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قسم / تخصص ماجستير إدارة المخاطر



عنوان البحث

إدارة المخاطر التعاقدية ومخاطر سلسلة الإمداد باستخدام الذكاء الاصطناعي وأثرها على الأداء المالي في مشاريع
الإنشاءات في المنطقة الشرقية بالمملكة العربية السعودية

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حقوق الطباعة

حقوق الطباعة تمتلكها جامعة ميد أوشن، حيث إن جميع المواد والمحتويات الواردة في هذا البحث هي ملك للجامعة، ولا يجوز استخدامها أو إعادة نشرها أو توزيعها بدون إذن مسبق من جامعة ميد أوشن.

الباحث

التهنئة

أهدي هذا العمل المتواضع إلى والديّ الكريمين، عرفانًا بفضلهما العظيم، وتقديرًا لما قدّماه لي من رعاية ودعم ودعاء كان له الأثر البالغ في مسيرتي العلمية والعملية.

إلى والدتي العزيزة، التي كانت بدعائها الصادق وحنانها الدائم وتشجيعها المستمر مصدر قوة وعزيمة لي في مختلف مراحل حياتي.

وإلى والدي العزيز، الذي غرس في نفسي قيم الصبر والمثابرة والاجتهاد، وعلمني أن النجاح ثمرة العمل الجاد والإصرار.

كما أهدي هذا الإنجاز إلى زوجتي الغالية، تقديرًا لما بذلته من صبر وتفهم ومساندة طوال هذه الرحلة، فكانت خير عون وسند، وكان لدعمها أثر كبير في إتمام هذا العمل.

وإلى أبنائي الأعزاء جني ومحمد والمعتصم بالله، أهدي هذا العمل اعتزازًا بهم ومحبةً لهم، راجيًا أن يكون هذا الإنجاز حافزًا لهم على طلب العلم، والتمسك بالطموح، والسعي الدائم نحو التميز والنجاح.

كما أتقدم بخالص الشكر والتقدير إلى أساتذتي الأفاضل، الذين كان لهم فضل التوجيه والإرشاد، ولم يخلوا بعلمهم وخبراتهم، فكانوا منارات علم ومعرفة في مسيرتي الأكاديمية.

وإلى زملائي وأصدقائي، الذين قدّموا لي الدعم والتشجيع، وكانوا عونًا لي في مختلف مراحل هذه الرحلة العلمية.

وأخيرًا، أهدي هذا العمل إلى كل من ساندني أو دعا لي أو أسهم في دعمي ولو بكلمة طيبة، سائلًا الله العليّ القدير أن يجعل هذا الجهد خالصًا لوجهه الكريم، وأن يكون خطوة مباركة في طريق العلم والعمل والنجاح.

شكر وتقدير

الحمد لله رب العالمين، الذي بنعمته تتم الصالحات، وبفضله وتوفيقه تتحقق الغايات،
والصلاة والسلام على سيدنا محمد، وعلى آله وصحبه أجمعين.

أتقدم بخالص الشكر وعظيم الامتنان إلى والديّ العزيزين، لما قدّماه لي من دعاء
ودعم وتشجيع مستمر، كان له الأثر الكبير في مسيرتي العلمية والعملية، وأسأل الله
أن يجزيهما عني خير الجزاء.

كما أتوجه بجزيل الشكر والتقدير إلى زوجتي الكريمة، لما قدمته من صبر وتفهم
ومساندة طوال فترة إعداد هذه الرسالة، فقد كانت عوناً وسنداً لي في هذه الرحلة
العلمية.

وأتقدم بخالص الشكر والتقدير إلى أساتذتي الأفاضل، الذين لم يخلوا عليّ بعلمهم
وتوجيهاتهم ونصائحهم القيّمة، وكان لإرشادهم أثر واضح في إنجاز هذا العمل.

وأخص بالشكر والتقدير مشرفيّ الكريمين، لما قدّماه من دعم علمي وتوجيه
أكاديمي وملاحظات بناءة أسهمت في تطوير هذه الرسالة وإخراجها بالصورة
المرجوة.

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د. فايز جرّاد

كما أتقدم بالشكر إلى زملائي وأصدقائي، الذين كانوا عوناً لي بدعمهم وتشجيعهم،
وكان لوقوفهم بجانبني أثر طيب في تجاوز كثير من الصعوبات.

وفي الختام، أتقدم بالشكر والتقدير إلى كل من ساهم بكلمة طيبة، أو نصيحة
صادقة، أو دعم مباشر، أو غير مباشر في إنجاز هذا العمل، سائلاً الله العليّ القدير أن
يجعل هذا الجهد نافعاً، وأن يوفقنا جميعاً لما فيه الخير والنجاح.

المستخلص

الأهداف: هدفت هذه الدراسة إلى فحص العلاقات بين إدارة المخاطر التعاقدية وإدارة مخاطر سلسلة الإمداد والأداء المالي المدرك في مشاريع الإنشاءات، مع دراسة دور تبني الذكاء الاصطناعي في دعم ممارسات إدارة المخاطر واتخاذ القرارات المالية. **مكان الدراسة:** تم تطبيق الدراسة على مشاريع الإنشاءات، بما في ذلك مشاريع الإنشاءات الصناعية، في المنطقة الشرقية بالمملكة العربية السعودية. **المنهجية:** اعتمدت الدراسة على المنهج الكمي الوصفي التحليلي، وتم جمع البيانات باستخدام استبانة إلكترونية وُزعت على مختصين في مجالات إدارة المشاريع، العقود، المشتريات، سلسلة الإمداد، المخاطر، الهندسة، والمالية. وبعد فحص البيانات، تم تحليل 34 استجابة صالحة باستخدام الإحصاء الوصفي، تحليل الثبات، الارتباط، الانحدار المتعدد، وتحليل الدور المعدل. **النتائج:** أظهرت نتائج تحليل الارتباط وجود علاقات إيجابية بين متغيرات الدراسة. كما أظهر تحليل الانحدار أن إدارة مخاطر سلسلة الإمداد كانت المتغير الأكثر وضوحًا في ارتباطه بالأداء المالي المدرك. ومع ذلك، لم تدعم اختبارات التفاعل وجود دور تعديلي ذي دلالة إحصائية لتبني الذكاء الاصطناعي في العلاقات بين إدارة المخاطر التعاقدية أو إدارة مخاطر سلسلة الإمداد والأداء المالي المدرك. الكلمات المفتاحية: إدارة المخاطر التعاقدية، إدارة مخاطر سلسلة الإمداد، الذكاء الاصطناعي، الأداء المالي، مشاريع الإنشاءات.

Abstract

Objectives: This study aimed to examine the relationships between contractual risk management, supply chain risk management, and perceived financial performance in construction projects, while investigating the role of adoption of artificial intelligence in supporting risk-management practices and financial decision-making. **Place of Study:** The study was conducted in construction projects, including industrial construction projects, in the Eastern Province of Saudi Arabia. **Methodology:** The study adopted a quantitative descriptive-analytical approach. Data were collected through an electronic questionnaire distributed to professionals in project management, contracts, procurement, supply chain, risk management, engineering, and finance. After data screening, 34 valid responses were analyzed using descriptive statistics, reliability analysis, correlation analysis, multiple regression, and moderation analysis. **Results:** Correlation analysis indicated positive associations among the study constructs. The regression analysis showed that supply chain risk management had the clearest association with perceived financial performance. However, the interaction tests did not support a statistically significant moderating role of artificial intelligence adoption in the relationships between contractual risk management or supply chain risk management and perceived financial performance.

Keywords: Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence, Financial Performance, Construction Projects

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List of Terminology

Term in English	المصطلح بالعربية
Contractual Risk Management	إدارة المخاطر التعاقدية
Supply Chain Risk Management	إدارة مخاطر سلسلة الإمداد
Artificial Intelligence Adoption	تبني الذكاء الاصطناعي
Perceived Financial Performance	الأداء المالي المدرك
Variation Order	أمر التغيير
Extension of Time	تمديد المدة
Critical Path	المسار الحرج
Liquidated Damages	الأضرار المقطوعة

List of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
AIA	Artificial Intelligence Adoption
CRM	Contractual Risk Management
SCRM	Supply Chain Risk Management
FP	Perceived Financial Performance
ERM	Enterprise Risk Management
SCM	Supply Chain Management
TAM	Technology Acceptance Model
RBV	Resource-Based View
DCT	Dynamic Capability Theory
EOT	Extension of Time
LDs	Liquidated Damages
ISO	International Organization for Standardization
COSO	Committee of Sponsoring Organizations of the Treadway Commission
UNCTAD	United Nations Conference on Trade and Development

CHAPTER ONE

INTRODUCTION

1.1 Introduction

The construction sector contributes to economic development through infrastructure provision and its intersectoral linkages with other areas of the economy (Giang & Pheng, 2011). Lafhaj et al. (2024) identified construction project complexity as a multidimensional phenomenon involving technical, organizational, and managerial factors. Construction projects also involve multiple stakeholders whose collaborative or adversarial relationships may influence project costs, schedules, claims, disputes, and risk-management effectiveness (Yang et al., 2023). Consequently, an integrated risk-management approach is required to identify, assess, and manage interconnected risks that may affect project delivery and organizational performance.

In Saudi Arabia, construction activity is closely linked to the implementation of Saudi Vision 2030 through national initiatives related to infrastructure, housing, industrial development, energy, logistics, and urban transformation. The National Industrial Development and Logistics Program aims to strengthen the Kingdom's industrial capabilities and develop Saudi Arabia into a leading global logistics hub (National Industrial Development and Logistics Program [NIDLP], 2024). These objectives support the broader Saudi Vision 2030 agenda of economic diversification and national transformation (Saudi Vision 2030, 2025). This national context is relevant to the present study because the implementation of large-scale development initiatives involves complex contractual arrangements, extensive procurement activities, multiple project stakeholders, and interconnected supply networks.

The Eastern Province provides a relevant empirical setting for this study because it combines energy-related industrial activities with extensive construction, manufacturing, and logistics operations. Its transport infrastructure, including highways, airports, and seaports, connects industrial projects and contracting organizations with domestic and international supply networks. The presence of King Salman Energy Park (SPARK), an integrated energy and industrial ecosystem located between Dammam and Al-Ahsa, further reinforces the Province's strategic role in supporting energy-sector localization, industrial development, and supply chain integration. This concentration of capital-intensive projects and interconnected supply arrangements makes the Eastern Province particularly suitable for examining contractual risk management, supply chain risk management, artificial intelligence adoption, and perceived financial performance (King Salman Energy Park [SPARK], n.d.; Saudi Vision 2030, n.d.).

Within this regional setting, construction and industrial projects often involve technically complex work packages, substantial financial commitments, multiple contracting parties, and supply chains extending across local and international markets. Their execution depends on the coordinated availability of construction materials, specialized equipment, and long-lead items. Construction supply chains may be exposed to supplier-related, procurement, transportation, operational, and external risks that can affect project continuity and performance (Baghalzadeh Shishehgarhaneh et al., 2024). In addition, disruptions affecting maritime routes, ports, and major transport chokepoints may increase delivery times, logistics costs, and uncertainty across international supply networks (United Nations Conference on Trade and Development [UNCTAD], 2024). The interaction of these factors highlights the importance of systematic construction supply chain risk management, particularly when delays in critical project inputs may affect schedules, costs, and contractual obligations.

Many projects experience delays, cost overruns, contractual disputes, procurement disruptions, resource shortages, and operational inefficiencies. These challenges frequently arise from uncertainties and risks that occur throughout the project lifecycle. Consequently, effective risk management has become a critical success factor for construction organizations seeking to improve project outcomes and maintain financial sustainability.

Construction projects are exposed to interrelated sources of uncertainty arising from planning and scheduling deficiencies, inaccurate cost estimation, design changes, contractual ambiguities, resource constraints, and external market conditions. Previous reviews indicate that these factors may interact and contribute to schedule delays, cost overruns, and weaker project performance, particularly during the project execution stage (Abdelalim et al., 2025; Gómez-Cabrera et al., 2024). In accordance with ISO 31000, risk management involves a structured process for identifying, analyzing, evaluating, treating, monitoring, and communicating risks that may affect organizational objectives. Applying this process throughout the project lifecycle is therefore important for managing potential effects on project schedules, costs, contractual obligations, and perceived financial performance (International Organization for Standardization [ISO], 2018).

Contractual risk in construction projects arises from the allocation of rights, responsibilities, and potential liabilities among project stakeholders. Construction contracts establish the parties' obligations regarding scope, payment, performance, variations, claims, time extensions, and dispute resolution. However, unclear contractual provisions,

inappropriate risk allocation, scope and design changes, delayed payments, and delays in work progress may generate claims and increase the time and cost required to resolve disagreements. Effective contractual risk management therefore requires clear risk allocation, systematic contract monitoring, timely communication, accurate documentation, and proactive claims administration throughout the project lifecycle (Antoniou & Tsioulpa, 2024; Tang et al., 2020).

Construction projects also depend on the coordinated flow of materials, equipment, services, information, and specialized subcontracting resources. Disruptions associated with supplier failure, procurement delays, transportation constraints, long-lead items, material shortages, and price volatility may propagate across the supply chain and adversely affect project schedules, costs, and contractual obligations. Accordingly, supply chain risk management requires systematic identification, assessment, mitigation, and monitoring of risks across procurement, supplier management, transportation, and logistics activities. It should also be integrated with contract administration because delayed or unavailable project inputs may result in additional costs, extension-of-time claims, disagreements over responsibility, and weaker perceived financial performance (Antoniou & Tsioulpa, 2024; Baghalzadeh Shishehgarkhaneh et al., 2024).

Where construction and industrial projects depend on imported materials, specialized equipment, and long-lead components, exposure to maritime transport conditions becomes an important dimension of supply chain risk. Disruptions affecting ports, shipping routes, or maritime chokepoints may extend transit times, increase freight and insurance costs, and reduce the reliability of scheduled deliveries. UN Trade and Development has emphasized that disruptions at major maritime chokepoints can place pressure on global supply chains through vessel rerouting, port congestion, longer transportation distances, and higher operating costs (United Nations Conference on Trade and Development [UNCTAD], 2024).

The Strait of Hormuz is particularly relevant to the Gulf context because it connects the Persian Gulf with the Gulf of Oman and represents one of the world's most important energy transit chokepoints (U.S. Energy Information Administration [EIA], 2025). For construction organizations, disruptions affecting Regional maritime routes may delay the delivery of critical project inputs and generate secondary contractual and financial consequences, including schedule slippage, additional logistics expenditure, extension-of-time claims, acceleration costs, cash-flow pressure, and reduced project margins. These relationships support the treatment of geopolitical and maritime disruptions as contextual

sources of contractual and supply chain risk rather than as separate variables within the study's conceptual model (Baghalzadeh Shishehgarkhaneh et al., 2024; UNCTAD, 2024).

Digital transformation has increased the availability of project-related data generated through enterprise systems, scheduling platforms, procurement records, contract management processes, and business intelligence tools. Within this digital environment, artificial intelligence refers to computational methods that enable systems to analyze structured and unstructured data, identify patterns, generate predictions, and support organizational decision-making. Relevant AI methods include machine learning, natural language processing, knowledge-based reasoning, optimization algorithms, and computer vision. In construction risk management, these methods have been applied to predictive modelling, document and compliance analysis, schedule and resource optimization, and real-time risk monitoring. However, their effective implementation remains dependent on data quality, model interpretability, organizational readiness, and the availability of appropriate technical skills (Tian et al., 2025).

For the present study, the relevance of artificial intelligence lies in its potential to integrate and analyze contractual, procurement, supplier, scheduling, and financial information. Natural language processing and machine-learning models can assist in reviewing construction contracts and identifying clauses associated with risks, responsibilities, rights, and obligations (Dikmen et al., 2025). Similarly, empirical research on artificial intelligence in supply chain management indicates that its organizational value depends on data and system requirements, implementation processes, interorganizational integration, and the context in which performance is assessed (Culot et al., 2024). Accordingly, this study does not assume that artificial intelligence automatically improves project outcomes; rather, it empirically examines whether AI adoption contributes to the effectiveness of contractual and supply chain risk management and whether it moderates their relationships with perceived financial performance.

Contractual and supply chain risks are closely interconnected within construction projects. Delays in the delivery of materials or specialized equipment may disrupt project schedules and subsequently generate additional costs, extension-of-time claims, disagreements regarding responsibility, and pressure on project cash flows. Similarly, delayed payments and unresolved contractual matters may weaken supplier relationships and disrupt procurement activities. Managing these risks therefore requires coordinated information from contract administration, procurement, supplier management, project

scheduling, cost control, and financial reporting. Artificial intelligence may support this coordination by identifying patterns and early warning signals across multiple data sources; however, its effectiveness depends on data quality, technological integration, organizational readiness, and the availability of appropriate analytical capabilities (Baghalzadeh Shishehgarkhaneh et al., 2024; Culot et al., 2024; Tian et al., 2025).

Financial performance in the present study refers to perceived financial performance as assessed by the study respondents, rather than to audited accounting records. It encompasses perceptions of project cost control, profitability, cash-flow stability, reduction of financial losses, and the organization's ability to limit the financial consequences of delays, claims, and supply chain disruptions. Although contractual risk management, supply chain risk management, artificial intelligence adoption, and financial performance have received increasing research attention, they have frequently been examined as separate areas.

Based on the literature reviewed, further empirical investigation is required to determine whether artificial intelligence adoption contributes to the effectiveness of contractual and supply chain risk management and whether it moderates their relationships with perceived financial performance.

1.2 Problem Statement

Despite advances in project planning and control practices, construction projects continue to experience schedule delays and cost overruns arising from interacting managerial, contractual, and supply chain factors. Previous research identifies inadequate planning, inaccurate cost estimation, scope and design changes, resource constraints, procurement difficulties, and market volatility among the recurring causes of project underperformance (Gómez-Cabrera et al., 2024). In addition, inappropriate contractual risk allocation may increase conflict negotiation costs, while supply chain disruptions may extend across procurement, logistics, and project execution activities (Baghalzadeh Shishehgarkhaneh et al., 2024; Tang et al., 2020). These interconnected problems may increase unplanned expenditure, prolong project duration, intensify contractual claims, and create pressure on the perceived financial performance of construction organizations.

The research problem is particularly relevant to contracting companies operating in the Eastern Province of Saudi Arabia, where energy-related industrial and construction activities are closely connected to local and international supply networks. The presence of integrated energy and industrial ecosystems such as King Salman Energy Park, together with connections to highways, airports, seaports, and railway infrastructure, illustrates the interdependence between project execution and logistics connectivity in the Province (King Salman Energy Park [SPARK], n.d.). Contractors operating in this environment may rely on imported equipment, specialized materials, multiple suppliers, and multilayered subcontracting arrangements. Consequently, project performance may be influenced by internal planning and execution practices as well as by external disruptions affecting procurement, transportation, and supplier networks (Baghalzadeh Shishehgarkhaneh et al., 2024).

Empirical evidence from Saudi public construction and industrial projects indicates that contractual and supply-related problems remain relevant to project performance. Bageis (2024) found that contractual issues represented the most frequently occurring category associated with payment delays in Saudi public construction projects, with slow decision-making regarding claims and the failure to approve variation orders among the most commonly reported causes. Similarly, Abdellatif and Alshibani (2019), in their study of industrial and manufacturing projects in the Eastern Province, identified late procurement, delayed material delivery, delayed progress payments, and slow decision-making as important causes of project delay. These findings indicate that contractual and supply chain risks may interact rather than operate independently, potentially affecting project schedules, cash flows, costs, and contractors' perceived financial performance.

Regional geopolitical escalation affecting the Strait of Hormuz illustrates how security-related events may develop into maritime transportation and supply chain risks. UN Trade and Development reported that military escalation in 2026 disrupted shipping flows through the Strait and generated wider effects across energy markets, maritime transport, and global supply chains. The disruption was also associated with increases in tanker freight rates, marine fuel costs, and war-risk insurance premiums (United Nations Conference on Trade and Development [UNCTAD], 2026). Given the Strait's strategic importance as a major transit route for oil and liquefied natural gas, uncertainty surrounding maritime access may reduce delivery reliability and increase transportation-related costs for organizations that depend on imported materials and equipment (U.S. Energy Information Administration

[EIA], 2025). In the present study, geopolitical developments are therefore treated as contextual sources of external supply chain risk rather than as an independent variable within the conceptual model.

For construction organizations operating in the Eastern Province, delays in imported equipment, specialized materials, or critical spare parts may interrupt scheduled project activities and extend project completion periods. These disruptions may also generate secondary contractual consequences, including extension-of-time claims, disagreements regarding responsibility for delays, and the need for acceleration or alternative procurement measures. From a financial perspective, delayed deliveries may increase procurement, transportation, expediting, site overhead, and idle-resource costs while postponing project billing and cash inflows. Therefore, the problem extends beyond logistics performance to include the combined effects of supply chain disruption and contractual exposure on contractors' perceived financial performance (Antoniou & Tsioulpa, 2024; Baghalzadeh Shishehgarkhaneh et al., 2024).

Digital project management, enterprise resource planning, scheduling, procurement, and business intelligence systems can generate substantial volumes of contractual, supplier, schedule, cost, and financial data. However, the availability of digital data does not necessarily indicate that it is effectively integrated or used for AI-enabled risk prediction. Research on artificial intelligence in construction risk management identifies continuing implementation challenges related to data quality, model interpretability, technological integration, and workforce skills (Tian et al., 2025). Similarly, empirical literature on artificial intelligence in supply chain management indicates that organizational value depends on data and system requirements, technology deployment processes, interorganizational integration, and the context in which performance is assessed (Culot et al., 2024). The unresolved practical problem is therefore whether construction organizations can integrate fragmented project information to generate timely and reliable warnings about interconnected contractual, supply chain, and financial risks.

Accordingly, the central research problem is the limited context-specific empirical understanding of the relationships among contractual risk management, supply chain risk management, artificial intelligence adoption, and perceived financial performance in construction and industrial projects in the Eastern Province of Saudi Arabia. In particular, it remains necessary to determine whether effective contractual and supply chain risk management are associated with stronger perceived financial performance, whether artificial

intelligence adoption contributes to the effectiveness of these risk management practices, and whether it moderates their relationships with perceived financial performance. The study therefore addresses this problem by testing an integrated conceptual model that incorporates these relationships within the selected Regional and sectoral context.

1.3 Significance of the Study

1.3.1 Academic Significance

The academic significance of this study lies in developing and empirically testing an integrated framework that examines contractual risk management, supply chain risk management, artificial intelligence adoption, and perceived financial performance within a single research model. Rather than examining contractual risks, supply chain risks, and artificial intelligence as separate management issues, the study evaluates their interrelationships within construction and industrial project environments in the Eastern Province of Saudi Arabia. This integration provides a more comprehensive basis for understanding how different organizational risk-management practices are associated with perceived financial outcomes.

The study also contributes by examining artificial intelligence adoption in two theoretically distinct roles. First, it assesses whether AI adoption is associated with the effectiveness of contractual and supply chain risk management. Second, it tests whether AI adoption moderates the relationship between these risk-management practices and perceived financial performance. By distinguishing between these roles, the study avoids assuming that the availability of artificial intelligence automatically improves project outcomes and instead subjects its proposed contribution to empirical examination. The study therefore provides context-specific evidence that may support the further development of research on technology-enabled risk management in construction projects.

1.3.2 Practical Significance

The practical significance of this study lies in the potential usefulness of its findings to professionals responsible for managing construction and industrial projects in the Eastern Province of Saudi Arabia. The results may assist project managers, contract managers, procurement managers, supply chain professionals, risk specialists, and financial controllers in identifying the contractual and supply chain risk-management practices most closely associated with perceived financial performance. This evidence may support the prioritization of risk responses, the improvement of supplier and procurement monitoring,

the timely administration of contractual notices and claims, and the coordination of project schedule, cost, and cash-flow information.

The study may also provide practical guidance regarding the organizational use of artificial intelligence in project risk management. By examining AI adoption empirically, rather than assuming its effectiveness, the study may help organizations determine whether greater integration of contractual, procurement, supplier, schedule, and financial data is associated with stronger risk identification and decision support. The findings may therefore assist managers in evaluating where AI-enabled tools can add value, what organizational capabilities are required for their implementation, and which risk-management activities should remain subject to professional judgment and managerial oversight.

1.3.3 Policy and Strategic Significance

The policy and strategic significance of this study derives from its relevance to national priorities concerning economic diversification, digital transformation, infrastructure development, and the efficient delivery of capital projects under Saudi Vision 2030. These priorities emphasize the development of institutional capabilities, the use of digital technologies, and the improvement of government and organizational performance. In addition, the Government Expenditure and Projects Efficiency Authority seeks to improve the quality and efficiency of government-funded projects, assets, facilities, and infrastructure planning, which reinforces the strategic importance of systematic project risk management (Digital Government Authority [DGA], 2025; Government Expenditure and Projects Efficiency Authority [EXPRO], n.d.; Saudi Vision 2030, 2025).

By examining contractual risk management, supply chain risk management, and artificial intelligence adoption within an integrated empirical model, the study may provide context-specific evidence for public and private organizations involved in construction and industrial projects. Such evidence may inform discussions concerning project governance, risk-informed planning, digital decision support, procurement resilience, and the efficient allocation of project resources. However, the study does not claim to produce direct policy outcomes; rather, its findings may contribute empirical insights that support organizational and policy discussions related to the delivery of capital projects in the Eastern Province of Saudi Arabia.

1.4 Research Objectives

1. To identify the major contractual risks affecting contracting companies involved in construction projects, including industrial construction projects, in the Eastern Province of Saudi Arabia.
2. To identify the major supply chain risks affecting contracting companies in the Eastern Province, particularly those related to imported materials, long lead-time equipment, supplier delays, logistics disruptions, import restrictions, price fluctuations, and geopolitical uncertainty.
3. To evaluate the perceived contribution of artificial intelligence adoption to risk identification, risk prediction, and risk-management decision-making in construction projects.
4. To examine the relationships between contractual risk management, supply chain risk management, and perceived financial performance in construction projects.
5. To test whether artificial intelligence adoption is associated with the effectiveness of contractual risk management and supply chain risk management and whether it moderates their relationships with perceived financial performance within an integrated conceptual model.

1.5 Research Questions

1. What are the major contractual risks affecting contracting companies involved in construction and industrial projects in the Eastern Province of Saudi Arabia?
2. What are the major supply chain risks affecting contracting companies in the Eastern Province, particularly those related to imported materials, long lead-time equipment, logistics disruptions, supplier delays, import restrictions, price fluctuations, and geopolitical uncertainty?
3. How does artificial intelligence adoption contribute to risk identification, risk prediction, and risk-management decision-making in construction projects?
4. What are the relationships between contractual risk management, supply chain risk management, and perceived financial performance in construction projects?

5. Is artificial intelligence adoption associated with the effectiveness of contractual risk management and supply chain risk management, and does it moderate their relationships with perceived financial performance?

1.6 Research Hypotheses

H1: Contractual Risk Management is positively associated with perceived Financial Performance.

H2: Supply Chain Risk Management is positively associated with perceived Financial Performance.

H3: Artificial Intelligence Adoption is positively associated with Contractual Risk Management effectiveness.

H4: Artificial Intelligence Adoption is positively associated with Supply Chain Risk Management effectiveness.

H5: Artificial Intelligence Adoption positively moderates the relationship between Contractual Risk Management and perceived Financial Performance.

H6: Artificial Intelligence Adoption positively moderates the relationship between Supply Chain Risk Management and perceived Financial Performance.

1.7 Scientific Theory Adopted for Research

The study adopts an integrated theoretical perspective consisting of Enterprise Risk Management Theory, Supply Chain Management Theory, Project Management Theory, Technology Acceptance Model, Resource-Based View, and Dynamic Capability Theory. Collectively, these theories provide a comprehensive explanation of how organizations manage risks, adopt technological innovations, develop strategic capabilities, and improve financial performance in complex project environments.

Enterprise Risk Management Theory (ERM)

Enterprise Risk Management Theory explains how organizations identify, assess, respond to, and monitor risks within an integrated organizational framework (Committee of Sponsoring Organizations of the Treadway Commission [COSO], 2017). In this study, ERM supports the analysis of contractual risks and supply chain risks as organizational risks that may affect project objectives and financial performance. It also supports the need to move from fragmented risk handling to enterprise-wide risk visibility.

Supply Chain Management Theory (SCM)

Supply Chain Management Theory emphasizes the coordination of materials, information, services, and relationships among supply chain participants (Christopher, 2023). In the construction context, effective supply chain management ensures the availability of materials, equipment, services, and information at the right time, cost, and quality. This theory supports the study's focus on vendor delays, long lead-time items, logistics disruptions, import restrictions, and price escalation.

Project Management Theory

Project Management Theory focuses on planning, executing, monitoring, and controlling projects within scope, time, cost, quality, and resource constraints (Project Management Institute [PMI], 2021). This theory supports the analysis of how contractual and supply chain risks affect project schedules, cost control, claims, and overall project success.

Technology Acceptance Model (TAM)

The Technology Acceptance Model explains technology adoption primarily through perceived usefulness and perceived ease of use (Davis, 1989). In this study, TAM helps explain whether construction professionals accept and use AI tools for risk identification, risk prediction, contract analysis, and procurement decision-making.

Resource-Based View (RBV)

The Resource-Based View proposes that organizations may achieve sustained competitive advantage when they possess resources that are valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). In the present study, integrated project data, AI-enabled systems, supplier-performance information, analytical expertise, and digital platforms are regarded as strategic organizational resources that may strengthen contractual risk management, supply chain risk management, and perceived financial performance.

Dynamic Capabilities Theory

Dynamic Capabilities Theory explains how organizations integrate, build, and reconfigure internal and external competencies in response to rapidly changing environments (Teece et al., 1997). The inclusion of geopolitical uncertainty and supply chain disruptions within the Eastern Province context supports the application of this theoretical perspective. Construction organizations exposed to changing shipping conditions, supplier disruptions,

and regional geopolitical tensions require dynamic capabilities to adapt their resources, processes, and risk responses. Artificial intelligence adoption may contribute to these capabilities by enabling faster data analysis, improved risk forecasting, and more informed decision-making.

1.8 Operational Definitions and Abbreviations:

For this study, the following operational definitions and abbreviations are adopted:

Term / Abbreviation	Operational Definition
Artificial Intelligence (AI)	Artificial Intelligence (AI) refers to computational technologies that enable systems to analyze data, identify patterns, learn from prior information, generate predictions, and support decision-making. In this study, AI includes machine learning, predictive analytics, natural language processing, expert systems, and intelligent dashboards used to support contractual and supply chain risk management.
Artificial Intelligence Adoption (AIA)	The extent to which a construction organization uses AI-based tools and data-driven systems to support risk identification, risk prediction, procurement planning, contract analysis, cost forecasting, and project decision-making.
Contractual Risk Management (CRM)	The process of identifying, analyzing, responding to, and monitoring risks arising from construction contracts. These risks may include payment delays, variation orders, scope changes, ambiguous contract clauses, contract interpretation disputes, claims, and dispute resolution issues.
Supply Chain Risk Management (SCRM)	The process of identifying, assessing, and mitigating risks that may affect the flow of materials, equipment, services, and information from suppliers to

	construction projects. These risks may include vendor delays, long lead-time items, import restrictions, logistics issues, price escalation, material shortages, and transportation disruptions.
Financial Performance (FP), Operationalized as Perceived Financial Performance	Financial Performance in this study refers to respondents' perceptions of the ability of a construction project or organization to achieve favorable financial outcomes. It is measured through questionnaire-based assessments rather than audited financial statements or actual accounting records. The construct includes perceived cost control, profitability, cash-flow stability, reduction of financial losses, and the ability to minimize the financial consequences of project delays and claims.
Enterprise Risk Management (ERM)	A structured and organization-wide approach to identifying, assessing, responding to, and monitoring risks that may affect strategic, operational, and financial objectives.
Supply Chain Management (SCM)	The coordination and control of materials, equipment, services, information, and financial flows among suppliers, contractors, subcontractors, and project owners.
Technology Acceptance Model (TAM)	A theoretical model that explains technology adoption based on perceived usefulness and perceived ease of use. In this study, it supports the explanation of AI acceptance in construction risk management.
Resource-Based View (RBV)	A strategic theory suggests that organizations can achieve competitive advantage through valuable, rare, and difficult-to-imitate resources. In this study, AI capabilities, data systems, and analytical skills may be considered strategic resources.
	A theory explains how organizations adapt, integrate, and reconfigure resources and capabilities in response

Dynamic Capability Theory (DCT)	to changing environments. In this study, it supports the explanation of how construction organizations can use AI to respond to supply chain disruptions and contractual uncertainties.
Long Lead-Time Items	Materials or equipment that require extended time for procurement, manufacturing, shipping, inspection, or installation. Examples include transformers, pumps, valves, control systems, electrical panels, steel structures, and specialized mechanical equipment.
Variation Orders	Formal changes to the original contract scope, quantities, specifications, schedule, or project requirements. They may affect project cost, duration, and financial performance.
Claims	Formal requests submitted by one contracting party seeking additional time, additional payment, or contractual relief due to events that affect project execution.
Geopolitical Risk	Political, military, or diplomatic events that may affect business operations, trade routes, supply chains, energy prices, investment decisions, or project delivery. In this study, Iran–Israel escalation and risks around the Strait of Hormuz are examples of geopolitical risks that may influence construction supply chains in the Eastern Province.
Critical Path	The sequence of project activities determines the minimum completion time of the project. A delay in any activity on the critical path may delay the overall project completion date.
Extension of Time (EOT)	A contractual mechanism through which a contractor may request additional time to complete the project due to qualifying delay events.

Liquidated Damages (LDs)	Pre-agreed damages stated in the contract may be applied when the contractor fails to complete the project within the agreed completion time, subject to the contract terms.
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1.9 Scope and Context of the Study

The geographical scope of this study covers construction projects in the Eastern Province of Saudi Arabia, including projects delivered within industrial environments. Its sectoral scope includes building construction, infrastructure, mechanical construction, industrial facilities, manufacturing-support activities directly related to construction project delivery, and construction-related operations and maintenance activities.

The study population comprises professionals working in project management, contract management, procurement, supply chain management, risk management, engineering, and financial control. These respondents were selected because their professional responsibilities involve contractual obligations, supplier relationships, procurement activities, project schedules, claims, cost control, and financial performance.

The study examines four principal constructs: Contractual Risk Management and Supply Chain Risk Management as independent variables, Artificial Intelligence Adoption as a predictor of risk-management effectiveness and a moderating variable, and Financial Performance—operationalized in this study as perceived financial performance—as the dependent variable.

The study is limited to contractual and supply chain risks and does not examine all technical, environmental, safety, political, or operational risks affecting construction projects. Geopolitical and maritime disruptions are treated as contextual sources of supply chain uncertainty rather than as independent research variables.

The temporal context primarily covers project and market conditions between 2020 and 2026, including post-pandemic supply chain volatility, digital transformation, and recent disruptions affecting regional logistics networks. Company-related examples are included only to illustrate the practical setting and are not treated as empirical evidence.

1.10 Practical Company Context and Illustrative Examples

To strengthen the practical relevance of this study, illustrative examples are drawn from the operational environment of a leading construction and industrial contracting group operating in the Eastern Province of Saudi Arabia. The company context is used only to demonstrate how contractual risk management, supply chain risk management, artificial intelligence adoption, and financial performance may interact in actual contracting operations. These examples are not treated as empirical findings and do not change the population of the study, which remains contracting companies operating in the Eastern Province of Saudi Arabia.

The company and its operating entities are involved in engineering, procurement and construction activities, operations and maintenance, mechanical construction, industrial fabrication, infrastructure works, building construction, ready-mix activities, and logistics support. These activities involve multiple clients, suppliers, subcontractors, consultants, financial institutions, and regulatory authorities. As a result, the company operates in a complex environment in which project performance depends on effective coordination among contract management, procurement, supply chain, project controls, finance, engineering, and site operations. From a contractual risk perspective, the company's projects may be exposed to delayed payments, scope changes, variation orders, delayed client approvals, disputed quantities, extension-of-time claims, retention recovery issues, performance guarantees, advance payment guarantees, and potential liquidated damages. These risks may directly affect project cash flow, cost recovery, profitability, and the company's ability to meet its financial and contractual obligations.

From a supply chain perspective, the company's projects depend on the timely availability of materials, equipment, fabricated items, specialized spare parts, and subcontracted services. Certain projects require imported pipes, pumps, valves, electrical panels, control systems, cables, steel materials, and other long lead-time items. Delays in manufacturing, inspection, shipping, customs clearance, inland transportation, or supplier delivery may affect critical project activities and create additional financial and contractual consequences.

An illustrative scenario relevant to the company's operating context involves a shipment of pipes originally scheduled to arrive at Dammam Port. Under conditions of uncertainty affecting regional maritime routes, the contractor might decide to redirect the

shipment to Jeddah Port to reduce the potential impact on the project schedule and maintain progress on critical construction activities.

Although such a diversion could help protect the project schedule, it might generate additional logistics and inland transportation costs associated with moving the materials from Jeddah to the project location. Urgently required materials might also need to be transported by air freight to avoid disruption to critical project activities, thereby creating further cost implications.

This illustrative scenario demonstrates the relationship between geopolitical risk, supply chain risk management, contractual obligations, and perceived financial performance. Without timely mitigation, the project could experience delays, idle manpower and equipment, disruption to critical activities, extension-of-time issues, and potential exposure to contractual penalties. However, the selected mitigation measures could require the contractor to accept additional short-term costs in order to reduce the probability of a more substantial schedule delay and its associated contractual consequences.

From a risk-management perspective, the decision would represent a trade-off between schedule protection and cost control. The mitigation action would not eliminate the financial impact of the disruption; rather, it would aim to avoid a potentially greater loss arising from delayed completion, reduced productivity, prolonged site overheads, or contractual penalties. The scenario therefore illustrates how effective supply chain risk management may preserve project continuity while simultaneously creating short-term pressure on project costs and profit margins.

The company also uses digital systems and management tools to support project, procurement, financial, and performance monitoring. These systems generate information related to purchase orders, supplier performance, project schedules, project costs, invoices, collections, claims, variation orders, guarantees, and project progress. However, the availability of digital data does not necessarily mean that artificial intelligence is fully integrated across all risk management activities.

Artificial intelligence adoption may strengthen the use of the company's existing data by integrating information from contracts, procurement, scheduling, supplier performance, finance, and project control systems. For example, an AI-enabled system could compare planned delivery dates with supplier performance, identify purchase orders that may affect the critical path, detect abnormal cost increases, forecast potential delivery delays, and estimate the possible financial impact of supply chain disruption.

In the practical case described above, an AI-supported early warning system could potentially have combined shipping information, supplier delivery status, port conditions, procurement records, and project schedule requirements to identify the risk at an earlier stage. Such information could support faster decisions regarding shipment diversion, air freight, alternative suppliers, work resequencing, contractual notices, and cost impact assessment.

The company context therefore illustrates that contractual risk management and supply chain risk management are closely connected. A supply chain disruption may initially appear as a procurement or logistics issue, but it may later create contractual claims, additional costs, cash flow pressure, schedule delays, and reduced profitability. Artificial intelligence adoption may strengthen the organization's ability to identify such risks earlier, analyze their possible consequences, and select appropriate mitigation actions.

Accordingly, these practical examples illustrate the conceptual relationships examined in this study. Contractual Risk Management and Supply Chain Risk Management are treated as independent variables associated with perceived Financial Performance, while Artificial Intelligence Adoption is examined both as a predictor of risk-management effectiveness and as a moderating variable in the relationships between CRM, SCRM, and perceived Financial Performance. The examples are included solely to clarify the practical context and are not treated as empirical or statistical evidence.

1.11 Chapter Summary

This chapter established the general foundation of the study by presenting its background, research problem, significance, objectives, questions, hypotheses, theoretical foundations, operational definitions, and scope. It explained the relevance of construction and industrial projects in the Eastern Province of Saudi Arabia and identified contractual and supply chain risks as interconnected sources of project and financial uncertainty. Geopolitical and maritime disruptions were treated as contextual factors that may intensify supply chain exposure rather than as independent variables in the research model. The chapter also clarified the proposed roles of artificial intelligence adoption as a predictor of contractual and supply chain risk-management effectiveness and as a potential moderator of their relationships with perceived financial performance. Chapter Two reviews the relevant empirical literature, develops the theoretical and conceptual foundations of the study, and identifies the research gap addressed by the model.

CHAPTER TWO

PREVIOUS STUDIES

2.1 Introduction

Chapter Two reviews previous studies and theoretical foundations related to contractual risk management, supply chain risk management, artificial intelligence adoption, and financial performance in construction projects. In accordance with the structure required for the final project, this chapter is titled Previous Studies and includes the literature review, theoretical framework, research gap analysis, and conceptual framework development.

The study focuses on contracting companies operating in the Eastern Province of Saudi Arabia. The Eastern Province is a highly relevant research context because it includes major industrial, oil and gas, manufacturing, infrastructure, and building construction activities.

It also hosts strategic development initiatives such as King Salman Energy Park, which is described by Saudi Vision 2030 as a major industrial hub in Eastern Saudi Arabia, and it includes a wide portfolio of projects reported by the Sharqia Development Authority, including energy, infrastructure, urban development, and public-facility projects (Saudi Vision 2030, n.d.; Sharqia Development Authority, n.d.).

The chapter also considers practical examples from a diversified contracting and industrial group operating in the Eastern Province. The examples are used only for practical illustration and do not limit the population of the study. The broader population remains contracting companies operating in the Eastern Province, including companies engaged in oil and gas, industrial, mechanical construction, operations and maintenance, building construction, and infrastructure projects.

The literature reviewed in this chapter indicates that construction risks rarely occur in isolation. A delayed shipment of imported equipment may become a procurement problem, a schedule delay, a contractual claim, a cash flow issue, and ultimately a financial performance problem. Similarly, ambiguous contract clauses may affect claims management, supplier coordination, extension-of-time decisions, and the allocation of additional costs. For this reason, the current study reviews contractual risk management and supply chain risk management as interconnected fields rather than isolated practices.

Artificial intelligence adoption is examined as a strategic capability that may strengthen risk management effectiveness. AI-enabled systems can analyze historical project data, procurement records, supplier performance, schedule information, contract documentation, cost reports, and external market signals. Therefore, the literature review

gives special attention to predictive analytics, early warning systems, AI-enabled decision support, and the potential of AI to improve project financial outcomes.

2.2 Previous Studies

This section reviews empirical and conceptual studies related to the four main constructs of the study: Contractual Risk Management (CRM), Supply Chain Risk Management (SCRM), Artificial Intelligence Capabilities/Adoption (AIA), and Financial Performance (FP). The review also covers studies and reports relevant to the Eastern Province project environment and geopolitical supply chain risk.

2.2.1 Previous Studies on Contractual Risk Management

Contractual Risk Management (CRM) is a critical area of construction project management because contracts establish the legal and administrative framework through which project stakeholders define scope, obligations, responsibilities, payment terms, change procedures, risk allocation, and dispute resolution mechanisms.

In construction projects, poor contract administration frequently leads to disputes, claims, delays, cost overruns, and financial losses.

The literature shows that contractual risks are particularly important in large-scale industrial and infrastructure projects, where several parties interact under complex technical and commercial conditions. Typical contractual risks include payment delays, variation orders, scope changes, unclear clauses, contract interpretation disputes, claims, liquidated damages, and extension-of-time issues.

These risks affect not only project execution but also project cash flow and profitability. Payment delay is one of the most frequently reported contractual risks in the Saudi construction industry. Bageis (2024) found that contractual issues were among the leading causes of payment delays in Saudi public construction projects.

Payment delays weaken contractor cash flow, affect supplier payments, reduce subcontractor confidence, and may create secondary risks in procurement and workforce productivity. Variation orders and change orders are also widely discussed in construction literature.

In Saudi public construction projects, recent evidence suggests that change orders can create a domino effect by affecting cost, time, productivity, and stakeholder relationships (Alsulami, 2025).

In the Eastern Province, variation orders may become more complex when projects involve imported equipment, specialized materials, or industrial interfaces. For example, a change in the specification of a mechanical system may require procurement of a new long lead-time item, which can then affect both schedule and cost.

Contract interpretation disputes are another important area. Construction contracts often contain technical specifications, commercial conditions, special terms, and risk allocation clauses. When these clauses are unclear or interpreted differently by owners, contractors, subcontractors, and suppliers, disputes may arise.

This is especially relevant in projects where supply chain disruptions or geopolitical events affect material delivery, because parties may disagree over whether such events justify time extension, cost compensation, or contract variation.

The literature generally supports the view that effective CRM improves project outcomes. Proper contract administration, timely documentation, claims management, notice procedures, risk allocation, and dispute avoidance mechanisms can reduce uncertainty and protect financial performance. However, many previous studies examine contractual risks independently and do not sufficiently integrate them with supply chain disruptions or AI-enabled analytics.

Table 2.1 Summary of Previous Studies on Contractual Risk Management

Main Findings	Focus	Country/Context	Year	Author(s)
Effective administration of project obligations supports project success and reduces disputes.	Project management and contract administration	USA / Global	2022	Kerzner
Contractual issues were identified as important causes of payment delays.	Payment delays in public construction projects	Saudi Arabia	2024	Bageis
Change orders may create a domino effect on cost, time, productivity, and claims.	Change orders in public construction projects	Saudi Arabia	2025	Alsulami
Contractors face significant exposure when delays are not documented or managed properly.	Claims, extension of time, and liquidated damages	Saudi Arabia	2025	Zheng
Risk management and clear project controls are necessary for achieving project objectives.	Project management practices	Arab context	2018	Al-Ali

Critical Evaluation of CRM Literature

The reviewed literature confirms the importance of CRM in construction projects. Nevertheless, three limitations are evident. First, many studies examine contractual risks separately from procurement and supply chain risks, even though these risks often interact in practice.

Second, previous studies frequently focus on project performance indicators such as time and cost rather than direct financial performance indicators such as profitability, cash flow stability, and cost control.

Third, few studies examine how AI-enabled systems can support contract analysis, claims prediction, early warning of disputes, and financial impact forecasting.

2.2.2 Previous Studies on Supply Chain Risk Management

Supply Chain Risk Management (SCRM) has become a strategic concern for construction companies because projects depend heavily on the timely availability of materials, equipment, specialized subcontractors, logistics providers, and supplier services.

Construction supply chains are often fragmented, project-based, and exposed to external disruptions, making them more vulnerable than repetitive manufacturing supply chains. Construction projects in the Eastern Province of Saudi Arabia are particularly exposed to supply chain risks because many oil and gas, industrial, mechanical,

infrastructure, and building projects depend on imported materials and specialized equipment.

Examples include pumps, valves, electrical panels, control systems, steel structures, cables, heavy equipment, and other long lead-time items. Delays in these items may directly affect the critical path of a project. Shishehgharkhaneh et al. (2024) reviewed construction supply chain risk management research and reported that the field has evolved toward more systematic risk identification, classification, and assessment approaches, including emerging interest in AI applications.

Saudi-focused evidence has also highlighted the importance of construction supply chain risk. Alqahtani (2026) provided a systematic assessment of construction supply chain risks in the Saudi context and identified critical risk factors through literature review, expert consultation, and survey analysis.

Common supply chain risks include vendor delays, poor supplier reliability, long lead-time items, import restrictions, customs delays, logistics disruptions, port congestion, material shortages, and price escalation. These risks may reduce productivity, increase idle resources, force procurement changes, and generate additional costs. When supply chain risks affect contractual obligations, they may also create claims and disputes. Recent geopolitical conditions have increased the importance of supply chain resilience. The escalation between Iran and Israel and related risks affecting the Strait of Hormuz provide a relevant example of geopolitical supply chain risk. UNCTAD (2026) reported that disruptions in the Strait of Hormuz can create ripple effects beyond the Province, affecting energy markets, maritime transportation, and global supply chains. For contracting companies in the Eastern Province, such disruptions may increase uncertainty around shipping, insurance, fuel prices, freight rates, and delivery schedules.

These geopolitical risks should be treated cautiously and academically as examples of external supply chain risk rather than political analysis. Their relevance to this study lies in their potential impact on imported construction materials, heavy equipment, and long lead-time industrial components. If shipping routes are disrupted or costs increase, projects may face procurement delays, cost escalation, extension-of-time claims, acceleration expenses, and reduced profitability. Effective SCRM therefore requires more than supplier follow-up. It involves supplier qualification, procurement planning, logistics monitoring, alternative sourcing, inventory buffers for critical materials, price escalation analysis, and early warning

systems. AI can strengthen these practices by analyzing supplier data, procurement history, shipping indicators, market prices, and project schedules.

Table 2.2 Summary of Previous Studies on Supply Chain Risk Management

Main Findings	Focus	Country/Context	Year	Author(s)
Resilient supply chains help organizations anticipate and recover from disruption.	Supply chain resilience	UK / Global	2016/2023	Christopher
Digital technologies improve visibility, disruption response, and adaptive supply chain decisions.	Digital supply chains and resilience	Global	2021/2022	Ivanov
CSCRM research increasingly addresses risk classification and AI applications.	Construction supply chain risk management review	Global construction	2024	Shishehgarkhaneh et al.
Saudi construction projects face multiple critical supply chain risk factors.	Saudi construction supply chain risks	Saudi Arabia	2026	Alqahtani
Disruptions may affect energy markets, maritime transport, and global supply chains.	Strait of Hormuz disruptions	Global trade / Gulf context	2026	UNCTAD

Critical Evaluation of SCRM Literature

Although SCRM has been widely studied, important limitations remain. Many SCRM studies focus on manufacturing environments rather than project-based construction settings. In addition, limited research integrates SCRM with CRM, despite the fact that supplier delays frequently create contractual claims. Moreover, Saudi and Eastern Province evidence remains limited, especially in diversified contracting firms working across oil and gas, industrial, O&M, mechanical construction, building construction, and infrastructure projects. Finally, the role of AI as a moderating capability in the SCRM–financial performance relationship remains underdeveloped.

2.2.3 Previous Studies on Artificial Intelligence Adoption (AIA)

Artificial Intelligence Adoption (AIA) has become an important research area in construction project management, supply chain management, and risk management. AI refers to technologies that enable systems to analyze data, recognize patterns, generate predictions, automate analysis, and support decision-making. In construction projects, AI applications include schedule prediction, cost forecasting, risk classification, document review, contract analysis, claims analytics, supplier assessment, and early warning systems.

Recent research indicates that AI and machine learning can improve supply chain risk assessment by enhancing predictive capability and identifying patterns that may not be

visible through traditional analysis. Jahin et al. (2024) reviewed AI in supply chain risk assessment and reported that AI/ML techniques can improve precision in risk assessment and support resilient contingency planning.

AI is also increasingly relevant to construction project management. Gao et al. (2026) reviewed AI applications in construction project management and highlighted applications in cost, time, and safety management, while also identifying challenges related to cross-domain integration and practical implementation. These findings are relevant to the current study because construction risk management requires integration between cost, time, procurement, contracts, and financial control.

In practical contracting environments, AI adoption does not occur in isolation. It depends on the availability of digital data and project systems. A diversified contracting company in the Eastern Province may use SAP, ERPNext, Primavera P6, and Power BI to manage procurement, finance, scheduling, project controls, and reporting.

These systems can provide the data foundation for AI-enabled risk analysis. For example, Primavera P6 schedule data can be linked with procurement records to identify long lead-time items that threaten the critical path, while Power BI dashboards can visualize risk indicators for management review. However, AI adoption faces barriers. These include data quality problems, fragmented systems, lack of skilled employees, cybersecurity concerns, cost of implementation, resistance to change, and uncertainty about AI reliability. In addition, AI outputs must be governed carefully because project decisions may have legal, contractual, safety, and financial consequences.

From a theoretical perspective, the Technology Acceptance Model explains AI adoption through perceived usefulness and perceived ease of use. The Resource-Based View explains AI as a strategic resource, while Dynamic Capability Theory explains how AI can help organizations sense risks, seize response options, and transform operating practices under uncertainty.

Table 2.3 Summary of Previous Studies on Artificial Intelligence Adoption

Main Findings	Focus	Context	Year	Author(s)
AI applications in project management were still developing, with gaps in procurement and communication processes.	AI in project management review	Project management	2020	Davahli
AI/ML improves predictive risk assessment and supports resilient planning.	AI/ML in supply chain risk assessment	Supply chain risk	2024	Jahin et al.
AI techniques increasingly support risk identification, assessment, mitigation, and monitoring.	AI applications for supply chain risk management	SCRM	2025	Ordibazar et al.
AI supports cost, time, and safety management, but implementation challenges remain.	AI in construction project management	Construction	2026	Gao et al.
Modern project success requires strategic decision-making, adaptability, and value creation.	Future of project work and business acumen	Project management	2024/2025	PMI

Critical Evaluation of AI Adoption Literature

AI literature provides strong support for the potential of predictive analytics and decision support. Nevertheless, several gaps remain. First, many studies discuss AI benefits conceptually rather than empirically testing AI adoption in real construction organizations. Second, limited research examines AI as a moderating variable that strengthens the relationship between risk management and financial performance. Third, relatively few studies address how existing systems such as SAP, ERPNext, Primavera P6, and Power BI can serve as a practical data foundation for AI-enabled risk management in contracting companies.

2.2.4 Previous Studies on Financial Performance

Financial Performance (FP) represents the dependent variable in this study. In construction companies, financial performance reflects the ability to control costs, protect profit margins, maintain cash flow, reduce losses, and achieve financial sustainability. Unlike general project performance, which may include time, quality, safety, and stakeholder satisfaction, financial performance focuses specifically on the economic consequences of project decisions and risks. Previous studies generally show that effective risk management improves financial outcomes. Contractual disputes, claims, payment delays, procurement disruption, material price escalation, and project delays often increase costs and reduce profitability. Conversely, proactive risk management supports cost control, reduces unnecessary claims, improves cash flow predictability, and protects margins.

Financial performance is especially important for contracting companies because the industry typically operates with high working capital requirements and payment cycles that may be affected by project progress, certifications, changing approvals, and client payment practices. If a contractor experiences delayed payments while also facing supplier price escalation or equipment delays, the combined effect may weaken liquidity and profitability. AI-enabled systems can support financial performance by improving cost forecasting, procurement planning, risk-based budgeting, claims analysis, and cash flow monitoring. For example, an AI-enabled dashboard may combine cost data from ERP systems, schedule progress from Primavera P6, and procurement data from SAP or ERPNext to forecast the financial impact of delayed materials or unresolved claims.

However, financial performance has often been treated as a general outcome in previous studies rather than being directly linked to CRM, SCRM, and AI adoption in an integrated model. This limitation justifies the present study's focus on the direct effects of CRM and SCRM on FP and the moderating role of AIA.

Table 2.4 Summary of Previous Studies on Financial Performance

Main Findings	Focus	Context	Year	Author(s)
Financial indicators remain essential for evaluating organizational success.	Balanced performance measurement	Strategic performance	1992/2022	Kaplan & Norton
Project success increasingly requires strategic value creation beyond time, cost, and scope.	Project success and business value	Project management	2024/2025	PMI
Digital and AI capabilities can enhance decision-making and operational efficiency.	AI and organizational performance	Digital transformation	2024	Deloitte
Saudi public-sector initiatives emphasize project quality, spending efficiency, and improved project outcomes.	Expenditure and project efficiency	Saudi Arabia	2024/2026	EXPRO
AI adoption can contribute to productivity and financial performance when supported by governance and capabilities.	AI and performance	Global	2025	PwC

2.2.5 Literature Related to the Eastern Province Project Environment

The Eastern Province provides a distinctive empirical context for the present study. It includes major industrial cities, ports, oil and gas facilities, manufacturing zones, energy projects, and urban infrastructure developments. The Sharqia Development Authority reports a portfolio of projects and initiatives aligned with Vision 2030, while Saudi Vision 2030 identifies King Salman Energy Park as a key industrial hub in Eastern Saudi Arabia (Saudi Vision 2030, n.d ; Sharqia Development Authority, n.d.).

Contracting companies in the Eastern Province may operate in several project types simultaneously, including operations and maintenance, mechanical construction, manufacturing support, building construction, infrastructure works, and industrial facilities. This diversified portfolio increases managerial complexity and creates interdependencies among contracts, procurement, suppliers, project controls, and finance. The Saudi Contractors Authority has a national role in organizing and developing the contracting sector, while EXPRO aims to improve project quality and spending efficiency in government entities (Saudi Contractors Authority, n.d.; EXPRO, n.d.). These institutional developments highlight the importance of professional risk management, project governance, and performance improvement in the Saudi construction sector.

Practical examples from the focal contracting and industrial group indicate that companies in the Eastern Province may use digital systems such as SAP, ERPNext, Primavera P6, and Power BI. These systems can support procurement, finance, project scheduling, reporting, and operational visibility. However, their value depends on how well they are integrated and whether the company uses data analytically to predict risk rather than only report historical performance.

Table 2.5 Relevance of Eastern Province Project Environment to the Study Variables

Project Environment	Practical Characteristics	Relevance to Study Variables
Oil & Gas / Industrial Projects	Complex interfaces, strict specifications, critical equipment, long lead-time materials	CRM: claims, scope changes, EOT; SCRM: imported equipment, vendor delays; FP: high cost exposure
Mechanical Construction	Dependence on pumps, valves, piping, rotating equipment, and specialized vendors	SCRM: supplier performance and logistics; AI: predictive procurement alerts
Operations and Maintenance (O&M)	Continuous service obligations and penalties for service disruption	CRM: service-level obligations; FP: penalties and cash flow impact
Building Construction	Design changes, variation orders, subcontractor coordination	CRM: variation orders and claims; FP: cost control and margin protection
Infrastructure Projects	Public interfaces, permits, logistics, utilities, and stakeholder coordination	SCRM: material availability; CRM: scope and delay disputes
Manufacturing Support	Integration between production, procurement, and project delivery	AI: linking ERP data with project risk indicators

2.2.6 Literature on Geopolitical Supply Chain Risk

Geopolitical supply chain risk refers to political, military, diplomatic, or regional security developments that may affect trade routes, shipping conditions, energy prices, insurance costs, or supplier reliability. For this study, geopolitical risk is not examined as a separate political variable. Instead, it is treated as an external supply chain risk factor that may influence construction procurement and project delivery in the Eastern Province.

The Iran–Israel escalation and the resulting concern around Gulf maritime routes, including the Strait of Hormuz, provide a current and relevant example. UNCTAD (2026) indicates that disruption in the Strait of Hormuz can affect energy markets, maritime transport, and global supply chains. Reuters and other market sources have also reported uncertainty in shipping and transit conditions during periods of heightened tension. Such events may influence construction projects indirectly through shipping delays, increased insurance premiums, fuel cost volatility, and supplier delivery uncertainty.

In construction projects, this type of risk becomes operational when imported materials or equipment are delayed or become more expensive. It becomes contractual when parties disagree about responsibility for delay, entitlement to extension of time, escalation compensation, acceleration costs, or liquidated damages. It becomes financial when delayed delivery causes idle resources, delayed revenue, increased overheads, or lower profit margins.

AI-enabled risk management can help companies respond more proactively to such risks. AI tools may monitor supplier delivery performance, shipping indicators, price movements, customs lead times, and project schedule sensitivity. These tools can identify which purchase orders affect critical path activities and estimate the financial consequences of delay. This supports early decisions such as alternative sourcing, schedule resequencing, buffer stock, supplier diversification, or contractual notices.

Table 2.6 Geopolitical Supply Chain Risks and Potential Impact on Construction Projects

Risk Example	Supply Chain Effect	Potential Contractual and Financial Impact
Shipping route uncertainty	Delayed delivery of imported equipment	Schedule delay; extension-of-time claims
Higher freight and insurance costs	Increase in procurement cost	Budget overrun; reduced profit margin
Energy price volatility	Increase in logistics and material prices	Cost escalation and cash flow pressure
Supplier rescheduling	Change in delivery commitments	Procurement re-planning and potential claims
Port or customs congestion	Longer clearance and delivery times	Idle resources and project delay

2.2.7 Comparative Literature Review Matrix

Table 2.7 Comparative Literature Review Matrix

Variable/Theme	Most Common Findings	Research Limitation	Current Study Contribution
CRM	Contract administration reduces claims, disputes, and cost exposure.	Often studied separately from SCRM and AI.	Integrates CRM with SCRM, AIA, and FP in Eastern Region contracting companies.
SCRM	Supplier reliability, logistics, and long lead-time items affect project performance.	Limited construction-focused evidence in Saudi Eastern Region.	Examines SCRM in oil & gas, industrial, building, and infrastructure contexts.
AIA	AI supports prediction, decision support, early warnings, and analytics.	Limited use as a moderating variable.	Examines AIA as a moderator strengthening CRM/SCRM effects on FP.
FP	Risk management improves cost control, profitability, and cash flow stability.	Often measured as a general performance outcome.	Uses FP as the dependent variable linked to integrated risk practices.
Eastern Region Context	Major industrial and infrastructure environment under Vision 2030.	Limited empirical focus on Eastern Region contracting companies.	Focuses specifically on contracting companies operating in the Eastern Region.
Geopolitical Supply Chain Risk	External shocks affect logistics, prices, and availability.	Often treated broadly rather than linked to construction contracts.	Connects geopolitical supply risk with procurement delay, claims, and financial impact.

2.3 Theoretical Framework

The theoretical framework provides the intellectual foundation for explaining the relationships among CRM, SCRM, AIA, and FP. The current study integrates Enterprise Risk Management Theory, ISO 31000, COSO ERM, Supply Chain Management Theory, Technology Acceptance Model, Resource-Based View, and Dynamic Capability Theory. These theories collectively explain how contracting companies identify and manage risks, adopt digital technologies, develop organizational capabilities, and improve financial performance.

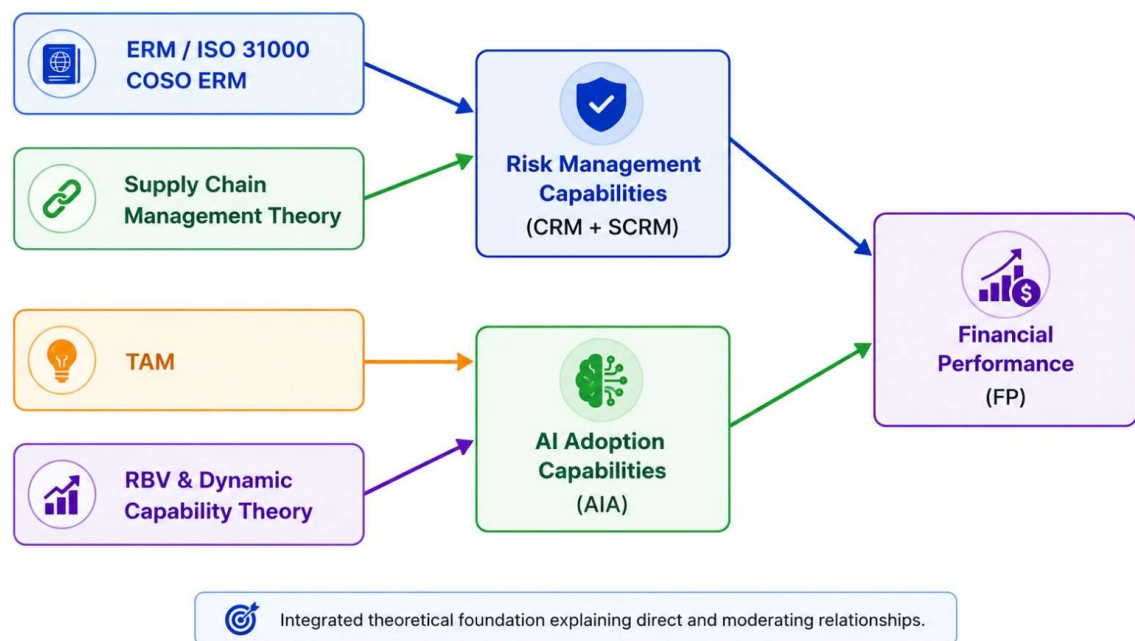


Figure 2.1 Integrated Theoretical Framework.

2.3.1 Enterprise Risk Management Theory

Enterprise Risk Management (ERM) provides a comprehensive approach to risk management. Instead of treating risks as isolated events, ERM encourages organizations to identify, assess, respond to, and monitor risks across the organization. In construction companies, ERM is relevant because project risks are interconnected across contracts, procurement, project controls, finance, and operations.

ERM supports the direct relationships in this study. Effective CRM can reduce contractual claims and financial losses, while effective SCRM can reduce procurement disruption and cost escalation. Therefore, ERM supports H1 and H2 by explaining how structured risk management practices contribute to financial performance.

2.3.2 ISO 31000 Risk Management Framework

ISO 31000:2018 provides internationally recognized guidelines for risk management. It emphasizes principles, a framework, and a process for risk management, including communication and consultation, risk assessment, risk treatment, monitoring, review, recording, and reporting (ISO, 2018).

In the context of this study, ISO 31000 is relevant because contracting companies in the Eastern Province need systematic procedures for identifying contractual and supply chain risks. The framework is applicable to different project types, including oil and gas, industrial, O&M, building, and infrastructure projects.

2.3.3 COSO Enterprise Risk Management Framework

COSO Enterprise Risk Management emphasizes the integration of risk management with strategy and performance. COSO (2017) highlights that risk should be considered in strategy-setting and performance management rather than treated as a separate compliance activity.

This perspective is relevant to the study because the dependent variable is financial performance. Contractual and supply chain risks are not only operational concerns; they influence strategic outcomes such as profitability, cost control, and cash flow stability. COSO therefore strengthens the theoretical basis for linking CRM and SCRM to FP.

2.3.4 Supply Chain Management Theory

Supply Chain Management Theory explains how organizations coordinate suppliers, manufacturers, logistics providers, subcontractors, and project sites to deliver value. In construction projects, the supply chain is often temporary, project-specific, and exposed to design changes, procurement constraints, and external market risks.

Supply chain resilience is particularly relevant to the Eastern Province because contracting companies often depend on imported equipment and long lead-time materials. SCM Theory supports H2 by explaining how effective SCRM improves financial performance, and it supports H4 and H6 by explaining how AI adoption may improve supply chain visibility and resilience.

2.3.5 Project Management Theory

Project Management Theory provides a structured perspective on the planning, execution, monitoring, and control of projects within scope, schedule, cost, quality, resource, and stakeholder constraints (Project Management Institute [PMI], 2021). In the present study,

this perspective supports the analysis of how contractual and supply chain risks may influence project schedules, cost control, claims administration, and perceived financial performance. It also provides a contextual basis for integrating risk-management decisions with project planning, monitoring, and control processes.

2.3.6 Technology Acceptance Model

The Technology Acceptance Model (TAM) explains technology adoption through perceived usefulness and perceived ease of use. In this study, AI adoption is more likely when project managers, contract managers, procurement managers, and finance professionals believe that AI improves risk prediction, decision-making, reporting, and financial control.

TAM supports H3 and H4 because AI adoption can improve contractual and supply chain risk management effectiveness when users perceive AI tools as useful and usable. For example, an AI-enabled dashboard linked to Primavera P6, and ERP data is more likely to be adopted if it clearly identifies delays, procurement risks, and financial impacts.

2.3.7 Project Management Theory

Project Management Theory emphasizes systematic planning, execution, monitoring, and control of project activities in order to achieve defined objectives within scope, time, cost, quality, and resource constraints (Project Management Institute [PMI], 2021). In construction projects, contractual obligations, procurement activities, supplier performance, project schedules, and financial controls are closely interconnected. Weak contract administration or supply chain disruption may therefore affect project duration, cost recovery, cash flow, and perceived financial performance. In the present study, Project Management Theory provides a practical basis for explaining how effective Contractual Risk Management and Supply Chain Risk Management may support project control and financial outcomes. It is particularly relevant to H1 and H2 because these hypotheses examine the relationships between CRM, SCRM, and perceived Financial Performance.

2.3.8 Resource-Based View

The Resource-Based View (RBV) argues that organizations achieve competitive advantage through valuable, rare, inimitable, and non-substitutable resources. In the present study, data, digital systems, AI tools, experienced employees, supplier databases, contract repositories, and project control capabilities can be considered strategic resources.

Practical examples from the focal company show that systems such as SAP, ERPNext, Primavera P6, and Power BI may create a valuable data foundation. However, these systems

create stronger value when integrated with AI analytics and managerial decision-making. RBV therefore supports H3, H4, H5, and H6.

2.3.9 Dynamic Capability Theory

Dynamic Capability Theory extends RBV by focusing on the organization's ability to sense changes, seize opportunities, and transform resources under changing conditions. This is highly relevant in construction environments characterized by uncertainty, supply chain volatility, and contractual complexity.

AI adoption can strengthen dynamic capabilities by enabling faster risk detection, more accurate forecasting, and better response planning. For example, AI can help a contracting company sense supplier delay, seize alternative procurement options, and transform schedule or resource plans before the delay causes major financial damage. Dynamic Capability Theory therefore provides a strong justification for H5 and H6, where AIA moderates the CRM–FP and SCRM–FP relationships.

Table 2.8 Relationship Between Theories and Research Hypotheses

Theory	Core Idea	Application in the Study	Supported Hypotheses
ERM	Integrated identification, assessment, and response to organizational risks	CRM and SCRM	H1, H2
ISO 31000	Structured risk management process	Risk identification, assessment, treatment, monitoring	H1, H2
COSO ERM	Risk integration with strategy and performance	Financial performance and governance	H1, H2
SCM Theory	Coordination of suppliers, logistics, and information flows	SCRM and supply chain resilience	H2, H4, H6
TAM	User acceptance of technology	AI adoption in risk management	H3, H4
RBV	Strategic value of resources and capabilities	AI systems, data, skills, digital platforms	H3, H4, H5, H6
DCT	Sensing, seizing, and transforming under uncertainty	AI as adaptive capability	H5, H6

2.4 Research Gap Analysis and Conceptual Framework Development

2.4.1 Research Gap Analysis

The literature review indicates that contractual risk management, supply chain risk management, artificial intelligence adoption, and financial performance have been studied extensively, but mostly as separate research streams. Construction companies, however, experience these issues simultaneously. A supplier delay may create a contractual claim, a

contract ambiguity may complicate procurement decisions, and both may affect financial performance.

Several research gaps justify the current study. First, limited studies integrate CRM and SCRM into one model. Second, limited research examines AI adoption as a capability that may directly improve contractual and supply chain risk management effectiveness and may also moderate the relationships between risk management practices and financial performance. Third, relatively few studies focus on the Eastern Province of Saudi Arabia, despite its strategic importance in industrial, oil and gas, infrastructure, and construction projects. Fourth, limited empirical work examines diversified contracting companies that operate across O&M, mechanical construction, manufacturing, building construction, and infrastructure. Fifth, many previous studies focus on time and cost performance rather than financial performance as a dependent variable.

Table 2.9 Detailed Research Gap Matrix

Research Gap Area	Existing Knowledge	Research Limitation	Current Study Contribution
Integrated CRM and SCRM	CRM and SCRM are often studied separately.	In practice, procurement delays often create contractual claims.	Examines CRM and SCRM together.
AI as moderator	AI is commonly studied as a tool or implementation issue.	Limited moderation analysis in risk–performance relationships.	Tests AIA as a moderating variable.
Financial performance	Many studies focus on cost/time project performance.	Fewer studies examine profitability, cash flow, and financial sustainability.	Uses FP as dependent variable.
Eastern Region focus	Saudi studies exist but are not always region-specific.	Limited empirical focus on Eastern Region contracting companies.	Focuses on companies operating in the Eastern Region.
Diversified contracting firms	Studies often focus on one project type.	Limited evidence for firms operating across O&M, manufacturing, mechanical, building, and infrastructure.	Uses practical examples from a diversified company.
Geopolitical supply chain risk	Often treated generally in supply chain studies.	Limited linkage to construction contracts and claims.	Links external supply risk to SCRM, CRM, and FP.

2.4.2 Conceptual Framework Development

The conceptual framework is developed based on the reviewed literature and theoretical foundations. It includes two independent variables: Contractual Risk Management and Supply Chain Risk Management. The dependent variable is Financial Performance, measured in this study as perceived financial performance. Artificial Intelligence Adoption is included in two related roles. First, AIA is examined as a predictor that may improve CRM and SCRM effectiveness. Second, AIA is examined as a moderating variable that may strengthen the effects of CRM and SCRM on FP.

CRM is expected to influence FP because effective contract administration, claims management, payment control, and variation management can reduce financial losses. SCRM is expected to influence FP because effective supplier management, procurement planning, logistics control, and price escalation management can reduce delays and cost increases. AIA is expected to improve CRM and SCRM effectiveness and to strengthen their relationship with FP through predictive analytics, early warning systems, and decision support.

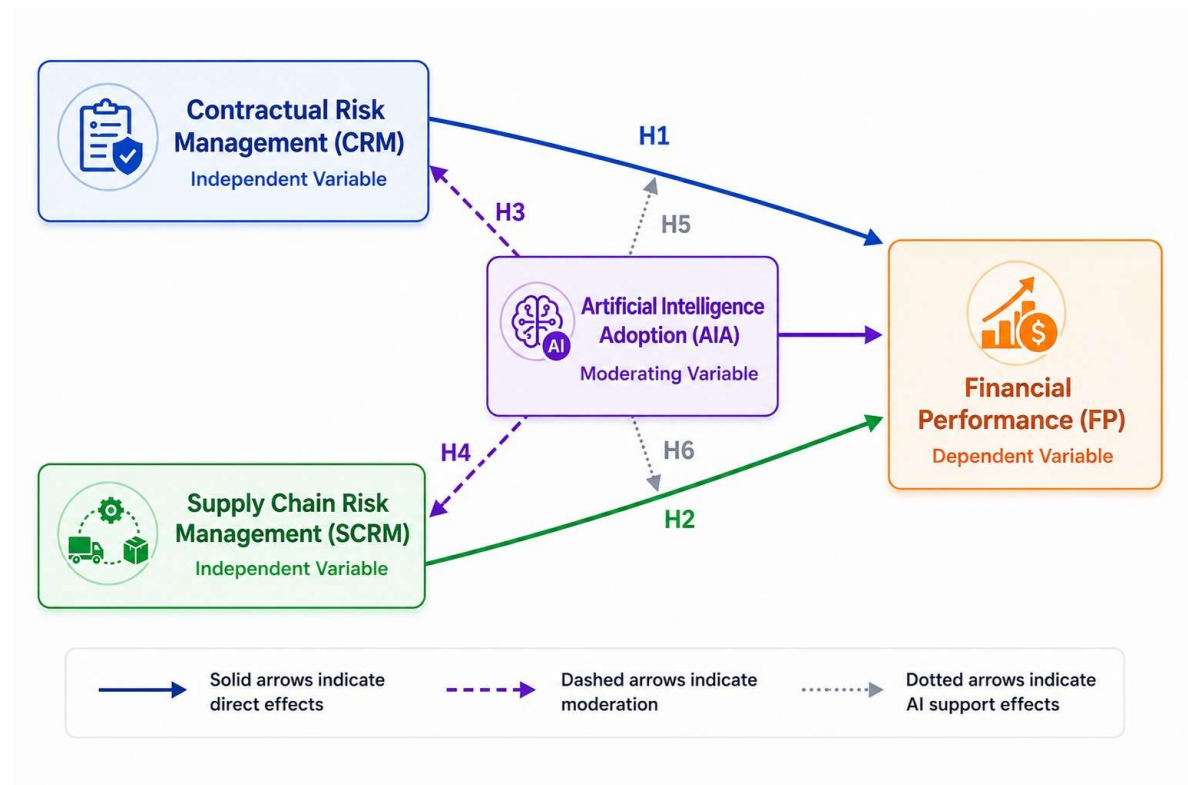


Figure 2.2 Conceptual Framework.

Explanation of Variables in the Conceptual Framework

Table 2.10 Study Variables and Their Role in the Conceptual Framework

Variable	Role	Key Dimensions	Expected Relationship
Contractual Risk Management (CRM)	Independent Variable	Payment delays, variation orders, scope changes, claims, contract interpretation disputes	Expected to improve FP when risks are managed effectively.
Supply Chain Risk Management (SCRM)	Independent Variable	Vendor delays, long lead-time items, import restrictions, logistics issues, price escalation	Expected to improve FP by reducing disruption and cost escalation.
Artificial Intelligence Capabilities/Adoption (AIA)	Moderating Variable	Predictive analytics, early warning systems, decision support, AI-enabled dashboards	Expected to strengthen the CRM-FP and SCRM-FP relationships.
Financial Performance (FP)	Dependent Variable	Profitability, cost control, cash flow stability, financial sustainability	Represents the outcome affected by risk management practices.

2.4.3 Operational Definitions of Research Constructs

Table 2.11 Operational Definitions of Study Variables

Construct	Operational Definition
CRM	The systematic identification, assessment, mitigation, and monitoring of contractual uncertainties that may affect project obligations, claims, delays, and financial outcomes.
SCRM	The systematic management of supplier, procurement, logistics, import, material, equipment, and price-related risks that may affect project continuity and cost performance.
AIA	AI-enabled capabilities used for early risk identification, risk prediction, decision support, contract risk monitoring, supply chain visibility, delay detection, and financial forecasting.
FP	The ability of contracting companies and projects to achieve cost control, profitability, cash flow stability, reduced losses, and financial sustainability.

2.4.4 Variables, Dimensions, and Measurement Indicators

Table 2.12 Variables, Dimensions, and Measurement Indicators

Variable / Code	Dimension	Questionnaire-Aligned Practical Indicator
CRM / CRM1	Contract clarity	Clarity of contract clauses and responsibilities.
CRM / CRM2	Approvals and amendments	Impact of delayed approvals and contract amendments.
CRM / CRM3–CRM4	Payment delays	Impact on cash flow and project risk.
CRM / CRM5–CRM6	Variation orders	Impact on cost and schedule.
CRM / CRM7–CRM9	Scope and unauthorized works	Risk of work without approval or outside approved scope.
CRM / CRM10	Contract management effectiveness	Reduction of contractual risks.
SCRM / SCRM1	Supplier reliability	Effect on project success.
SCRM / SCRM2–SCRM3	Material delivery and shortages	Impact on schedules and performance.
SCRM / SCRM4	Supplier failure	Potential for major project disruption.
SCRM / SCRM5	Transportation and logistics	Impact on project delays.
SCRM / SCRM6–SCRM8	Price and disruption impacts	Effect on project risks, costs, and delays.
AIA / AI1–AI2	Early risk identification and prediction	Early identification and improved prediction accuracy.
AIA / AI3–AI4	Decision support and contract monitoring	Better decisions and contractual risk monitoring.
AIA / AI5–AI6	Supply chain visibility and delay detection	Improved visibility and early delay detection.
AIA / AI7–AI8	Risk effectiveness and financial forecasting	Improved risk management and financial planning.
FP / FP1–FP2	Profitability and cost control	Improved profitability and cost control.
FP / FP3–FP5	Delay, cost overrun, and profitability impact	Financial effects of delays, contractual risks, and SCRM risks.
FP / FP6–FP7	AI-driven financial outcomes	Better financial performance and overall project outcomes.

2.4.5 Development of Research Hypotheses

H1: Contractual Risk Management significantly affects Financial Performance.

Justification: Effective CRM reduces claims, disputes, payment issues, and delay-related costs. Therefore, improved CRM is expected to improve cost control, cash flow, and profitability.

H2: Supply Chain Risk Management significantly affects Financial Performance.

Justification: Effective SCRM reduces supplier delays, logistics disruption, long lead-time item delays, and price escalation. Therefore, improved SCRM is expected to protect financial performance.

H3: Artificial Intelligence Adoption significantly improves Contractual Risk Management effectiveness.

Justification: AI can support contract analysis, documentation review, claims prediction, and early identification of contractual risk indicators.

H4: Artificial Intelligence Adoption significantly improves Supply Chain Risk Management effectiveness.

Justification: AI can support supplier performance analysis, delivery forecasting, price monitoring, and logistics risk prediction.

H5: Artificial Intelligence Adoption positively moderates the relationship between Contractual Risk Management and Financial Performance.

Justification: AI may strengthen the financial benefits of CRM by improving early warning, response speed, and financial impact analysis.

H6: Artificial Intelligence Adoption positively moderates the relationship between Supply Chain Risk Management and Financial Performance.

Justification: AI may strengthen the financial benefits of SCRM by improving visibility, forecasting, and proactive procurement decisions.

Table 2.13 Hypotheses Justification Matrix

Hypothesis	Supported Theory	Relationship	Expected Direction
H1	ERM, ISO 31000, COSO	CRM → FP	Positive/significant effect
H2	ERM, SCM Theory, ISO 31000	SCRM → FP	Positive/significant effect
H3	TAM, RBV	AIA → CRM effectiveness	Positive/significant effect
H4	TAM, SCM Theory, RBV	AIA → SCRM effectiveness	Positive/significant effect
H5	RBV, DCT	AIA moderates CRM → FP	Positive moderation
H6	SCM Theory, RBV, DCT	AIA moderates SCRM → FP	Positive moderation

2.4.6 Measurement Model

The measurement model is aligned with the actual questionnaire administered in this study. The instrument included six demographic questions and 33 Likert-scale measurement items: 10 items for Contractual Risk Management (CRM1–CRM10), 8 items for Supply Chain Risk Management (SCRM1–SCRM8), 8 items for Artificial Intelligence Adoption (AI1–AI8), and 7 items for perceived Financial Performance (FP1–FP7). For statistical analysis, a composite score was calculated for each construct by averaging its corresponding questionnaire items.

Table 2.14 Measurement Structure

Construct	Number of Items	Main Dimensions
Contractual Risk Management (CRM)	10	Contract clarity, approvals, payments, variation orders, scope control, contract management
Supply Chain Risk Management (SCRM)	8	Supplier reliability, material delivery, shortages, supplier failure, logistics, price fluctuation, disruptions
Artificial Intelligence Adoption (AIA)	8	Risk identification, prediction, decision support, contract monitoring, supply chain visibility, delay detection, financial forecasting
Perceived Financial Performance (FP)	7	Profitability, cost control, delay impact, cost overruns, supply chain profitability impact, AI-driven outcomes

2.5 Chapter Summary

This chapter reviewed previous studies related to contractual risk management, supply chain risk management, artificial intelligence adoption, and perceived financial performance. The literature indicates that each construct has received considerable attention; however, limited studies have integrated these constructs within a single empirical framework, particularly in the context of contracting companies operating in the Eastern Province of Saudi Arabia. The chapter also developed the theoretical framework by integrating Enterprise Risk Management, ISO 31000, the COSO Enterprise Risk Management Framework, Supply Chain Management Theory, Project Management Theory, Technology Acceptance Model, the Resource-Based View, and Dynamic Capability Theory. Collectively, these theoretical perspectives and risk-management frameworks provide support for the hypothesized relationships among CRM, SCRM, AIA, and perceived financial performance, including the proposed moderating role of AIA. The chapter further identified the principal research gaps, developed the conceptual framework, clarified the role of each study variable, and presented the research hypotheses and measurement model. The next chapter presents the research methodology, including research philosophy, approach, design, population, sampling procedures, data-collection instrument, measurement of the study variables, reliability and validity procedures, ethical considerations, and statistical analysis methods.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodological procedures adopted to examine the relationship between Contractual Risk Management (CRM), Supply Chain Risk Management (SCRM), Artificial Intelligence Capabilities/Adoption (AIA), and Financial Performance (FP) within contracting companies operating in the Eastern Province of Saudi Arabia. The chapter explains the research design, methodological approach, research population, sampling technique, data collection method, questionnaire structure, measurement scales, validity and reliability procedures, statistical analysis plan, ethical considerations, and research boundaries.

The methodology is designed to be consistent with the objectives of the study and the conceptual framework developed in Chapter Two. The study investigates how contractual and supply chain risk management practices affect financial performance and whether AI capabilities strengthen these relationships. Because the research questions and hypotheses require measurable evidence from professionals working in construction-related environments, a quantitative survey approach is adopted.

In accordance with the final project template of Midocean University, Chapter Three focuses on the research methodology, methodology and research methods, research population, and research boundaries. However, additional sub-sections are included to make the chapter more complete and practically applicable to the field context of contracting companies in the Eastern Province.

3.2 Methodology and Research Methods

3.2.1 Research Philosophy

The study follows a positivist research philosophy. Positivism is suitable when the researcher aims to test hypotheses, measure relationships among variables, and analyze data objectively using statistical techniques. In the current study, the relationships among CRM, SCRM, AIA, and FP are examined through structured questionnaire responses that can be converted into numerical data and analyzed statistically.

This philosophical position is appropriate because the study does not seek to interpret individual experiences qualitatively, but rather to identify measurable patterns across a sample of professionals. Respondents' perceptions are used as indicators of actual practices related to contract management, supply chain management, AI-supported risk management, and financial outcomes in construction and industrial project environments.

3.2.2 Research Approach

The research adopts a deductive approach. The deductive approach begins with theories and prior literature, develops hypotheses, collects data, and then tests the proposed relationships empirically. In this study, the hypotheses were developed based on Enterprise Risk Management Theory, Supply Chain Management Theory, the Technology Acceptance Model, the Resource-Based View, and Dynamic Capability Theory.

The deductive approach is appropriate because the study has a clearly defined conceptual framework. CRM and SCRM are treated as independent variables, AIA is treated as a moderating variable, and FP is treated as the dependent variable. The statistical analysis will determine whether the collected data supports the proposed hypotheses.

3.2.3 Research Design

The study employs a quantitative, descriptive, analytical, and cross-sectional research design. It is quantitative because it relies on numerical data collected through a structured questionnaire. It is descriptive because it describes the current practices and perceptions of professionals regarding contractual risks, supply chain risks, AI capabilities, and financial performance. It is analytical because it examines the relationships among the variables and tests the proposed hypotheses.

The design is cross-sectional because data are collected at one point in time from respondents working in contracting companies in the Eastern Province of Saudi Arabia. This design is suitable for master's-level applied business research because it provides practical evidence within a manageable timeframe.

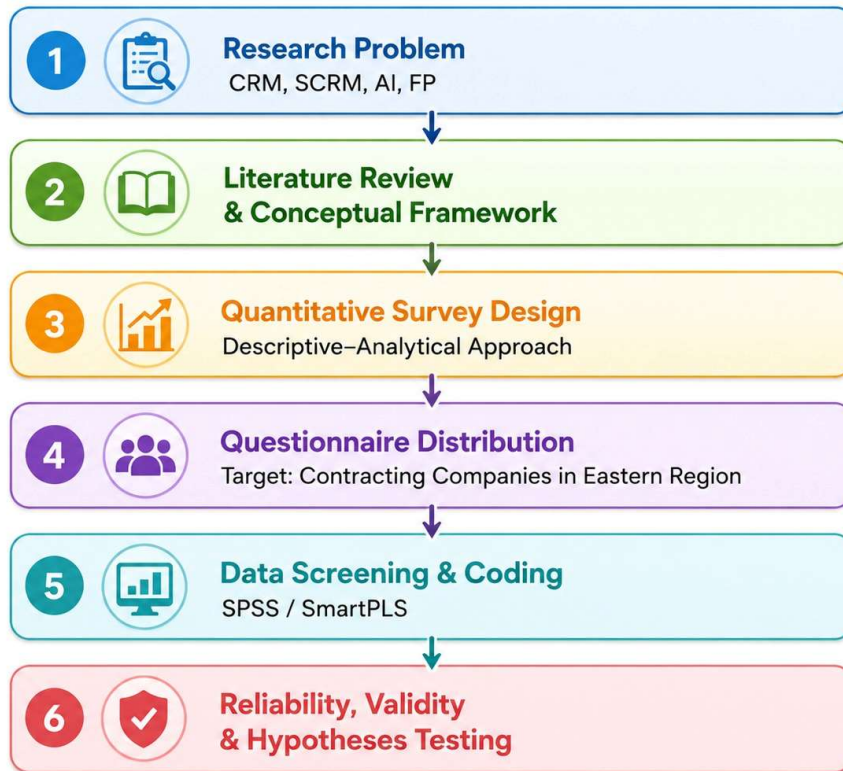


Figure 3.1 Research Design Flow

Figure 3.1 summarizes the methodological flow adopted in the study. The research begins with the problem and literature review, proceeds to the quantitative survey design, and then moves to data collection, data coding, reliability and validity assessment, and hypotheses testing.

3.2.4 Methodological Framework

Table 3.1 Methodological Framework of the Study

Methodological Element	Adopted Approach	Justification
Research philosophy	Positivism	Suitable for testing hypotheses and measuring relationships statistically.
Research approach	Deductive	The study tests relationships derived from theories and previous studies.
Research design	Quantitative, descriptive, analytical, cross-sectional	Appropriate for measuring perceptions of professionals at a specific point in time.
Data collection method	Structured questionnaire	Enables collection of standardized responses from a relatively broad group of respondents.
Measurement scale	Five-point Likert scale	Allows respondents to express the degree of agreement with each statement.
Analysis software	SPSS and/or SmartPLS	Supports descriptive statistics, reliability analysis, correlation, regression, and PLS-SEM.
Target respondents	Professionals in contracting companies	Respondents are directly involved in project, contract, procurement, supply chain, risk, engineering, finance, or IT functions.

3.3 Research Population

The research population consists of professionals working in contracting companies operating in the Eastern Province of Saudi Arabia. The Eastern Province is selected because it includes a high concentration of oil and gas, industrial, mechanical construction, operations and maintenance, building construction, and infrastructure projects. These project environments are exposed to complex contractual arrangements, procurement requirements, long lead-time materials, supplier dependency, logistics risks, and financial pressure.

The study does not focus on one company only. Instead, the population includes contracting companies operating in the Eastern Province. However, practical examples are drawn from a diversified contracting and industrial group operating in the Province. The company context is used illustratively because it includes business segments such as operations and maintenance, mechanical construction, manufacturing, building construction, and infrastructure, and because it uses digital systems such as SAP, ERPNext, Primavera P6, and Power BI. These systems provide a realistic foundation for discussing the potential role of AI-enabled risk management.

3.3.1 Target Respondents

The target respondents are professionals who have knowledge or experience related to construction project delivery, contract administration, procurement, supply chain management, risk management, finance, engineering, supervision, or project information systems. These respondents are appropriate because they are directly or indirectly involved in decisions that influence project risk and financial performance.

Table 3.2 Target Respondents and Their Relevance to the Study

Respondent Category	Relevance to the Study
Project Managers	Manage project execution, schedules, costs, risks, and coordination among stakeholders.
Contract Managers	Handle contract clauses, claims, variation orders, approvals, and contractual disputes.
Procurement Managers	Manage purchasing, suppliers, long lead-time items, and procurement planning.
Supply Chain Managers	Monitor supply chain continuity, logistics, supplier reliability, and material availability.
Risk Managers	Identify, assess, monitor, and mitigate project and enterprise risks.
Engineers and Supervisors	Observe site-level delays, material shortages, scope changes, and execution risks.
Financial Managers	Assess cash flow, cost control, profitability, and financial consequences of project risks.
IT Managers / Digital Systems Users	Understand the role of ERP, dashboards, analytics, and AI-supported systems.

3.3.2 Practical Company Context Used for Illustration

To make the methodology more connected to real practice, the study considers practical examples from a diversified contracting and industrial company operating in the Eastern Province. The company is not treated as the only research population; rather, it is used as an illustrative context showing how contracting companies may operate across several project types and digital systems.

Table 3.3 Practical Company Context Used as Illustrative Evidence

Practical Context Element	Illustrative Description	Methodological Relevance
Business segments	O&M, mechanical construction, manufacturing, building construction, and infrastructure	Reflects the mixed portfolio of many contracting companies in the Eastern Region.
Project environment	Oil and gas, industrial, infrastructure, and building-related works	Supports the focus on contractual and supply chain risks in complex projects.
Digital systems	SAP, ERPNext, Primavera P6, and Power BI	Supports the operational measurement of AI capabilities through data visibility, forecasting, and decision support.
Employee base	Large workforce with multiple technical and managerial functions	Provides realistic access to different professional categories.
Risk exposure	Payment delays, variation orders, scope changes, vendor delays, logistics issues, and price escalation	Directly aligned with the questionnaire dimensions.

3.4 Sampling Technique and Sample Size

The study uses a non-probability purposive sampling technique. Purposive sampling is appropriate because the study requires respondents who possess relevant knowledge of construction projects, contracts, procurement, supply chain risks, AI-supported systems, and financial performance. Random sampling is difficult in this context because the total number of eligible professionals across all contracting companies in the Eastern Province is not precisely known to the researcher.

The intended sample size was between 80 and 120 respondents, with a minimum preferred number of approximately 40 valid responses. This target was considered practical for a master's research project using a structured questionnaire and statistical analysis. However, after data screening in Chapter Four, the final cleaned dataset included 34 unique valid responses because fully duplicated records were excluded. Therefore, the findings are interpreted cautiously as exploratory evidence, and this limitation is reported explicitly in the data screening and limitations sections.

Table 3.4 Sampling Technique and Sample Size Plan

Sampling Element	Description
Sampling method	Non-probability purposive sampling
Target sample	Professionals in contracting companies operating in the Eastern Region
Preferred sample size	80–120 valid responses
Minimum practical sample	Approximately 40 valid responses
Selection criterion	Experience or involvement in projects, contracts, procurement, supply chain, risk, finance, engineering, or digital systems
Justification	The study requires informed respondents rather than general public participants

3.5 Data Collection Method

Primary data are collected using a structured questionnaire distributed electronically through Google Forms. The questionnaire is suitable for this study because it allows standardized measurement of respondents' perceptions regarding contractual risk management, supply chain risk management, AI capabilities/adoption, and financial performance. Electronic distribution also facilitates access to professionals working in different locations and project sites within the Eastern Province.

Secondary data is used to support the theoretical and methodological foundations of the study. These include academic books, journal articles, professional reports, risk management standards, project management references, and digital transformation literature. Secondary sources help justify the constructs, hypotheses, and statistical procedures adopted in the study.

3.5.1 Questionnaire Structure

The questionnaire consists of five sections. Section 1 collects demographic information. Sections 2 to 5 measure the four main constructs using a five-point Likert scale ranging from Strongly Disagree to Strongly Agree. The actual questionnaire includes 6 demographic questions and 33 Likert-scale measurement items.

Table 3.5 Questionnaire Structure

Section	Construct / Content	Item Codes	Number of Items
Section 1	Demographic Information	Gender, age, education, experience, position, and company type	6
Section 2	Contractual Risk Management	CRM1–CRM10	10
Section 3	Supply Chain Risk Management	SCRM1–SCRM8	8
Section 4	Artificial Intelligence Adoption	AI1–AI8	8
Section 5	Perceived Financial Performance	FP1–FP7	7
Total	Demographic and Likert-scale items	—	39

3.5.2 Likert Scale Coding

The questionnaire uses a five-point Likert scale to measure the degree of agreement with each statement. The use of a Likert scale is appropriate because the study measures perceptions and attitudes related to risk management practices, AI capabilities, and financial performance.

Table 3.6 Five-Point Likert Scale Coding

Response Option	Code	Interpretation
Strongly Disagree	1	Very low agreement with the statement
Disagree	2	Low agreement with the statement
Neutral	3	Moderate or uncertain agreement
Agree	4	High agreement with the statement
Strongly Agree	5	Very high agreement with the statement

3.6 Measurement of Study Variables

The study variables are measured using questionnaire indicators derived from the literature review and aligned with the actual survey instrument. CRM and SCRM are treated as independent variables, FP is treated as the dependent variable, and AIA is treated in two related ways: as a predictor of CRM and SCRM effectiveness and as a moderating variable in the relationships between CRM, SCRM, and FP. Financial Performance is measured as perceived financial performance based on respondents' assessments.

AI capabilities/adoption are operationally measured through practical AI-related capabilities such as early risk identification, risk prediction, decision support, contractual risk monitoring, supply chain visibility, delay detection, risk management effectiveness, and financial forecasting. In the hypotheses testing stage, AIA is examined both as a direct predictor of CRM and SCRM effectiveness and as a moderator through interaction terms with CRM and SCRM.

Table 3.7 Study Variables, Model Roles, and Questionnaire Items

Construct	Role in Model	Item Codes	Practical Measurement Focus
Contractual Risk Management (CRM)	Independent variable	CRM1–CRM10	Clarity of contract clauses, approvals, payment delays, variation orders, scope control, unauthorized works, and dispute reduction.
Supply Chain Risk Management (SCRM)	Independent variable	SCRM1–SCRM8	Supplier reliability, material delivery delays, shortages, supplier failure, logistics problems, price fluctuation, disruption cost, and delay reduction.
Artificial Intelligence Adoption (AIA)	Moderating variable	AI1–AI8	Early risk identification, prediction accuracy, decision support, contract monitoring, supply chain visibility, delay prediction, risk effectiveness.
Perceived Financial Performance (FP)	Dependent variable	FP1–FP7	Profitability, cost control, delay impact, cost overruns, profitability pressure from supply chain risks, AI-driven financial improvement, and

3.6.1 Dimensions and Practical Indicators

The following table presents the dimensions and practical indicators aligned with the questionnaire. This table is important because it connects the theoretical constructs in Chapter Two with the actual survey items used for empirical analysis.

Table 3.8 Dimensions and Practical Indicators Aligned with the Questionnaire

Construct	Dimension	Practical Indicator	Item Code
CRM	Contract clarity and responsibilities	Contract clauses and responsibilities are clearly defined.	CRM1
CRM	Approval and amendment delays	Delays in approvals and contract amendments negatively affect project performance.	CRM2
CRM	Payment delay risk	Payment delays significantly affect project cash flow; delayed owner payments increase project risks.	CRM3–CRM4
CRM	Variation order risk	Variation orders frequently increase project costs and extend project schedules.	CRM5–CRM6
CRM	Unauthorized work and scope control	Executing work before approval or outside approved scope increases contractual risks.	CRM7–CRM9
CRM	Contract management effectiveness	Effective contract management reduces contractual risks.	CRM10
SCRM	Supplier reliability	Supplier reliability significantly affects project success.	SCRM1
SCRM	Material delivery and shortages	Delays in material delivery and shortages create project performance risks.	SCRM2–SCRM3
SCRM	Supplier failure	Supplier failures can cause major project disruptions.	SCRM4
SCRM	Transportation and logistics	Transportation and logistics problems frequently delay projects.	SCRM5
SCRM	Price fluctuation	Price fluctuations of construction materials increase project risks.	SCRM6
SCRM	Supply chain disruption impact	Supply chain disruptions increase project costs; effective SCRM reduces project delays.	SCRM7–SCRM8
AIA	Early risk identification	AI helps identify project risks early.	AI1
AIA	Risk prediction accuracy	AI improves the accuracy of risk prediction.	AI2
AIA	Decision support	AI supports better project decision-making.	AI3
AIA	Contract risk monitoring	AI helps monitor contractual risks effectively.	AI4
AIA	Supply chain visibility	AI improves supply chain visibility.	AI5
AIA	Delay detection	AI helps detect potential project delays before they occur.	AI6
AIA	Risk management effectiveness	AI improves overall risk management effectiveness.	AI7
AIA	Financial forecasting	AI supports financial forecasting and planning.	AI8
FP	Profitability and cost control	Effective risk management improves profitability and helps control project costs.	FP1–FP2
FP	Delay financial impact	Project delays negatively affect financial performance.	FP3
FP	Contractual cost overrun impact	Contractual risks contribute to cost overruns.	FP4
FP	Supply chain profitability impact	Supply chain risks negatively affect project profitability.	FP5
FP	AI-driven financial performance	AI-driven risk management contributes to better financial performance.	FP6
FP	Overall financial outcomes	AI improves overall project financial outcomes.	FP7

Figure 3.2 shows the model structure. CRM and SCRM are independent variables expected to influence FP. AIA is also expected to improve CRM and SCRM effectiveness. In addition, AIA represents the moderate variable because AI capabilities may strengthen the effect of risk management practices on financial performance. Therefore, the empirical model tests both direct relationships and moderation relationships, and forecasting.

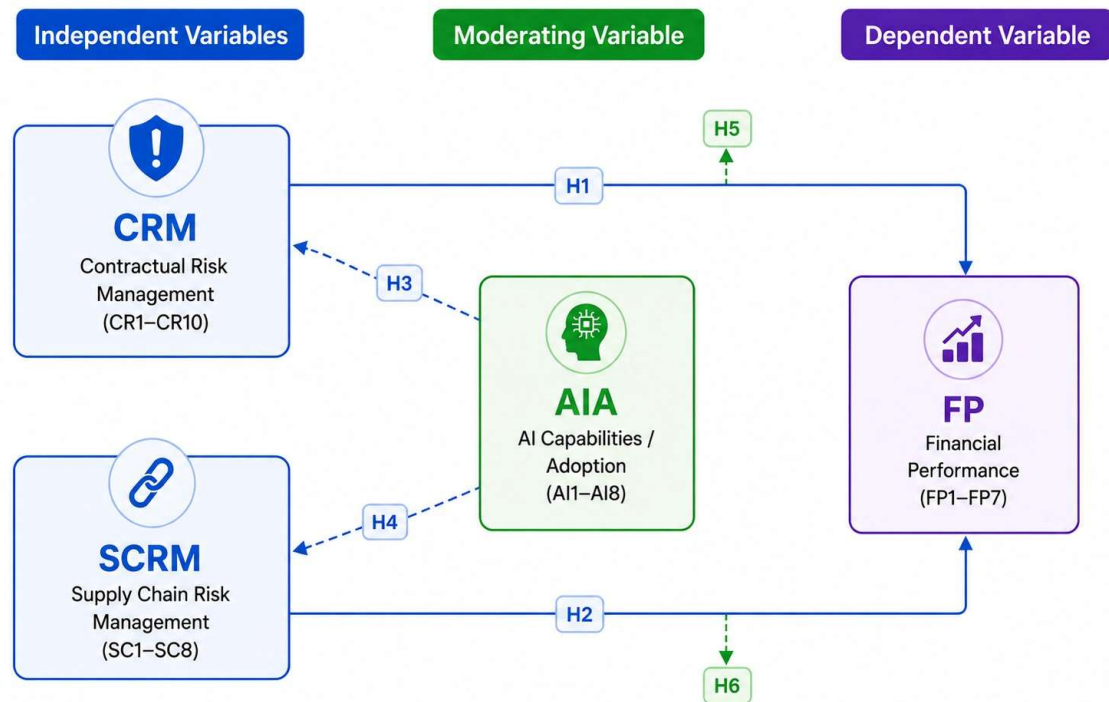


Figure 3.2 Measurement and Structural Model

Figure 3.2 shows the model structure. CRM and SCRM are independent variables expected to influence FP. AIA represents the moderating variable because AI capabilities may strengthen the effect of risk management practices on financial performance. AIA is also expected to improve CRM and SCRM effectiveness because AI tools can support risk prediction, monitoring, visibility, and forecasting.

3.7 Data Preparation and Coding

After data collection, the responses were downloaded from Google Forms and prepared for statistical analysis. Each response was assigned a unique code. Demographic variables were coded according to their categories, while Likert-scale responses were coded from 1 to 5. The dataset was reviewed for missing values, invalid responses, and fully duplicated records.

Incomplete responses may be excluded if they contain substantial missing data. Fully duplicated responses may also be excluded when all demographic and Likert-scale answers are identical, because such cases may distort statistical results. If a small number of missing values appear in otherwise valid responses, the researcher may apply an appropriate treatment method depending on the extent and pattern of missingness. The final dataset is reviewed before reliability analysis, descriptive statistics, correlation analysis, regression analysis, and moderation testing.

Table 3.9 Data Preparation and Coding Procedures

Data Preparation Step	Purpose	Expected Action
Response screening	Ensure that only valid responses are included	Remove incomplete or duplicate responses.
Coding	Convert responses into numerical values	Code Likert responses from 1 to 5.
Missing data check	Identify unanswered items	Exclude or treat missing values based on their level.
Outlier review	Detect unusual response patterns	Review extreme or inconsistent responses.
Composite score creation	Prepare variables for analysis	Calculate mean scores for CR, SC, AI, and FP if needed.
Data export	Prepare analysis file	Export to SPSS and/or SmartPLS format.

3.8 Data Analysis Methods

The cleaned data were analyzed using SPSS-style statistical procedures. SPSS-style tables were prepared for descriptive statistics, demographic analysis, reliability testing using Cronbach's Alpha, correlation analysis, multiple regression analysis, and moderation regression using interaction terms. SmartPLS was not applied because the final cleaned sample size was limited and was not considered suitable for a full measurement and structural model.

The analysis will proceed in stages. First, descriptive statistics will summarize the demographic profile of respondents and the general pattern of responses. Second, reliability and validity tests will evaluate the quality of the measurement instrument. Third, correlation

and regression or PLS-SEM analysis will examine the relationships among the variables and test the hypotheses.



Figure 3.3 Data Analysis Procedure

3.8.1 Descriptive Statistics

Descriptive statistics will be used to summarize respondents' demographic characteristics, including gender, age, education level, years of experience, current position, and company type. Frequencies and percentages will be used for categorical variables, while means and standard deviations will be used for Likert-scale items.

3.8.2 Reliability Analysis

Reliability analysis was conducted to examine the internal consistency of the measurement items. Cronbach's Alpha and corrected item-total correlations were calculated using SPSS. Cronbach's Alpha values of 0.70 or above were considered indicative of acceptable internal consistency, while lower values were interpreted cautiously in light of the exploratory nature and limited sample size of the study.

3.8.3 Validity Assessment

Validity assessment focused on content validity and the structural alignment of the questionnaire. Content validity was supported by systematically aligning the questionnaire items with literature review, research objectives, hypotheses, operational definitions, and study constructs. Because the final valid sample consisted of 34 responses, exploratory factor analysis, confirmatory factor analysis, Average Variance Extracted, and the HTMT ratio were not applied. Cronbach's Alpha and corrected item-total statistics were reported as evidence of reliability rather than as direct tests of construct validity. Accordingly, conclusions

regarding validity were limited to content alignment and questionnaire structure and were interpreted cautiously.

3.8.4 Correlation and Hypotheses Testing

Pearson correlation analysis was used to examine the strength and direction of the relationships among Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance. Multiple regression analysis was used to test H1 and H2, while simple regression analysis was used to test H3 and H4. The moderating relationships in H5 and H6 were tested using mean-centered interaction terms, specifically CRM $\times$ AIA and SCRM $\times$ AIA. All statistical analyses were conducted using SPSS based on the final cleaned dataset of 34 valid responses.

Table 3.10 Data Analysis Plan

Analysis Stage	Statistical Technique	Purpose	Software
Data screening	Missing-data checks, duplicate-response checks, and response-validity review	Prepare the cleaned dataset for analysis	SPSS / Microsoft Excel
Demographic analysis	Frequencies and percentages	Describe the respondents' demographic profile	SPSS
Item-level analysis	Means and standard deviations	Describe response patterns and central tendencies	SPSS
Reliability analysis	Cronbach's Alpha and corrected item-total correlations	Assess the internal consistency of the measurement items	SPSS
Content validity	Alignment of questionnaire items with the literature, research objectives, and study constructs	Assess the relevance and coverage of the measurement items	Conceptual review
Correlation analysis	Pearson correlation	Assess the strength and direction of relationships among CRM, SCRM, AIA, and FP	SPSS
Direct-hypothesis testing	Multiple regression and simple regression	Test H1–H4	SPSS
Moderation analysis	Mean-centering and interaction-term regression	Test H5 and H6	SPSS

3.9 Hypotheses Testing Procedures

The hypothesis-testing plan was aligned with the conceptual framework and questionnaire structure. The study included six hypotheses. H1 and H2 examined the positive associations between Contractual Risk Management, Supply Chain Risk Management, and perceived Financial Performance. H3 and H4 examined the positive associations between Artificial Intelligence Adoption and the effectiveness of Contractual Risk Management and Supply Chain Risk Management. H5 and H6 examined whether Artificial Intelligence Adoption moderated the relationships between CRM, SCRM, and perceived Financial Performance. All hypotheses were tested using SPSS through correlation analysis, regression

analysis, and interaction-term moderation analysis based on the cleaned questionnaire dataset.

Table 3.11 Hypotheses Testing Plan

Hypothesis	Relationship	Type of Relationship	Expected Direction	Statistical Test
H1	CRM → Perceived FP	Direct association	Positive	Multiple regression
H2	SCRM → Perceived FP	Direct association	Positive	Multiple regression
H3	AIA → CRM effectiveness	Direct association	Positive	Simple regression
H4	AIA → SCRM effectiveness	Direct association	Positive	Simple regression
H5	CRM × AIA → Perceived FP	Moderating relationship	Positive moderation	Mean-centered interaction-term regression
H6	SCRM × AIA → Perceived FP	Moderating relationship	Positive moderation	Mean-centered interaction-term regression

3.10 Reliability and Validity Criteria

To ensure methodological credibility, reliability was assessed using Cronbach's Alpha and corrected item-total statistics. Content validity was supported by aligning the questionnaire items with the literature review, research objectives, hypotheses, operational definitions, and study constructs. Because the final valid sample consisted of 34 responses, formal factor-based validity procedures, including exploratory factor analysis, confirmatory factor analysis, Average Variance Extracted, and HTMT, were not applied. Therefore, validity conclusions were interpreted cautiously and were limited to content alignment, questionnaire structure, and internal consistency evidence.

Table 3.12 Reliability and Validity Criteria

Criterion	Recommended Procedure / Decision Rule	Purpose
Cronbach's Alpha	A value of 0.70 or above was considered indicative of acceptable internal consistency. Lower values were interpreted cautiously.	Assess the internal consistency of the items within each construct.
Corrected Item-Total Statistics	Corrected item-total correlations and Cronbach's Alpha if item deleted were reviewed together with the theoretical relevance of each item.	Evaluate the contribution of individual questionnaire items to their respective constructs.
Content Validity	Questionnaire items were aligned with the literature review, research objectives, hypotheses, operational definitions, and study constructs.	Assess whether the instrument adequately covered the concepts examined in the study.
Questionnaire Structure	Items were grouped according to CRM, SCRM, AIA, and perceived FP as specified in the conceptual and measurement models.	Ensure consistency between the questionnaire, study variables, and conceptual framework.
Factor-Based Validity	Exploratory factor analysis, confirmatory factor analysis, Average Variance Extracted, and HTMT were not applied because the final valid sample consisted of 34 responses.	Clarify the methodological limitation and prevent unsupported claims regarding convergent and discriminant validity.
Validity Interpretation	Validity conclusions were based on content alignment, questionnaire structure, reliability results, and cautious interpretation of the item-level statistics.	Provide an appropriately limited interpretation of measurement quality.

3.11 Ethical Considerations

The study was conducted in accordance with the ethical principles applicable to academic research. Participation was voluntary, and respondents were informed that the questionnaire was intended solely for academic purposes. No personal identifiers or sensitive company information were requested. The collected responses were treated confidentially and were used only for the purposes of present research.

Respondents were not required to disclose their names, employee numbers, confidential project values, client names, supplier names, or proprietary commercial information. This precaution was particularly important because the study involved professionals working in contracting companies, where contractual, procurement, and financial information may be commercially sensitive. The questionnaire therefore focused on respondents' perceptions and general organizational practices rather than confidential operational records.

Table 3.13 Ethical Considerations

Ethical Principle	Application in This Study
Voluntary Participation	Participation was voluntary, and respondents were free to decide whether to complete the questionnaire.
Confidentiality	The collected responses were treated confidentially and used solely for academic research purposes.
Anonymity	No names, employee numbers, or sensitive company identifiers were requested or collected.
Protection from Harm	The questionnaire avoided questions that could expose respondents or their organizations to professional, commercial, or reputational risk.
Data Use	The data were used only for statistical analysis related to the objectives and hypotheses of the study.
Academic Integrity	The data were screened, analyzed, and reported without fabrication, manipulation, or intentional misrepresentation.

3.12 Research Boundaries

The research boundaries define the conditions within which the findings of the study should be interpreted. They clarify the geographical, sectoral, subject, population, methodological, measurement, temporal, and data-related limits of the research. The study was based on a cross-sectional questionnaire and a non-probability purposive sample of 34 valid respondents. Consequently, the findings provide exploratory evidence regarding statistical associations within the selected context and should not be interpreted as proof of causal relationships or generalized automatically to all construction companies in Saudi Arabia.

Table 3.14 Research Boundaries

Boundary Type	Scope and Limitation of the Study
Geographical Boundary	The study was limited to professionals involved in construction and industrial projects in the Eastern Province of Saudi Arabia. The findings should therefore be generalized cautiously to other regions.
Sectoral Boundary	The study covered construction, infrastructure, industrial, mechanical construction, oil and gas-related projects, building construction, manufacturing support, and operations and maintenance activities.
Subject Boundary	The study examined Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance. Geopolitical and maritime disruptions were treated as contextual risk factors rather than independent study variables.
Population Boundary	The study focused on professionals working in project management, contract management, procurement, supply chain management, risk management, engineering, finance, digital systems, and project supervision.
Sampling Boundary	A non-probability purposive sampling technique was used. After data screening, the final dataset consisted of 34 unique valid responses; therefore, the results were interpreted as exploratory evidence.
Methodological Boundary	The study used a quantitative, descriptive-analytical, and cross-sectional survey design. The statistical findings indicate associations among the variables but do not establish causal relationships.
Measurement Boundary	The study relied on self-reported Likert-scale responses. Financial performance was measured as perceived Financial Performance rather than through audited accounting statements or actual company financial records.
Validity Boundary	Measurement quality was assessed through content alignment, Cronbach's Alpha, and corrected item-total statistics. Formal factor-based validity procedures were not applied because of the limited final sample size.
Time Boundary	The questionnaire captured respondents' perceptions during the data-collection period, while the contextual discussion considered project and market conditions relevant to the period 2020–2026.
Data Boundary	No confidential contract values, supplier records, client information, audited financial statements, or proprietary project documents were collected or analyzed.

3.13 Practical Value of Methodology

The methodology was designed to generate context-specific evidence that could support both academic analysis and practical decision-making in construction and industrial contracting organizations. By collecting questionnaire data from professionals working in project management, contract management, procurement, supply chain management, risk management, engineering, finance, and digital systems, the study captured perceptions from several operational and managerial functions. This multidisciplinary coverage supported a broader examination of how Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance are understood across different professional roles. The practical value of the methodology also lies in its use of descriptive statistics, reliability analysis, correlation analysis, regression analysis, and interaction-term moderation analysis.

These procedures provided an empirical basis for examining the relationships among the study variables and assessing whether Artificial Intelligence Adoption was associated with the effectiveness of contractual and supply chain risk management and whether it moderated their relationships with perceived Financial Performance. However, because the study used a purposive sample of 34 valid respondents, its practical implications should be interpreted as exploratory and applied cautiously within the selected geographical and sectoral context.

3.14 Chapter Summary

This chapter presented the research methodology adopted in the study. The research followed a positivist philosophy, a deductive approach, a quantitative descriptive-analytical design, and a cross-sectional survey method. The target population comprised professionals involved in construction and industrial projects in the Eastern Province of Saudi Arabia. A non-probability purposive sampling technique was used, and the final cleaned dataset consisted of 34 valid responses. The questionnaire contained six demographic questions and 33 Likert-scale measurement items covering Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance. The chapter also explained the research population, sampling procedures, data-collection method, questionnaire structure, variable measurement, data preparation and coding procedures, statistical analysis methods, hypotheses-testing plan, reliability assessment, content-validity approach, ethical considerations, research boundaries, and the practical value of the methodology. Because of the limited sample size, formal factor-based validity procedures were not applied, and the findings were interpreted as exploratory evidence of statistical associations rather than proof of causal relationships. Chapter Four presents the data analysis, results, discussion, and recommendations derived from the final cleaned questionnaire dataset.

CHAPTER FOUR

**DATA ANALYSIS, RESULTS, DISCUSSION,
AND RECOMMENDATIONS**

4.1 Introduction

This chapter presents the statistical analysis, results, discussion, and recommendations of the study. The purpose of the analysis was to examine the relationships among Contractual Risk Management (CRM), Supply Chain Risk Management (SCRM), Artificial Intelligence Adoption (AIA), and perceived Financial Performance (FP) in construction and industrial projects in the Eastern Province of Saudi Arabia. In accordance with the conceptual framework, CRM and SCRM were examined as independent variables, perceived FP was examined as the dependent variable, and AIA was examined both as a predictor of risk-management effectiveness and as a moderating variable.

The questionnaire responses were collected through Google Forms, exported to Microsoft Excel for initial organization and screening, and subsequently imported into IBM SPSS Statistics for statistical analysis. All analyses were conducted using the final cleaned dataset of 34 valid responses. The reported statistical values, significance levels, and interpretations were derived from the actual SPSS analysis of the questionnaire data. The analysis included data screening, demographic frequencies and percentages, item-level descriptive statistics, reliability analysis using Cronbach's Alpha and corrected item-total statistics, Pearson correlation analysis, regression analysis, interaction-term moderation analysis, and a summary of the hypotheses-testing results. The findings were interpreted as evidence of statistical associations within the selected sample and context rather than as proof of causal relationships.

4.2 Data Screening and Preparation

The original Google Forms dataset contained 49 submitted records and 40 variables. These variables comprised one timestamp variable, six demographic variables, and 33 Likert-scale measurement items. The measurement items consisted of 10 items for Contractual Risk Management (CRM), 8 items for Supply Chain Risk Management (SCRM), 8 items for Artificial Intelligence Adoption (AIA), and 7 items for perceived Financial Performance (FP). Before conducting the statistical analysis, the dataset was screened for missing values, values outside the permitted Likert-scale range, and duplicated data records. No missing values or invalid Likert-scale values were identified among the retained cases. However, 15 rows were identified as exact duplicates of earlier rows, with identical timestamps and response patterns.

These duplicated data records were removed to prevent artificial inflation of the sample size and distortion of the statistical results. Following data screening, the final dataset imported into IBM SPSS Statistics consisted of 34 unique valid cases, all of which were included in the statistical analysis.

Table 4.1 Data Screening Summary

Data Screening Item	Result
Original records in the Google Forms dataset	49
Exact duplicate data records removed	15
Missing values among retained cases	0
Invalid Likert-scale values among retained cases	0
Final unique valid cases included in the analysis	34

Source: Statistical analysis of questionnaire data.

The questionnaire used a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with higher values indicating stronger agreement with each statement. No questionnaire items required reverse coding because all measurement items were positively worded in the direction of their respective constructs. Composite scores for CRM, SCRM, AIA, and perceived FP were calculated by averaging the relevant items assigned to each construct.

Table 4.2 Likert Scale Coding

Response Category	Code
Strongly Disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Source: Research questionnaire coding scheme.

For the descriptive interpretation of mean scores, the width of each category was calculated as $(5-1) \div 5 = 0.80$. Accordingly, mean scores from 1.00 to 1.80 were interpreted as very low, 1.81 to 2.60 as low, 2.61 to 3.40 as moderate, 3.41 to 4.20 as high, and 4.21 to 5.00 as very high. These categories were used only for descriptive interpretation and were not treated as evidence of statistical significance.

4.3 Respondents' Demographic Profile

This section presents the demographic profile of the 34 valid respondents included in the statistical analysis. The demographic variables comprised gender, age, education level, years of professional experience, current position, and company type. Frequencies and percentages were calculated using IBM SPSS Statistics to describe the composition and professional characteristics of the study sample.

Table 4.3 Respondents' Demographic Profile

Variable	Category	Frequency	Percent
Gender	Male	27	79.40%
	Female	7	20.60%
Age	Less than 30	7	20.60%
	30 - 39	11	32.40%
	40 - 49	12	35.30%
	50 and above	4	11.80%
Education Level	Diploma	4	11.80%
	Bachelor	27	79.40%
	Master	3	8.80%
Years of Experience	Less than 5 years	6	17.60%
	5 – 10 years	8	23.50%
	11 – 15 years	5	14.70%
	More than 15 years	15	44.10%
Company Type	Contractor	28	82.40%
	Supplier	3	8.80%
	Consultant	1	2.90%
	Owner/Client	1	2.90%
	Government Entity	1	2.90%
Current Position	Project Manager	6	17.60%
	Supervisor	6	17.60%
	Engineer	5	14.70%
	Contract Manager	2	5.90%
	Business Development Manager	1	2.90%
	Coordination head	1	2.90%
	Executive secretary	1	2.90%
	Governance, Risk & Compliance Director	1	2.90%
	Internal Audit Manager	1	2.90%
	IT Manager	1	2.90%
	Material Manager	1	2.90%
	Planning Manager	1	2.90%
	Process Auditor	1	2.90%
	Procurement Manager	1	2.90%
	QA Manager	1	2.90%
	Risk Manager	1	2.90%
	Safety Officer	1	2.90%
	Senior Material Control Engineer	1	2.90%

Source: Statistical analysis of questionnaire data.

The demographic results indicated that the majority of respondents were male and held bachelor's degrees. Most participants worked in contractor organizations, while smaller proportions represented suppliers, consultants, clients, and government entities. A substantial proportion of the respondents had more than 15 years of professional experience, indicating that the sample included participants with considerable practical exposure. The respondents represented a diverse range of current positions related to project management, engineering, contract management, procurement, supply chain activities, risk management, auditing, quality, safety, information technology, and other relevant professional functions. Eligibility was determined according to relevant professional experience and involvement in the study context rather than current job title alone. Because several job categories contained only one respondent, demographic subgroup comparisons and group-based inferential tests were not considered statistically appropriate.

4.4 Descriptive Analysis

Descriptive statistics were calculated for the four main study constructs using the composite mean score of the items assigned to each construct. Table 4.4 presents the number of valid cases, minimum and maximum scores, means, standard deviations, and descriptive interpretations for Contractual Risk Management (CRM), Supply Chain Risk Management (SCRM), Artificial Intelligence Adoption (AIA), and perceived Financial Performance (FP).

Table 4.4 Descriptive Statistics for Main Constructs

Construct Code	Construct Name	N	Minimum	Maximum	Mean	Std. Deviation	Interpretation
CRM	Contractual Risk Management	34	2.9	4.8	4.147	0.465	High
SCRM	Supply Chain Risk Management	34	2.5	5	4.136	0.517	High
AIA	Artificial Intelligence Adoption	34	2.75	5	3.857	0.489	High
FP	Perceived Financial Performance	34	2.43	5	4.008	0.501	High

Source: IBM SPSS Statistics analysis of the study questionnaire data.

The descriptive results showed high mean scores for all four study constructs. Contractual Risk Management recorded the highest mean score ($M = 4.147$, $SD = 0.465$), indicating a high level of agreement with the questionnaire items related to contractual risk identification, monitoring, documentation, claims, variations, payment issues, and contract-management practices. Supply Chain Risk Management also recorded a high mean score ($M = 4.136$, $SD = 0.517$), indicating that respondents reported a high level of agreement with items concerning supplier reliability, material availability, logistics disruptions, long lead-time equipment, price fluctuations, and supply chain monitoring. Perceived Financial Performance recorded a high mean score ($M = 4.008$, $SD = 0.501$), showing that respondents

generally reported favorable perceptions regarding cost control, profitability, cash-flow stability, financial-loss reduction, and the management of financial consequences associated with project risks. Artificial Intelligence Adoption recorded the lowest mean among the four constructs, although its mean remained within the high descriptive category ($M = 3.857$, $SD = 0.489$). This result indicates generally positive perceptions regarding the adoption of AI-enabled tools for risk identification, prediction, information visibility, forecasting, and decision support. However, these descriptive findings reflect respondents' levels of agreement and should not be interpreted as evidence of statistically significant relationships or causal effects.

Table 4.5 Item-Level Descriptive Statistics

Item	Statement	N	Mean	Std. Deviation	Interpretation
CRM1	Contract clauses and responsibilities are clearly defined.	34	4.059	0.694	High
CRM2	Delays in approvals and contract amendments negatively affect project performance.	34	4.088	1.026	High
CRM3	Payment delays significantly affect project cash flow.	34	4.382	0.739	Very high
CRM4	Delayed owner payments increase project risks.	34	4.353	0.544	Very high
CRM5	Variation orders frequently increase project costs.	34	3.794	0.88	High
CRM6	Variation orders frequently extend project schedules.	34	3.824	0.904	High
CRM7	Executing work before obtaining required approvals increases contractual risks.	34	4.471	0.662	Very high
CRM8	Executing work outside the approved contract scope increases project risks.	34	4.235	0.855	Very high
CRM9	Performing additional works without formal approval creates contractual disputes.	34	4.029	1	High
CRM10	Effective contract management reduces contractual risks.	34	4.235	0.699	Very high
SCRM1	Supplier reliability significantly affects project success.	34	4.059	0.919	High
SCRM2	Delays in material delivery negatively affect project schedules.	34	4.471	0.507	Very high
SCRM3	Material shortages create project performance risks.	34	4.176	0.797	High
SCRM4	Supplier failures can cause major project disruptions.	34	4.206	0.687	High
SCRM5	Transportation and logistics problems frequently delay projects.	34	4.118	0.478	High
SCRM6	Price fluctuations of construction materials increase project risks.	34	4.029	0.834	High
SCRM7	Supply chain disruptions increase project costs.	34	3.912	0.933	High
SCRM8	Effective supply chain management reduces project delays.	34	4.118	0.686	High
AI1	Artificial Intelligence helps identify project risks early.	34	3.882	0.729	High
AI2	AI improves the accuracy of risk prediction.	34	3.971	0.674	High
AI3	AI supports better project decision-making.	34	3.706	0.836	High
AI4	AI helps monitor contractual risks effectively.	34	3.941	0.776	High
AI5	AI improves supply chain visibility.	34	3.882	0.686	High
AI6	AI helps detect potential project delays before they occur.	34	3.588	0.857	High
AI7	AI improves overall risk management effectiveness.	34	4	0.603	High
AI8	AI supports financial forecasting and planning.	34	3.882	0.808	High
FP1	Effective risk management improves project profitability.	34	4.176	0.797	High
FP2	Effective risk management helps control project costs.	34	4.147	0.61	High
FP3	Project delays negatively affect financial performance.	34	4.324	0.535	Very high
FP4	Contractual risks contribute to cost overruns.	34	3.941	0.6	High
FP5	Supply chain risks negatively affect project profitability.	34	3.941	0.736	High
FP6	AI-driven risk management contributes to better financial performance.	34	3.676	0.843	High
FP7	AI improves overall project financial outcomes.	34	3.853	0.821	High

Source: Statistical analysis of questionnaire data.

4.5 Reliability and Content Validity Assessment

The internal consistency reliability of the four study constructs was assessed using Cronbach's Alpha in IBM SPSS Statistics. A Cronbach's Alpha coefficient of 0.70 or above was considered indicative of acceptable internal consistency. Table 4.6 presents the reliability coefficients for Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance.

The item-level descriptive results indicated that all questionnaire items received high or very high mean scores. This pattern shows generally strong respondent agreement with the statements used to measure contractual risk management, supply chain risk management, artificial intelligence adoption, and perceived financial performance.

Regarding contractual risk management, the highest-ranked item was CRM7, which concerned the increased contractual risks associated with executing work before obtaining the required approvals ($M = 4.471$, $SD = 0.662$). This was followed by CRM3, concerning the significant effect of payment delays on project cash flow ($M = 4.382$, $SD = 0.739$), and CRM4, concerning the increase in project risks resulting from delayed owner payments ($M = 4.353$, $SD = 0.544$). All three items were classified within the "Very high" category. These results indicate that approval-related exposure and payment delays were perceived as the most prominent contractual risks affecting construction projects in the Eastern Province.

Regarding supply chain risk management, the highest-ranked item was SCRM2, which concerned the negative effect of material-delivery delays on project schedules ($M = 4.471$, $SD = 0.507$). This was followed by SCRM4, concerning the potential of supplier failures to cause major project disruptions ($M = 4.206$, $SD = 0.687$), and SCRM3, concerning the performance risks created by material shortages ($M = 4.176$, $SD = 0.797$). SCRM2 was classified within the "Very high" category, while SCRM4 and SCRM3 were classified within the "High" category. These results indicate that material-delivery delays, supplier failures, and material shortages were perceived as the most significant supply chain risks affecting construction projects in the Eastern Province.

The lowest item mean was recorded for AI6, which examined whether artificial intelligence helps detect potential project delays before they occur ($M = 3.588$, $SD = 0.857$). This was followed by FP6, concerning the perceived contribution of AI-driven risk management to better financial performance ($M = 3.676$, $SD = 0.843$), and AI3, concerning AI-supported project decision-making ($M = 3.706$, $SD = 0.836$). Although these items recorded the lowest means, they remained within the "High" descriptive category. The

relatively lower ratings of these AI-related items may indicate that respondents viewed artificial intelligence positively but remained cautious about its current ability to predict delays and generate direct financial benefits.

These item-level findings directly address Research Questions 1 and 2 by identifying the contractual and supply chain risks that received the highest ratings from the study respondents. However, the descriptive results represent respondents' perceptions only and do not establish statistically significant relationships or causal effects.

Table 4.6 Reliability Statistics

Construct Code	Construct Name	Number of Items	Cronbach's Alpha	Interpretation
CRM	Contractual Risk Management	10	0.771	Acceptable
SCRM	Supply Chain Risk Management	8	0.844	Acceptable
AI	Artificial Intelligence Adoption	8	0.806	Acceptable
FP	Perceived Financial Performance	7	0.827	Acceptable

Source: IBM SPSS Statistics analysis of the study questionnaire data.

Cronbach's Alpha coefficients were 0.771 for Contractual Risk Management, 0.844 for Supply Chain Risk Management, 0.806 for Artificial Intelligence Adoption, and 0.827 for perceived Financial Performance. All four coefficients exceeded the adopted threshold of 0.70, indicating acceptable internal consistency reliability for the study constructs. Supply Chain Risk Management recorded the highest reliability coefficient, followed by perceived Financial Performance, Artificial Intelligence Adoption, and Contractual Risk Management.

The questionnaire items were retained for the calculation of the composite construct scores used in the subsequent correlation, regression, and moderation analyses. Corrected item-total correlations and Cronbach's Alpha coefficients if an item was deleted were also examined to evaluate the contribution of each measurement item to its respective construct. These results are presented in Table 4.7.

Table 4.7 Item-Total Statistics

Construct	Item	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CRM	CRM1	-0.138	0.812
CRM	CRM2	0.527	0.739
CRM	CRM3	0.686	0.721
CRM	CRM4	0.13	0.781
CRM	CRM5	0.598	0.728
CRM	CRM6	0.585	0.73
CRM	CRM7	0.215	0.776
CRM	CRM8	0.599	0.729
CRM	CRM9	0.705	0.708
CRM	CRM10	0.37	0.76
SCRM	SCRM1	0.643	0.818
SCRM	SCRM2	0.547	0.833
SCRM	SCRM3	0.743	0.803
SCRM	SCRM4	0.504	0.834
SCRM	SCRM5	0.017	0.872
SCRM	SCRM6	0.692	0.81
SCRM	SCRM7	0.811	0.791
SCRM	SCRM8	0.614	0.822
AIA	AI1	0.284	0.816
AIA	AI2	0.566	0.778
AIA	AI3	0.433	0.799
AIA	AI4	0.635	0.766
AIA	AI5	0.379	0.803
AIA	AI6	0.626	0.766
AIA	AI7	0.664	0.768
AIA	AI8	0.612	0.769
FP	FP1	0.554	0.808
FP	FP2	0.443	0.823
FP	FP3	0.398	0.828
FP	FP4	0.622	0.799
FP	FP5	0.684	0.785
FP	FP6	0.753	0.77
FP	FP7	0.571	0.805

The corrected item-total statistics indicated that most questionnaire items were positively related to the remaining items within their respective constructs. However, several items recorded relatively weak corrected item-total correlations. CRM1 recorded a negative corrected item-total correlation (-0.138), while CRM4 (0.130), CRM7 (0.215), SCRM5 (0.017), and AI1 (0.284) recorded values below the commonly applied reference level of 0.30 .

The Cronbach's Alpha coefficient for Contractual Risk Management would increase from 0.771 to 0.812 if CRM1 were deleted, while the coefficient for Supply Chain Risk Management would increase from 0.844 to 0.872 if SCRM5 were deleted. The reliability coefficient for Artificial Intelligence Adoption would also increase slightly from 0.806 to 0.816 if AI1 were deleted. Nevertheless, the overall Cronbach's Alpha coefficients for all four constructs remained above the adopted threshold of 0.70 .

The items were therefore retained because they had been specified in the questionnaire and measurement structure before data collection and removing them after

examining the results could alter the predefined measurement model. The weak item-total correlations should, however, be treated as a measurement limitation and considered when interpreting the findings. Future research should review the wording and theoretical alignment of CRM1, CRM4, CRM7, SCRM5, and AI1 and reassess them using a larger sample.

Formal factor-based validity procedures were not conducted because the final valid sample consisted of 34 cases. Accordingly, the results in this section provide evidence of internal consistency reliability only and should not be interpreted as confirmation of convergent or discriminant validity.

4.6 Pearson Correlation Analysis

Pearson correlation analysis was conducted using IBM SPSS Statistics to examine the strength, direction, and statistical significance of the bivariate relationships among Contractual Risk Management (CRM), Supply Chain Risk Management (SCRM), Artificial Intelligence Adoption (AIA), and perceived Financial Performance (FP). The correlation coefficients, two-tailed significance values, and number of valid cases are presented in Table 4.8.

Table 4.8 Pearson Correlations

Variable	Statistic	CRM	SCRM	AIA	FP
CRM	Pearson Correlation	1	0.761	0.452	0.724
	Sig. (2-tailed)	—	< .001	0.007	< .001
	N	34	34	34	34
SCRM	Pearson Correlation	0.761	1	0.541	0.795
	Sig. (2-tailed)	< .001	—	< .001	< .001
	N	34	34	34	34
AIA	Pearson Correlation	0.452	0.541	1	0.794
	Sig. (2-tailed)	0.007	< .001	—	< .001
	N	34	34	34	34
FP	Pearson Correlation	0.724	0.795	0.794	1
	Sig. (2-tailed)	< .001	< .001	< .001	—
	N	34	34	34	34

The Pearson correlation results indicated positive and statistically significant bivariate associations among all four study constructs. Supply Chain Risk Management recorded the strongest correlation with perceived Financial Performance ($r = .795$, $p < .001$), closely followed by Artificial Intelligence Adoption ($r = .794$, $p < .001$). Contractual Risk

Management was also positively and significantly correlated with perceived Financial Performance ($r = .724, p < .001$).

Contractual Risk Management and Supply Chain Risk Management were positively and strongly correlated ($r = .761, p < .001$), indicating that the two risk-management practices were closely associated within the surveyed project environment. Artificial Intelligence Adoption was positively correlated with Supply Chain Risk Management ($r = .541, p < .001$) and Contractual Risk Management ($r = .452, p = .007$).

Although all correlations were statistically significant, these bivariate results do not indicate the independent contribution of each predictor when the other variables are controlled. They also do not establish causal relationships. The regression analyses presented in the following section were therefore used to assess the statistical contribution of the study variables to perceived Financial Performance and risk-management effectiveness.

4.7 Regression Analysis

Multiple regression analysis was conducted using IBM SPSS Statistics to examine the independent statistical contributions of Contractual Risk Management (CRM), Supply Chain Risk Management (SCRM), and Artificial Intelligence Adoption (AIA) to perceived Financial Performance (FP). Perceived FP was entered as the dependent variable, while CRM, SCRM, and AIA were entered simultaneously as predictors. This model enabled the association of each predictor with perceived FP to be assessed while statistically controlling for the other predictors.

Table 4.9 Model Summary for Main-Effects Regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
CRM, SCRM, and AIA predicting perceived FP	0.918	0.843	0.827	0.208	1.513

Table 4.10 ANOVA for Main-Effects Regression

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	6.983	3	2.328	53.717	< .001
Residual	1.3	30	0.043	—	—
Total	8.283	33	—	—	—

Table 4.11 Coefficients for Main-Effects Regression

Variable	B	Std. Error	Standardized Beta	t	Sig.	95% CI Lower	95% CI Upper
Constant	-.407	0.361	—	-1.125	0.269	-1.144	0.331
CRM	0.252	0.12	0.234	2.093	0.045	0.006	0.498
SCRM	0.336	0.115	0.346	2.92	0.007	0.101	0.57
AIA	0.514	0.088	0.501	5.813	< .001	0.333	

Source: IBM SPSS Statistics analysis of the study questionnaire data.

The multiple regression model was statistically significant, $F(3, 30) = 53.717$, $p < .001$. The three predictors collectively explained 84.3% of the variance in perceived Financial Performance ($R^2 = .843$), while the adjusted R^2 was .827. Because the study used a relatively small purposive sample, this high explanatory value should be interpreted cautiously and within the context of the surveyed respondents.

After controlling the other predictors, Contractual Risk Management was positively and statistically associated with perceived Financial Performance ($B = .252$, $\beta = .234$, $t = 2.093$, $p = .045$, 95% CI [.006, .498]). Supply Chain Risk Management also demonstrated a positive and statistically significant association with perceived Financial Performance ($B = .336$, $\beta = .346$, $t = 2.920$, $p = .007$, 95% CI [.101, .570]). These findings provided statistical support for H1 and H2 within the main-effects model.

Artificial Intelligence Adoption recorded the largest standardized coefficient in the model ($B = .514$, $\beta = .501$, $t = 5.813$, $p < .001$, 95% CI [.333, .694]). This coefficient indicates that AIA was positively associated with perceived Financial Performance after controlling for CRM and SCRM. However, the direct relationship between AIA and perceived FP was not specified as a separate hypothesis and was included in the model primarily as part of the main-effects structure preceding the moderation analysis.

In a supplementary model containing only CRM and SCRM as predictors of perceived FP, SCRM remained statistically significant, whereas CRM did not reach the .05 significance level ($p = .087$). Accordingly, the support for H1 should be interpreted cautiously, while the evidence supporting H2 was more consistent. The following simple regression models examine the associations of AIA with CRM effectiveness and SCRM effectiveness in relation to H3 and H4.

Table 4.12 Model Summary for AIA Predicting CRM and SCRM

Regression Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
AIA predicting CRM	0.452	0.204	0.18	0.421	2.04
AIA predicting SCRM	0.541	0.292	0.27	0.442	1.882

Source: IBM SPSS Statistics analysis of the study questionnaire data.

Table 4.13 Coefficients for AIA Predicting CRM and SCRM

Dependent Variable	Predictor	B	Std. Error	Standardized Beta	t	Sig.	95% CI Lower	95% CI Upper
CRM	Constant	2.487	0.584	—	4.261	< .001	1.298	3.676
CRM	AIA	0.43	0.15	0.452	2.867	0.007	0.125	0.736
SCRM	Constant	1.93	0.612	—	3.155	0.003	0.684	3.176
SCRM	AIA	0.572	0.157	0.541	3.634	< .001	0.251	0.893

Source: IBM SPSS Statistics analysis of the study questionnaire data.

The simple regression results indicated that Artificial Intelligence Adoption was positively and statistically associated with Contractual Risk Management effectiveness. AIA explained 20.4% of the variance in CRM ($R^2 = .204$; adjusted $R^2 = .180$) and recorded a positive statistically significant coefficient ($B = .430$, $\beta = .452$, $t = 2.867$, $p = .007$, 95% CI [.125, .736]). This result provided statistical support for H3 within the sample surveyed.

Artificial Intelligence Adoption was also positively and statistically associated with Supply Chain Risk Management effectiveness. AIA explained 29.2% of the variance in SCRM ($R^2 = .292$; adjusted $R^2 = .270$) and recorded a positive statistically significant coefficient ($B = .572$, $\beta = .541$, $t = 3.634$, $p < .001$, 95% CI [.251, .893]). This result provided statistical support for H4 within the sample surveyed.

The association between AIA and SCRM was stronger than the association between AIA and CRM, based on the standardized coefficients and explained variance. However, because the study used a cross-sectional purposive sample of 34 valid respondents, these results should be interpreted as statistical associations rather than evidence that Artificial Intelligence Adoption causally improves risk-management effectiveness.

4.8 Moderation Analysis

Moderation analysis was conducted using IBM SPSS Statistics to examine whether Artificial Intelligence Adoption (AIA) moderated the relationship between Contractual Risk Management (CRM) and perceived Financial Performance (FP), and the relationship

between Supply Chain Risk Management (SCRM) and perceived FP. Before constructing the interaction terms, CRM, SCRM, and AIA were mean-centered. Two separate hierarchical regression models were then estimated: the first included the CRM $\times$ AIA interaction term to test H5, while the second included the SCRM $\times$ AIA interaction term to test H6. The statistical significance of each interaction was assessed using the change in R^2 , the F-change test, and the coefficient of the corresponding interaction term.

Table 4.14 Moderation Model Summary

Model	R Square	Adjusted R Square	R Square Change	F Change	Sig. F Change
Main-effects model	0.843	0.827	—	—	—
H5 model: CRM $\times$ AIA interaction added	0.851	0.83	0.008	1.491	0.232
H6 model: SCRM $\times$ AIA interaction added	0.847	0.826	0.004	0.693	0.412

Source: IBM SPSS Statistics analysis of the study questionnaire data.

Table 4.15 Interaction Coefficients for Moderation Analysis

Hypothesis	Interaction Term	B	Std. Error	Standardized Beta	t	Sig.	Decision
H5	CRM $\times$ AIA	-.179	0.146	-.094	-1.221	0.232	Not Supported
H6	SCRM $\times$ AIA	-.083	0.1	-.064	-.832	0.412	

Source: IBM SPSS Statistics analysis of the study questionnaire data.

The addition of the CRM $\times$ AIA interaction term increased the explained variance in perceived Financial Performance by only 0.8% ($\Delta R^2 = .008$). This increase was not statistically significant, F-change = 1.491, $p = .232$. The interaction coefficient was also negative and not statistically significant ($B = -.179$, $\beta = -.094$, $t = -1.221$, $p = .232$). Accordingly, the results did not support H5, which proposed that Artificial Intelligence Adoption positively moderates the relationship between Contractual Risk Management and perceived Financial Performance.

Similarly, adding the SCRM $\times$ AIA interaction term increased the explained variance in perceived Financial Performance by only 0.4% ($\Delta R^2 = .004$). The increase was not statistically significant, F-change = .693, $p = .412$. The interaction coefficient was negative and not statistically significant ($B = -.083$, $\beta = -.064$, $t = -.832$, $p = .412$). Therefore, H6, which proposed that Artificial Intelligence Adoption positively moderates the relationship

between Supply Chain Risk Management and perceived Financial Performance, was not supported.

These findings indicate that, although AIA demonstrated positive direct associations with the study variables in the preceding analyses, the available sample did not provide evidence that the strength of the CRM–FP or SCRM–FP relationships varied significantly according to the level of AIA. The absence of statistically significant moderation should be interpreted cautiously because interaction effects generally require substantial statistical power, while the present analysis was based on 34 valid responses.

4.9 Hypotheses Testing Summary

Table 4.16 summarizes the results of the six research hypotheses. Statistical support was assessed using a significance level of $\alpha = .05$ and the regression procedures specified in the research methodology. The decisions were based on the direction and statistical significance of the relevant regression and interaction coefficients. Because the analysis was based on a purposive sample of 34 valid respondents, the results were interpreted within the selected study context and should not be generalized beyond it without caution.

Table 4.16 Hypotheses Testing Summary

Hypothesis	Hypothesis Statement	Statistical Test	Key Statistical Result	Decision
H1	Contractual Risk Management is positively associated with perceived Financial Performance.	Multiple regression	$B = .252, \beta = .234, t = 2.093, p = .045$	Supported with caution
H2	Supply Chain Risk Management is positively associated with perceived Financial Performance.	Multiple regression	$B = .336, \beta = .346, t = 2.920, p = .007$	Supported
H3	Artificial Intelligence Adoption is positively associated with Contractual Risk Management effectiveness.	Simple regression: AIA $\rightarrow$ CRM	$B = .430, \beta = .452, t = 2.867, p = .007$	Supported
H4	Artificial Intelligence Adoption is positively associated with Supply Chain Risk Management effectiveness.	Simple regression: AIA $\rightarrow$ SCRM	$B = .572, \beta = .541, t = 3.634, p < .001$	Supported
H5	Artificial Intelligence Adoption positively moderates the relationship between Contractual Risk Management and perceived Financial Performance.	Interaction-term regression: CRM $\times$ AIA	$B = -.179, \beta = -.094, t = -1.221, p = .232$	Not Supported
H6	Artificial Intelligence Adoption positively moderates the relationship between Supply Chain Risk Management and perceived Financial Performance.	Interaction-term regression: SCRM $\times$ AIA	$B = -.083, \beta = -.064, t = -.832, p = .412$	Not Supported

Source: IBM SPSS Statistics analysis of the study questionnaire data.

The hypotheses-testing results provided statistical support for H1, H2, H3, and H4, while H5 and H6 were not supported. H1 was supported with caution because CRM was statistically significant in the main-effects regression model ($p = .045$), but it did not reach the .05 significance level in the supplementary model containing only CRM and SCRM as

predictors ($p = .087$). This result indicates that the independent association between CRM and perceived Financial Performance may be sensitive to model specification.

H2 received clearer statistical support because SCRM demonstrated a positive and significant association with perceived Financial Performance in the main-effects model. H3 and H4 were also supported, indicating positive associations between AIA and the effectiveness of CRM and SCRM, respectively.

H5 and H6 were not supported because the $\text{CRM} \times \text{AIA}$ and $\text{SCRM} \times \text{AIA}$ interaction coefficients were not statistically significant. Accordingly, the available data did not provide evidence that AIA significantly changed the strength of the relationships between CRM, SCRM, and perceived Financial Performance. These findings should not be interpreted as proof that moderation is absent in the wider population, particularly given the limited statistical power associated with the final sample of 34 respondents.

4.10 Discussion of Findings

The findings of this study provide context-specific empirical evidence regarding the relationships among Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance in construction and industrial projects in the Eastern Province of Saudi Arabia. The high descriptive mean scores recorded for CRM, SCRM, AIA, and perceived FP indicate that respondents generally recognized the importance of contractual risk control, supply chain resilience, technology-enabled decision support, and financial risk management. However, the inferential results demonstrate that positive perceptions of the study constructs did not automatically translate into support for every hypothesized relationship.

The results provided statistical support for H1, which proposed a positive association between Contractual Risk Management and perceived Financial Performance. CRM was positively correlated with perceived FP and remained statistically significant in the main-effects regression model ($B = .252$, $\beta = .234$, $p = .045$). This finding suggests that systematic contract administration, timely management of contractual notices, documentation of claims and variations, monitoring of payment obligations, and control of approval-related risks were associated with more favorable perceptions of financial performance. The result is consistent with previous research emphasizing that delayed payments, unresolved variation orders, unclear risk allocation, and contractual disputes may increase project costs, disrupt cash flow, and weaken project performance (Bageis, 2024; Tang et al., 2020).

Nevertheless, H1 should be interpreted cautiously because CRM did not reach the .05 significance level in the supplementary regression model containing CRM and SCRM only ($p = .087$). This sensitivity may reflect the close interdependence between contractual and supply chain risks in construction projects. For example, a delayed material delivery may initially arise as a procurement issue but may subsequently generate extension-of-time claims, additional costs, disputed responsibilities, and payment consequences. Therefore, the financial contribution attributed to CRM may partially overlap with the contribution of SCRM. This interpretation is consistent with the integrated risk-management perspective adopted in the study, which views contractual and supply chain risks as interconnected rather than isolated organizational issues.

The findings provided clearer support for H2. Supply Chain Risk Management was positively and significantly associated with perceived Financial Performance in both the correlation and multiple regression analyses ($B = .336$, $\beta = .346$, $p = .007$). This result indicates that supplier monitoring, timely delivery of materials and equipment, management of long lead-time items, logistics planning, alternative sourcing, and disruption-response procedures were associated with stronger perceived financial outcomes. The finding is consistent with previous construction supply chain research showing that supplier failure, procurement delays, transportation constraints, material shortages, and price volatility may affect schedules, project costs, contractual obligations, and cash-flow stability (Antoniou & Tsioulpa, 2024; Baghalzadeh Shishehgharkhaneh et al., 2024). It also corresponds with evidence from industrial and manufacturing projects in the Eastern Province, where late procurement and delayed material delivery were identified as important contributors to project delay (Abdellatif & Alshibani, 2019).

The stronger and more consistent result for SCRM may be explained by the operational characteristics of construction and industrial projects in the Eastern Province. Such projects frequently depend on imported materials, specialized equipment, multiple suppliers, maritime transport, customs procedures, and inland logistics. Consequently, disruptions in supply availability or delivery timing may create immediate effects on project activities, idle resources, site overheads, billing schedules, and cash flows. This finding supports Supply Chain Management Theory and Project Management Theory by demonstrating that coordination of procurement, logistics, time, cost, and project resources is closely associated with perceived financial performance.

The findings also supported H3 and H4. Artificial Intelligence Adoption was positively associated with Contractual Risk Management effectiveness ($B = .430$, $\beta = .452$,

$p = .007$) and Supply Chain Risk Management effectiveness ($B = .572$, $\beta = .541$, $p < .001$). The association between AIA and SCRM was stronger than the association between AIA and CRM. These results suggest that respondents who reported greater use of AI-enabled or data-driven tools also reported stronger risk identification, forecasting, monitoring, and decision-support practices. This finding is consistent with literature indicating that AI applications may support contract analysis, risk and responsibility identification, predictive modelling, supplier monitoring, logistics forecasting, and early-warning systems (Culot et al., 2024; Dikmen et al., 2025; Tian et al., 2025).

The positive associations identified for H3 and H4 support elements of the Technology Acceptance Model, Resource-Based View, and Dynamic Capability Theory. From a technology-acceptance perspective, organizational use of AI is more likely when professionals perceive the technology as useful for risk analysis and decision-making. From a resource-based perspective, integrated data, digital systems, analytical expertise, and AI-enabled tools may represent organizational resources that strengthen risk-management practices. From a dynamic-capability perspective, AI may assist organizations in identifying changes, evaluating emerging disruptions, and reconfiguring procurement, contractual, and project-control responses. Nevertheless, the cross-sectional design does not establish that AIA caused improvements in CRM or SCRM effectiveness.

Artificial Intelligence Adoption also recorded a positive and statistically significant coefficient in the main-effects model predicting perceived Financial Performance ($B = .514$, $\beta = .501$, $p < .001$). Although this relationship was not formulated as a separate research hypothesis, it indicates that AIA was associated with perceived FP after CRM and SCRM were statistically controlled. This result should be interpreted cautiously because financial performance was measured through respondent perceptions rather than audited financial records, and the study design does not permit causal conclusions.

In contrast, H5 and H6 were not supported. The CRM $\times$ AIA interaction was not statistically significant ($B = -.179$, $\beta = -.094$, $p = .232$), and the SCRM $\times$ AIA interaction was also not statistically significant ($B = -.083$, $\beta = -.064$, $p = .412$). Therefore, the findings did not provide evidence that AIA significantly changed the strength of the relationships between CRM, SCRM, and perceived Financial Performance. The results indicate that AIA may be directly associated with risk-management effectiveness and perceived financial outcomes without necessarily functioning as a moderating condition within the relationships examined.

The absence of statistically significant moderation may have several possible explanations. First, organizations may differ in the maturity of their AI systems, data quality, technical integration, user capabilities, and implementation processes. Second, respondents may have perceived AI as useful for general monitoring and decision support, while its integration with contractual, procurement, financial, and scheduling systems may remain insufficient to change the strength of the CRM–FP and SCRM–FP relationships. Third, moderation effects are statistically more difficult to detect than direct associations, particularly in a small sample. Literature on AI adoption similarly emphasizes that organizational value depends on data readiness, system integration, implementation capability, and the context in which performance is evaluated (Culot et al., 2024; Tian et al., 2025).

Overall, the findings partially supported the integrated conceptual model. CRM and SCRM were positively associated with perceived Financial Performance, while AIA was positively associated with the effectiveness of both risk-management practices. However, AIA did not demonstrate a statistically significant moderating role. The results therefore suggest that effective contractual and supply chain risk management remain important organizational practices in their own right, while AI adoption may provide complementary analytical and decision-support capabilities rather than automatically strengthening the financial contribution of existing risk-management practices. All findings should be interpreted within the limitations of the purposive sample of 34 respondents, the cross-sectional design, the reliance on self-reported perceptions, and the absence of audited financial and formal factor-validity data.

4.11 Practical Recommendations

First, contracting organizations should strengthen their contract-administration procedures, particularly those related to contractual documentation, approval tracking, variation-order control, payment follow-up, scope-change management, claims notices, and extension-of-time records. This recommendation is consistent with the positive association identified between Contractual Risk Management and perceived Financial Performance. However, because the statistical support for H1 was sensitive to model specification, organizations should integrate contractual controls with supply chain, schedule, cost, and financial monitoring rather than manage contractual risks in isolation.

Second, organizations should give priority to Supply Chain Risk Management because SCRM demonstrated a positive and statistically significant association with perceived Financial Performance. Practical measures should include systematic supplier qualification, periodic supplier-performance evaluation, early identification of long lead-time items, monitoring of manufacturing and delivery milestones, logistics-risk assessment, alternative-supplier planning, and the development of contingency arrangements for critical materials and equipment.

Third, construction and industrial contracting organizations should improve the integration of contract, procurement, supplier, schedule, cost, and financial information. Greater information integration may enable managers to identify emerging delays, cost exposure, cash-flow implications, and contractual consequences at an earlier stage. Such integration should be supported by clearly defined data ownership, standardized reporting procedures, and coordination among contract management, procurement, project controls, finance, engineering, and site operations.

Fourth, Artificial Intelligence Adoption should be implemented gradually through clearly defined and manageable use cases. Relevant applications may include supplier-delay alerts, contract-clause screening, identification of high-risk purchase orders, forecasting of potential schedule disruption, cost-variance monitoring, and risk dashboards. Pilot applications should be evaluated against practical criteria such as data accuracy, usefulness to decision-makers, interpretability of results, implementation cost, and consistency with existing organizational procedures.

Fifth, organizations should not assume that the adoption of AI automatically strengthens the relationships between contractual or supply chain risk management and perceived Financial Performance. The moderation hypotheses H5 and H6 were not supported. Accordingly, AIA should be accompanied by reliable data, system integration, employee training, clear governance procedures, professional review, and managerial oversight. AI-generated output should support, rather than replace, contractual, procurement, financial, and project-management judgment.

Finally, organizations should establish measurable indicators to monitor the practical outcomes of contractual, supply chain, and AI-enabled risk-management initiatives. Relevant indicators may include the frequency and value of unresolved variation orders, payment delays, supplier delivery performance, procurement lead-time deviations, logistics-cost

increases, extension-of-time events, cost variances, and the timeliness of risk-response decisions. However, the selection of specific targets should be based on the organization's actual project records and internal performance requirements.

4.12 Academic Recommendations

The findings support continued academic examination of Contractual Risk Management and Supply Chain Risk Management as theoretically distinct but operationally interconnected construction projects. Their strong correlation indicates that future conceptual models should account for the possibility of overlapping between contractual, procurement, logistics, schedule, and financial risks while maintaining clear definitions and measurement boundaries for CRM and SCRM.

Academic studies should also distinguish clearly between the different statistical roles of Artificial Intelligence Adoption. AIA may be examined as a predictor of risk-management effectiveness, as an independent predictor of organizational outcomes, or as a moderating variable. These roles should not be treated as interchangeable. In the present study, AIA demonstrated positive direct associations with CRM, SCRM, and perceived Financial Performance, but the proposed moderation relationships were not statistically supported.

Further instrument-development work is recommended to review the wording and theoretical alignment of CRM1, CRM4, CRM7, SCRM5, and AI1, which recorded relatively weak corrected item-total correlations. Any revised items should be evaluated through expert review, pilot testing, and larger-sample measurement assessment before being used to modify the existing construct structure.

Future academic research should employ sufficiently large samples to support exploratory factor analysis, confirmatory factor analysis, and formal assessment of convergent and discriminant validity. Larger samples would also provide greater statistical power for detecting interaction effects and comparing alternative conceptual models.

Finally, future theoretical development should examine whether AIA may operate through mechanisms other than moderation, such as mediation, organizational capability development, data integration, or decision-support quality. Such extensions should be theoretically justified and specified before data collection rather than introduced after reviewing the statistical results.

4.13 Suggestions for Future Research

Future research should examine the proposed relationships using larger and more diverse samples drawn from contractors, consultants, project owners, suppliers, subcontractors, and government-related project organizations. Extending data collection beyond the Eastern Province to other regions of Saudi Arabia would improve the geographical coverage of the research and allow the findings to be compared across different construction and industrial environments. Where feasible, probability-based sampling procedures should be used to strengthen the representativeness and generalizability of the results.

Future studies should complement questionnaire-based perceptions with objective projects and organizational indicators. Relevant measures may include project cost variance, schedule variance, gross margin, cash-flow performance, value and duration of claims, payment delays, procurement lead-time deviations, supplier delivery performance, logistics-cost increases, and the value of variation orders. Access to such information would require appropriate organizational authorization, confidentiality safeguards, and reliable company or project records.

Longitudinal research is also recommended to examine changes in Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and financial outcomes over time. Collecting data at multiple stages could help determine whether changes in AIA precede subsequent changes in risk-management effectiveness and project financial indicators. Such a design would provide stronger temporal evidence than the cross-sectional approach used in the present study, although causal conclusions would still require careful research design and control of alternative explanations.

Comparative studies could examine whether the relationships differ according to project type, organizational size, contractual arrangement, supply chain complexity, or level of dependence on imported materials and equipment. Comparisons could include oil and gas projects, industrial construction, infrastructure, building construction, manufacturing-support projects, and operations and maintenance activities.

Future research should also examine organizational conditions that may influence the effectiveness of AI-enabled risk management, including data quality, digital-system integration, AI readiness, employee skills, perceived usefulness, user acceptance, organizational culture, governance procedures, and managerial support. These variables may

help explain why Artificial Intelligence Adoption demonstrated positive direct associations in the present study but did not significantly moderate the CRM–FP or SCRM–FP relationships.

4.14 Chapter Summary

This chapter presented the statistical analysis, findings, discussion, and recommendations of the study. The original Google Forms dataset contained 49 submitted records. Following data screening, 15 exact duplicate records were removed, resulting in a final dataset of 34 unique valid responses. No missing values or values outside the permitted Likert-scale range were identified among the retained cases.

The reliability results demonstrated acceptable internal consistency for Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance. The descriptive findings indicated high levels of respondent agreement across all four constructs. Pearson correlation analysis showed positive and statistically significant bivariate associations among CRM, SCRM, AIA, and perceived FP.

The multiple regression results provided statistical support for H1 and H2, although the association between CRM and perceived FP was interpreted cautiously because it was sensitive to model specification. SCRM demonstrated a clearer and more consistent positive association with perceived FP. The simple regression analyses also supported H3 and H4, indicating positive associations between AIA and the effectiveness of CRM and SCRM, respectively.

In contrast, the moderation analyses did not support H5 or H6. Neither the CRM $\times$ AIA interaction term nor the SCRM $\times$ AIA interaction term was statistically significant. Therefore, the available data did not provide evidence that AIA significantly changed the strength of the relationships between CRM, SCRM, and perceived Financial Performance.

Based on these findings, the chapter recommended strengthening contract administration, prioritizing supply chain risk management, improving the integration of contractual, procurement, schedule, cost, and financial information, and implementing AI-enabled applications gradually through controlled and measurable use cases. The chapter also recommended larger and more diverse samples, longitudinal and comparative research designs, the inclusion of objective project and financial indicators, and further assessment of the questionnaire measurement structure.

The findings should be interpreted within the methodological boundaries of the study. The research used a non-probability purposive sample of 34 valid respondents, a cross-sectional questionnaire design, and self-reported measures of perceived Financial Performance rather than audited financial records. Formal factor-based validity procedures were not conducted because of the limited sample size. Accordingly, the results provide exploratory evidence of statistical associations within the selected study context and should not be interpreted as proof of causal relationships or generalized automatically to the wider construction sector.

Appendix A:

Questionnaire:

The following questionnaire was used as the primary data-collection instrument for this study. It consisted of five sections. Section One included six demographic questions concerning gender, age, education level, years of professional experience, current position, and company type. Sections Two to Five included 33 Likert-scale measurement items covering Contractual Risk Management, Supply Chain Risk Management, Artificial Intelligence Adoption, and perceived Financial Performance.

The measurement items comprised 10 items for Contractual Risk Management, 8 items for Supply Chain Risk Management, 8 items for Artificial Intelligence Adoption, and 7 items for perceived Financial Performance. Responses were recorded using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire is reproduced in this appendix in the form in which it was administered to the study participants.

SECTION 1: DEMOGRAPHIC INFORMATION

Code	Question	Response Options
D1	Gender	Male; Female
D2	Age	Less than 30; 30–39; 40–49; 50 and above
D3	Education Level	Diploma; Bachelor; Master; Doctorate
D4	Years of Experience	Less than 5 years; 5–10 years; 11–15 years; More than 15 years
D5	Current Position	Project Manager; Contract Manager; Procurement Manager; Supply Chain Manager; Risk Manager; Engineer; Supervisor; Financial Manager; IT Manager; Other
D6	Company Type	Contractor; Consultant; Owner/Client; Supplier; Government Entity

SECTION 2: CONTRACTUAL RISK MANAGEMENT (CR)

Response scale for all Likert-scale items: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Item Code	Questionnaire Item	Scale
CR1	Contract clauses and responsibilities are clearly defined.	1–5 Likert scale
CR2	Delays in approvals and contract amendments negatively affect project performance.	1–5 Likert scale
CR3	Payment delays significantly affect project cash flow.	1–5 Likert scale
CR4	Delayed owner payments increase project risks.	1–5 Likert scale
CR5	Variation orders frequently increase project costs.	1–5 Likert scale
CR6	Variation orders frequently extend project schedules.	1–5 Likert scale
CR7	Executing work before obtaining required approvals increases contractual risks.	1–5 Likert scale
CR8	Executing work outside the approved contract scope increases project risks.	1–5 Likert scale
CR9	Performing additional works without formal approval creates contractual disputes.	1–5 Likert scale
CR10	Effective contract management reduces contractual risks.	1–5 Likert scale

SECTION 3: SUPPLY CHAIN RISK MANAGEMENT (SC)

Response scale for all Likert-scale items: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Item Code	Questionnaire Item	Scale
SC1	Supplier reliability significantly affects project success.	1–5 Likert scale
SC2	Delays in material delivery negatively affect project schedules.	1–5 Likert scale
SC3	Material shortages create project performance risks.	1–5 Likert scale
SC4	Supplier failures can cause major project disruptions.	1–5 Likert scale
SC5	Transportation and logistics problems frequently delay projects.	1–5 Likert scale
SC6	Price fluctuations of construction materials increase project risks.	1–5 Likert scale
SC7	Supply chain disruptions increase project costs.	1–5 Likert scale
SC8	Effective supply chain management reduces project delays.	1–5 Likert scale

SECTION 4: ARTIFICIAL INTELLIGENCE CAPABILITIES (AI)

Response scale for all Likert-scale items: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Item Code	Questionnaire Item	Scale
AI1	Artificial Intelligence helps identify project risks early.	1–5 Likert scale
AI2	AI improves the accuracy of risk prediction.	1–5 Likert scale
AI3	AI supports better project decision-making.	1–5 Likert scale
AI4	AI helps monitor contractual risks effectively.	1–5 Likert scale
AI5	AI improves supply chain visibility.	1–5 Likert scale
AI6	AI helps detect potential project delays before they occur.	1–5 Likert scale
AI7	AI improves overall risk management effectiveness.	1–5 Likert scale
AI8	AI supports financial forecasting and planning.	1–5 Likert scale

SECTION 5: FINANCIAL PERFORMANCE (FP)

Response scale for all Likert-scale items: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Item Code	Questionnaire Item	Scale
FP1	Effective risk management improves project profitability.	1–5 Likert scale
FP2	Effective risk management helps control project costs.	1–5 Likert scale
FP3	Project delays negatively affect financial performance.	1–5 Likert scale
FP4	Contractual risks contribute to cost overruns.	1–5 Likert scale
FP5	Supply chain risks negatively affect project profitability.	1–5 Likert scale
FP6	AI-driven risk management contributes to better financial performance.	1–5 Likert scale
FP7	AI improves overall project financial outcomes.	1–5 Likert scale

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