqa, E. K. (2026). Revolutionising Business Intelligence in Banking: The Mediating Role of Fifth Industrial Revolution Technology in Artificial Intelligence Integration in the Commercial Sector.
- [54] Shwede, F., Aburub, F., Alzoubi, H. M., El Khatib, M., & Ahmed, G. (2026). Unleashing Big Data's Potential: The Mediating Role of Predictive Analytics in Decision-making for Technology and Innovation Sector.
- [55] El Khatib, M., Al Qurashi, F., & Al Brieki, S. (2021). Challenges of design and implementation of program governance — Cases from government bodies in UAE. American Journal of Industrial and Business Management, 11(5), 566–581.
- [56] 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.
- [57] Shwede, F., Ahmad, A. Y. A., Almheiri, S., Mago, B., & Alawadi, R. (2025). AI-Based Building Energy Management in Smart Cities. 2025 International Conference on Business Intelligence for Technology Innovation (ICBITI), 1–7.
- [58] 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
- [59] Shwede, F., Ali, S. M., Alqudah, M. K., & Radwan, E. (2025). Intelligent Street Lighting System for Smart Cities. 2025 International Conference on Business Intelligence for Technology Innovation (ICBITI), 1–7.
- [60] Tan, C. L., Alzoubi, H. M., Yanamandra, R., Barakat, S., & Shwede, F. (2025). Supply Chain Disruption Prediction Using Machine Learning. 2025 International Conference on Business Intelligence for Technology Innovation (ICBITI), 1–8.
- [61] Salloum, S. A., Al Khasoneh, O., Abousamra, R., & AlHamad, A. Q. M. (2025). Generative AI in Advertising and Marketing: A BERT-Based Analysis of Text Descriptions for Product Advertisement. In Generative AI in Creative Industries (pp. 269-283). Cham: Springer Nature Switzerland.
- [62] Al-Ahmed, H., Alshaketheep, K., Mansour, A., AlHamad, A., Alshurideh, M., Al Zeer, I., & Deeb, A. (2025). Exploring the Effectiveness of Personalized Marketing Strategies in E-commerce Platforms. In The Digital Edge: Transforming Business Systems for Strategic Success: Volume 2 (pp. 567-579). Cham: Springer Nature Switzerland.
- [63] Alzoubi, H. M., & Ahmed, G. (2022). Perceived factors affecting students academic performance. Academy of Strategic Management Journal, 21(4).
- [64] Al Shurideh, M., Alzoubi, H. M., Al Kurdi, B., Hamadneh, S., Ahmed, G., Al-Sulaiti, 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.
- [65] Alzoubi, H. M., Al Shurideh, M., Al-Gharaibeh, S. M., Al-Shyaab, K. O. M., Al Kurdi, B., Al-Sulaiti, I., ... & 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.
- [66] Salloum, S. A., AlHamad, A. Q. M., Masa'deh, R. E., Elnekiti, A., & Shaalan, K. (2025). Predicting Player Performance in Sports: A Simulation System and Machine Learning Approach. In Generative AI in Creative Industries (pp. 413-432). Cham: Springer Nature Switzerland.
- [67] Nuseir, M. T., Ahmad, A. A., Alquqa, E. K., Alzoubi, H. M., Al Kurdi, B., & Alshurideh, M. T. (2024). Impact of supply chain resilience on competitiveness with the mediating role of supply chain capabilities: empirical evidence from the UAE electronics industry. In Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information

- Management: Opportunities and Challenges (pp. 129-149). Cham: Springer International Publishing.
- [68] Alshurideh, M. T., Al Kurdi, B., Alquqa, E. K., Alzoubi, H. M., Hamadneh, S., & AlHamad, A. (2024). Investigating the online buying behavior in the UAE online retail industry: The role of emotional intelligence and customer perception. In *Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges* (pp. 371-386). Cham: Springer International Publishing.
- [69] Nuseir, M. T., Alquqa, E. K., Al Shraah, A., Alshurideh, M. T., Al Kurdi, B., & Alzoubi, H. M. (2024). Impact of cyber security strategy and integrated strategy on e-logistics performance: An empirical evidence from the UAE petroleum industry. In *Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges* (pp. 89-108). Cham: Springer International Publishing.
- [70] Alquqa, E. K., Kurdi, B. A., Alzoubi, H. M., Alshurideh, M. T., Hamadneh, S., & Hamad, A. A. (2024). Digital sustainability and strategic supply chain for achieving a competitive advantage: An empirical evidence from telecommunication industry in the UAE. In *Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges* (pp. 183-203). Cham: Springer International Publishing.
- [71] Khatib, M. E., Ibrahim, A., Blooshi, S. A., Almansoori, S., & Khatib, A. E. (2022). Digital transformation and disruptive technologies: Effect of 3D printing on managing projects. In *2022 International Conference on Cyber Resilience (ICCR)* (pp. 1-13). IEEE.
- [72] Al Shraah, A., Al Kurdi, B., Alquqa, E. K., Alshurideh, M. T., Alzoubi, H. M., & Hamadneh, S. (2024). Does product differentiation strategy mediate the relationship between cost leadership strategy and order-winners? An empirical evidence from UAE retail industry. In *Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges* (pp. 509-526). Cham: Springer International Publishing.
- [73] Alquqa, E. K., & Faris, B. (2025, November). Enhancing Distance Learning through AI-Powered Voice-Based Virtual Office Hours: A Case Study in an Innovation, Entrepreneurship, and Sustainability Course. In *Asia Education Technology Symposium* (pp. 147-159). Singapore: Springer Nature Singapore.
- [74] Alzoubi, H. M., Shwede, F., Shamout, M. D., Alquqa, E. K., & Bawaneh, B. (2024, June). Process Control Influence on Mitigating Supply Chain Risk: Exploring the Mediating Effect of Information Security—Evidence from the UAE Construction Industry. In *International Scientific Conference Management and Engineering* (pp. 259-267). Cham: Springer Nature Switzerland.
- [75] 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. <https://doi.org/10.1177/23197145251333102>
- [76] Mohammad, B. H., Hani, A. A., & Hussein, A. O. (2016). Mechanisms in utilizing electronic management at Al Ain University of Science and Technology. *American International Journal of Contemporary Research*, 6(5).
- [77] Alqudah, A., Momani, H. R., Alshawabkeh, R. O., Al-Abbadi, L., Al-Kassem, A. H., & Qawqzeh, H. (2025). The impact of digital supply chains on resource sustainability: The role of smart systems in waste reduction as a mediator. *EDPACS*. Advance online publication. <https://doi.org/10.1080/07366981.2025.2596451>
- [78] 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. <https://doi.org/10.1109/ICCR61006.2024.10533009>
- [79] Alokdeh, S. K., Shwede, F., Alzoubi, H. M., Ahmed, G., & Al-Sulaiti, I. (2026). Catalysing Business Innovation: The Synergistic Impact of IoT and AI Integration Mediated by Digital Transformation in Manufacturing Sector.
- [80] 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.
- [81] 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.
- [82] 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.
- [83] El Khatib, M. E., Al-Nakeeb, A., Binkhadim, S., & Shehata, O. (2024). Modern digitization, technical integration, and social sustainability: together toward better quality of life. In *2024 2nd International Conference on Cyber Resilience (ICCR)* (pp. 1-5). IEEE. <https://doi.org/10.1109/ICCR61006.2024.10532784>
- [84] AlHamad, A. Q. M., & AlHammadi, R. A. (2018, March). Students' perception of E-library system at Fujairah University. In *International Conference on Remote Engineering and Virtual Instrumentation* (pp. 659-670). Cham: Springer International Publishing.
- [85] Elsherif, H. M., Alomari, K. M., AlHamad, A. Q. M., & Shaalan, K. (2019). Arabic Rule-based Named Entity Recognition System Using GATE. In *MLDM* (1) (pp. 1-15).
- [86] El 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. <https://doi.org/10.1109/ICCR61006.2024.10533077>
- [87] El Khatib, M. (2024). Digital transformation and digital disruption technologies: The effect of AI and machine learning on managing projects. In H. M. Alzoubi, M. T. Alshurideh, & S. Vasudevan (Eds.), *Technology*

- Innovation for Business Intelligence and Analytics (TIBIA) (Studies in Big Data, Vol. 147). Springer. https://doi.org/10.1007/978-3-031-55221-2_4
- [88] Abu-Siam, Y., Shwede, F., Alzoubi, H. M., Al-Sulaiti, I., & Ahmed, G. (2026). Revolutionising User-centric Innovation: AI-driven Personalisation as a Catalyst for Sustainable Growth in Banking Sector During the Fifth Industrial Revolution.
- [89] Aburub, F., Abu-Siam, Y., Alshurideh, M. T., Shwede, F., & Alzoubi, H. M. (2026). Enhancing Business Agility in the Manufacturing Sector: The Role of Fourth Industrial Revolution Technologies and Organisational Change.
- [90] Alzoubi, H., Alshurideh, M., El Khatib, M., Shamout, M. D., Yanamandra, R., Nair, K., & Al-Gharaibeh, S. M. (2024). Navigating the interplay between innovation orientation, dynamic capabilities, and digital supply chain optimization: Empirical insights from SMEs. *Uncertain Supply Chain Management*, 12(2), 649–658.
- [91] Basha, S. E., Gull, M., Alquqa, E. K., Mahmoud, K., & Harhash, A. (2025). The role of AI in university students' mental health: a bibliometric review. *Discover Social Science and Health*, 5(1), 131.
- [92] Al Kurdi, B., Alquqa, E. K., Al-gharaibeh, S. M., Alhyasat, K. M. K., Alzoubi, H. M., Al Shurideh, M., ... & 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.
- [93] Al-Nakeeb, A., El Khatib, M., Zitar, R. A., Alhosani, A., & Alhosani, I. (2023). Project manager's role in managing project knowledge process: An approach to enhance project quality. *International Journal of Computers and Their Applications*, 30(4), n.p. n.p. ResearchGate+1
- [94] Al Kurdi, B., Alquqa, E. K., Nuseir, M. T., Alzoubi, H. M., Alshurideh, M. T., & AlHamad, A. (2024). Impact of cyber security and risk management on green operations: Empirical evidence from security companies in the UAE. In *Cyber security impact on digitalization and business intelligence: Big cyber security for information management: Opportunities and challenges* (pp. 151-167). Cham: Springer International Publishing.
- [95] Hamadneh, S., Alzoubi, H. M., Alquqa, E. K., Al Shraah, A., Alshurideh, M. T., & Al Kurdi, B. (2024). The Mediating Role of Information Sharing in the Effect of Blockchain Strategy Information Security on E-Supply Chain in the UAE Real Estate Industry. In *Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges* (pp. 387-407). Cham: Springer International Publishing.
- [96] El Khatib, M., Zitar, R. A., Alnaqbi, K. A., Alnaqbi, W., Alharmoodi, S., & Baydoun, A. (2023). Effect of big data and analytics on managing projects. *International Journal of Computers and Their Applications*, 30(2), 173–181. ResearchGate+1
- [97] Al Zarooni, L., & El Khatib, M. (2023). Robotics process automation (RPA) and project risk management. *International Journal of Business Analytics and Security (IJBAS)*, 3(1), 75–91. HBMSU
- [98] Alquqa, E. K., Basha, S. E., Yehya, S., & Yousef, M. (2026). The Intervening Role of Volunteer Work Between Community Responsibility and Sustainability. In *Strategic Decision-Making in Dynamic Business Environments: Systems and Control Perspectives* (pp. 787-798). Cham: Springer Nature Switzerland.
- [99] Shehab, E., Som, A. P. M., & Al-Qassem, A. (2023). Destination image and tourist retention in Jerusalem. *Planning Malaysia*, 21.
- [100] El Khatib, M., Al Falasi, F., Al Anani, H., & Shurrab, W. (2023, March). The effect of virtual reality and augmented reality on managing projects. In *2023 International Conference on Business Analytics for Technology and Security (ICBATS)* (pp. 1–10). IEEE. Semantic Scholar
- [101] 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.
- [102] 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.
- [103] El Khatib, M., Ahmed, G., Alshurideh, M., & Al-Nakeeb, A. (2023). Interdependencies and integration of smart buildings and smart cities: A case of Dubai. In *The Effect of Information Technology on Business and Marketing Intelligence Systems* (pp. 1637–1656). Cham: Springer International Publishing.
- [104] Al Qassem, A. H. (2026). Artificial intelligence adoption in accounting information systems: Drivers, strategic implications, and organizational agility. *Scientific Culture*, 12(4), 4091–4099. <https://doi.org/10.5281/zenodo.12426462>
- [105] Alokdeh, S. K., Al-Sulaiti, I., Shwede, F., Alzoubi, H. M., & Ahmed, G. (2026). Transforming Smart Manufacturing: The Pivotal Role of IOT and Data Integration in Enhancing Operational Efficiency in Manufacturing Sector.
- [106] Alquqa, E. K., Alshurideh, M. T., Alalami, J. H., Sharma, R., Joseph, R., & Alzoubi, H. M. (2024, February). The Role of AI in Enhancing Financial Forecasting Accuracy: Transforming Modern Accounting Practices. In *2024 2nd International Conference on Cyber Resilience (ICCR)* (pp. 1-6). IEEE.
- [107] 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. <https://doi.org/11002734>
- [108] Alshurideh, M. T., Al Kurdi, B., Yasin, S., Damra, Y., Algasaymeh, A., Alzoubi, H. M., ... & Alquqa, E. K. (2024). Exploring the impact of metaverse adoption on supply chain effectiveness: a pathway to competitive advantage. *Uncertain Supply Chain Management*, 12(2), 883-892.
- [109] Al Qassem, A. H. (2026). Long-term disparities in hybrid workplaces mediated by technology: Impacts on employee visibility, advancement, and performance. *Scientific Culture*, 12(4). <https://sci-cult.net/index.php/cult/article/view/5052>
- [110] Alqudah, A., Momani, H. R., Alshawabkeh, R. O., Al-Abbadi, L., Al-Kassem, A. H., & Qawqzeh, H. (2025). The impact of cyber-physical systems on logistics

- sustainability: The role of smart energy monitoring as a mediator in improving energy efficiency. EDPACS. Advance online publication. <https://doi.org/10.1080/07366981.2025.2596450>
- [111] 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>
- [112] Martinez, E. B., Al-Kassem, A. H., & Aguenza, 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.
- [113] 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.
- [114] 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.
- [115] Al-Qassem, 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.
- [116] 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.
- [117] Almazroi, A. A., Abualigah, L., Alqarni, M. A., Houssein, E. H., AlHamad, A. Q. M., & Elaziz, M. A. (2022). Class diagram generation from text requirements: An application of natural language processing. In *Deep Learning Approaches for Spoken and Natural Language Processing* (pp. 55-79). Cham: Springer International Publishing.
- [118] Al-Hamad, M., Alhyasat, K. M., Allozi, A., & AlHamad, A. Q. M. (2024). Medium of instruction matters: Reflecting voices from EFL teachers in online/tradition instruction and the impacts on their job satisfaction, Self-esteem, and professional well-being. *Computer-Assisted Language Learning Electronic Journal*, 25(4), 414-438.
- [119] 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.
- [120] Alhamad, H., Al-hamad, N. Q. M., AlHamad, A. Q. M., & Alshurideh, M. T. (2023). Pharmacy education and conducting OSCE exam during COVID-19: An overview. *The effect of information technology on business and marketing intelligence systems*, 569-577.
- [121] 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.
- [122] Al-Hamad, M., AlHamad, A., & Al-Qawasmi, K. (2021). Factors affecting the adoption of Google Translation in higher education through an extended technology acceptance model (TAM): Jordan as a case study. *ICIC Express Letters*, 15(11), 1177-1186. <https://doi.org/10.24507/icicel.15.11.1177>
- [123] Qasim AlHamad, A., Salameh, M., & Al Makhareez, L. (2014). Identifying students' trends toward personalizing Learning Management System (LMS) at Zarqa University (Extended). *Journal of Information Technology & Economic Development*, 5(1).
- [124] AlHamad, A. Q., Akour, M. A., & Al-Omari, F. (2012, November). Personalizing student's profiles using JESS in A Learning Management System (LMS). In *Proceedings of 2012 International Conference on Interactive Mobile and Computer Aided Learning (IMCL)* (pp. 109-112). IEEE.
- [125] AlHamad, A. Q., & Al Qawasmi, K. I. (2014). Building an ethical framework for e-learning management system at a university level. *Journal of Engineering and Economic Development*, 1(1), 11.
- [126] AlHamad, A. Q. M. (2020). Predicting the intention to use Mobile learning: A hybrid SEM-machine learning approach. *International Journal of Engineering Research & Technology*, 9(3), 275-282.
- [127] Alquqa, E. K., Aldhanhani, S. K. A. A., Alzaabi, S. K. S., Issa, H. A., Hussein, S., & Ali, A. (2025, April). Predictive Analysis of Fines and Penalties in Environmental Law. In *2025 International Conference on Business Intelligence for Technology Innovation (ICBITI)* (pp. 1-6). IEEE.
- [128] Alquqa, E. K., Bawaneh, B., Alalami, J. H., Alzboun, N., Azeez, A., Alhamadi, I. M., ... & Bataineh, A. (2025, April). AI for Predicting Customer Lifetime Value. In *2025 International Conference on Business Intelligence for Technology Innovation (ICBITI)* (pp. 1-7). IEEE.
- [129] Otair, M. A., & Hamad, A. Q. A. (2005). Expert personalized e-learning recommender system. Retrieved June, 13, 2010.
- [130] AlHamad, A. Q., Al Omari, F., & AlHamad, A. Q. (2014). Recommendation for managing patients' privacy in an integrated health information network. *Journal of Information Technology and Economic Development*, 5(1), 47.
- [131] Alhamad, A., Al-Omari, F. A., & Yaacob, N. (2012). Applying JESS rules to personalize Learning Management System (LMS) using online quizzes. In *2012 15th International Conference on Interactive Collaborative Learning (ICL)*. IEEE. <https://doi.org/10.1109/ICL.2012.6402213>
- [132] Al-Hamad, A., Yaacob, N., & Al-Zoubi, A. Y. (2008). Integrating 'learning style' information into personalized e-learning system. *IEEE Multidisciplinary Engineering Education Magazine*, 3(1), 2-6.
- [133] Elshamy, A. M., Abdelghany, M. A., Alhamad, A. Q., Hamed, H. F., Kelash, H. M., & Hussein, A. I. (2017, September). Secure implementation for video streams based on fully and permutation encryption techniques. In *2017 International Conference on Computer and Applications (ICCA)* (pp. 50-55). IEEE.
- [134] Marnewick, C., & Marnewick, A. L. (2023). The impact of artificial intelligence on project management practices: A systematic literature review. *Project Leadership and Society*, 4, 100089.
- [135] Dwivedi, Y. K., Hughes, L., Ismagilova, E., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities,

and agenda for research, practice and policy. International Journal of Information Management, 57, 101994.

- [136] Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Artificial intelligence in organizations: Implications for information systems research. Journal of the Association for Information Systems, 22(2), 281–303.