

أثر مهارات هندسة الأوامر للذكاء الاصطناعي التوليدي في تقليل العبء الذهني وتحسين جودة
اتخاذ القرار: دراسة تطبيقية على مديري المشاريع التقنية في المملكة العربية السعودية

إعداد:

رائد أحمد نقاش

253002775

إشراف:

د.فايز علي جراد

د.الفیصل عبدالحمید محمد

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المستخلص

استناداً إلى نظرية الحمل المعرفي ونموذج ملاءمة المهمة للتكنولوجيا، سعت هذه الدراسة إلى القياس التجريبي لأثر مهارات هندسة أوامر الذكاء الاصطناعي التوليدي في تقليل الحمل المعرفي الخارجي وتحسين جودة اتخاذ القرار الاستراتيجي لدى مديري المشاريع التقنية ضمن منظومة رؤية السعودية 2030. ولتحقيق أهداف الدراسة، تم الاعتماد على المنهج الكمي الوصفي من خلال استبانة إلكترونية وُزعت على عينة مستهدفة من مديري المشاريع التقنية، وُحُلَّت البيانات عبر برنامج الحزم الإحصائية للعلوم الاجتماعية باستخدام الإحصاء الوصفي، واختبار ارتباط بيرسون، وتحليل التباين الأحادي.

أظهرت النتائج دعماً للفرضيتين البديلتين الأولى والثانية؛ حيث كشفت عن وجود ارتباط عكسي ذي دلالة إحصائية بين كفاءة هندسة الأوامر والحمل المعرفي، مما يؤكد دورها كدعائم وسقالات معرفية تسهم في تصفية الهلوسات الخوارزمية وتقليل الإرهاق الذهني. كما ثبت وجود ارتباط طردي وثيق مع جودة اتخاذ القرار، إذ تسهم الأوامر الدقيقة في الحد من ظاهرة الانحياز للأتمتة وتضمن ملاءمة مخرجات التقنية للمتطلبات الهندسية المعقدة. وفيما يخص الفرضية الثالثة، تم قبول الفرضية الصفريّة في مجملها، مما يعكس الحيادية الديموغرافية للأداة؛ حيث لم تظهر فروق ذات دلالة إحصائية تعزى للعمر، أو المدينة، أو سنوات الخبرة. وكان الفارق الجوهري الوحيد يعود إلى معدل الاستخدام، مما يؤكد أن الممارسة المستمرة هي المحرك الفعلي لتعظيم الاستفادة. وبناءً على هذه النتائج، توصي الدراسة مكاتب إدارة المشاريع بتقديم تدريب هيكلي على هندسة الأوامر، والتشجيع المستمر لاستخدام الذكاء الاصطناعي التوليدي، وتطوير مكاتب أوامر معيارية، مع ضرورة المواءمة التامة مع الأطر الأخلاقية للهيئة السعودية للبيانات والذكاء الاصطناعي (سدايا).

الكلمات المفتاحية: الذكاء الاصطناعي التوليدي، هندسة الأوامر، الحمل المعرفي، جودة اتخاذ القرار، مديرو المشاريع التقنية.

Abstract

Grounded in Cognitive Load Theory (CLT) and the Task-Technology Fit (TTF) model, this study empirically investigated the impact of Generative AI prompt-engineering skills on reducing extraneous cognitive load and enhancing strategic decision-making quality among technical project managers within the Saudi Vision 2030 ecosystem. A quantitative descriptive approach was employed, utilizing an online survey distributed to a targeted sample of technical project managers. Data were analyzed via SPSS using descriptive statistics, Pearson correlation, and One-Way ANOVA.

The empirical findings supported the first and second alternative hypotheses. A statistically significant inverse correlation was identified between prompt-engineering proficiency and cognitive load, confirming its role as "cognitive scaffolding" that effectively filters algorithmic hallucinations and mitigates mental fatigue. Furthermore, a strong positive correlation was established with decision-making quality, demonstrating that precise prompting mitigates "automation bias" and aligns AI outputs with complex engineering demands. Regarding the third hypothesis, the null hypothesis was largely accepted, indicating the technology's "demographic neutrality." No significant differences were found based on age, city, or years of experience. The singular significant variance emerged from the "frequency of AI usage," underscoring that continuous practice is the primary driver of AI maximization. Consequently, the study recommends that Project Management Offices (PMOs) implement structured prompt-engineering training, actively encourage routine GenAI usage, and develop standardized prompt libraries. Crucially, these integrations must align strictly with the ethical frameworks of the Saudi Data and AI Authority (SDAIA) to ensure reliable, data-driven executive decisions.

Keywords: Generative AI, Prompt Engineering, Cognitive Load, Decision-Making Quality, Technical Project Management.

Dedication

To my beloved parents, the guiding lights and constant inspiration of my life. To my mother, for her unwavering love and boundless encouragement, which have been my lifelong catalyst. To my father, who instilled in me the values of perseverance and diligent labor.

To my dearest wife, my steadfast partner and supporter through every stage of this journey. This achievement is a tribute to her immense efforts, sacrifices, and immeasurable patience.

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List of Terminology:

Automation Bias: The psychological propensity for human operators to over-rely on or favor suggestions from automated decision-making systems (such as AI), sometimes ignoring contradictory human intuition or factual data, even when the automated system is incorrect.

Cognitive Friction: The mental resistance or excessive mental effort required to complete a task due to poorly designed interfaces, ambiguous instructions, or unpredictable technological outputs (such as AI hallucinations).

Cognitive Load: A psychological construct referring to the total amount of mental effort being utilized in human working memory. It is categorized into three types: Intrinsic (inherent task difficulty), Extraneous (unnecessary mental strain), and Germane (effort devoted to actual learning and strategic processing).

Cognitive Scaffolding: In this study, it refers to the use of structured Prompt Engineering as a supportive psychological framework. It externalizes the complexity of instructing an AI, thereby reducing the user's extraneous cognitive load and freeing up mental capacity for higher-level strategic thinking.

Extraneous Cognitive Load: The additional cognitive burden caused by the way information is presented, rather than by the intrinsic complexity of the task. In human-AI interaction, extraneous cognitive load increases when users must interpret ambiguous, irrelevant, or fabricated AI outputs.

Generative Artificial Intelligence (GenAI): A class of advanced artificial intelligence systems capable of generating novel, high-quality text, images, code, or other media in response to natural language user prompts (e.g., ChatGPT, Gemini, Claude, and etc.).

Germane Cognitive Load: This term refers to the cognitive resources allocated to the processing, construction, and automation of schemas. In project management, it denotes the mental effort effectively dedicated to strategic problem-solving and risk analysis.

Hallucination (Algorithmic): A phenomenon wherein a Large Language Model confidently generates a response that is factually incorrect, nonsensical, or completely ungrounded in the provided training data or prompt context.

Jagged Technological Frontier: A theoretical concept describing the uneven, unpredictable capabilities of modern Generative AI. It illustrates how AI can easily perform highly complex analytical tasks but unpredictably fail at seemingly simpler tasks, necessitating continuous human-in-the-loop oversight.

Large Language Model (LLM): Deep learning algorithms pre-trained on massive datasets of text that can recognize, summarize, translate, predict, and generate human-like language.

Project Management Office (PMO): A centralized organizational department or group that defines, maintains, and ensures standard project management methodologies, governance, and project portfolio success within an enterprise.

Prompt Engineering: The systematic, iterative practice of designing, structuring, and refining natural language inputs (prompts) to effectively guide Generative AI models to produce highly accurate, contextualized, and reliable outputs.

Task-Technology Fit (TTF): A theoretical model proposing that a technology is only effective and likely to be utilized if its specific capabilities perfectly align with the complex demands of the tasks the user must perform.

List of abbreviations:

AI: Artificial Intelligence

GenAI: Generative Artificial Intelligence

LLM: Large Language Model

CLT: Cognitive Load Theory

TTF: Task-Technology Fit

KPI: Key Performance Indicator

ANOVA: Analysis of Variance

PMO: Project Management Office

Chapter One: Research Introduction and Conceptual Framework

1.1 Introduction:

Technical project management in the Kingdom of Saudi Arabia is experiencing significant and rapid transformation. This evolution is heavily driven by the strategic imperatives of Saudi Vision 2030, which seeks to transition the nation from a resource-dependent economy to a robust, innovation-based digital powerhouse (Albaroudi et al., 2024). As part of this national agenda, the Kingdom of Saudi Arabia is currently executing complex technological mega-projects and digital infrastructure initiatives, with the government providing unparalleled institutional backing and heavy investment for emerging technologies (Albaroudi et al., 2024). The Digital Government Authority and the Saudi Data and AI Authority (SDAIA) have proactively established comprehensive operational frameworks, national standards, and ethical guidelines to safely and effectively integrate Generative AI (GenAI) across digital government operations and private sector projects (SDAIA, 2025). To understand the magnitude of this shift within the Project Management Office (PMO), one must trace the historical evolution of artificial intelligence in corporate environments (Afilali, 2026). Historically, project management relied on manual data aggregation, traditional methodologies, and human intuition to forecast risks. The first wave of AI introduced rule-based algorithms and predictive machine learning models that assisted project managers by analyzing historical data to forecast budget overruns or schedule delays (Obana, 2024). However, the recent advent of Large Language Models (LLMs) and Generative Artificial Intelligence represents a paradigm shift (Sahoo et al., 2024). Unlike previous systems that merely analyzed structured data, GenAI is a disruptive technological enabler capable of automating complex analytical reasoning, generating comprehensive project documentation, and augmenting human cognitive capabilities during real-time execution (Afilali, 2026; Obana, 2024).

In Saudi Arabia's high-pressure tech projects, managers have a lot on their minds. They have to deal with large amounts of disorganized information, manage complex risks, and make big decisions quickly (Afilali, 2026). While GenAI might seem like a solution to this problem, working with humans and AI together is actually really complicated (Santos, 2025). To make it work, you need to be good at "prompt engineering", which means being able to give clear, specific instructions to the GenAI models so they can produce accurate and useful results (Schulhoff et al., 2024). This is crucial because the models need to understand exactly what you want them to do, and the instructions have to be tailored to the specific situation (Schulhoff et al., 2024). If you can master prompt engineering, you can unlock the full potential of GenAI, effectively reduce your extraneous cognitive load, and make your job as a manager significantly easier and more productive (Afilali, 2026; Schulhoff et al., 2024).

However, it's not always easy to get it right, and it requires a deep understanding of how the models work and how to communicate with them effectively (Schulhoff et al., 2024). By getting it right, though, you can free up more time to focus on the big picture and make strategic decisions that drive your projects forward (Santos, 2025). Without profound prompt-engineering skills, project managers often encounter what is known as

the "jagged technological frontier" (Dell'Acqua et al., 2026). At this frontier, the capabilities of AI are highly unpredictable; the AI might perform a highly complex analytical task flawlessly, yet fail completely at a seemingly simple logical request (Dell'Acqua et al., 2026). Consequently, interacting with AI without structured prompting strategies paradoxically amplifies mental confusion and operational burden rather than alleviating it (Nagori et al., 2025; Saito & Yamada, 2026).

Furthermore, unstructured queries drastically increase the risk of "digital hallucinations", instances where AI models generate highly convincing, yet factually incorrect technical or financial data, posing a severe threat to project integrity (Phillips-Wren & Håkansson, 2025; Sahoo et al., 2024). Therefore, the practice of prompt engineering has transcended its origins as a mere computer science input technique; it has become a vital form of "cognitive scaffolding" for technical leaders (Aruleba et al., 2026). By using lightweight, structured prompt-engineering methodologies, project managers can achieve "cognitive alignment" between their strategic intent and the machine's processing patterns (Yaacoub et al., 2025). This alignment successfully minimizes extraneous cognitive load, freeing the project manager's mental capacity to focus on high-level strategic evaluation rather than trial-and-error data retrieval (Nagori et al., 2025). Ultimately, mastering this capability serves as a cognitive bridge that directly improves the speed, accuracy, and reliability of strategic decision-making within the PMO (Phillips-Wren & Håkansson, 2025). As Saudi Arabia accelerates its Vision 2030 digital initiatives, it is imperative to investigate how technical project managers can seamlessly harness GenAI through prompt engineering, ensuring that their projects remain innovative, efficient, and strictly aligned with the nation's ethical and technological frameworks (Albaroudi et al., 2024).

1.2 Problem Statement:

While the current body of literature extensively documents the theoretical and macroeconomic benefits of Generative AI (GenAI) in corporate domains, a critical empirical gap remains regarding the precise human-centric skills required to operate these advanced models successfully in high-stress execution environments (Obana, 2024; Santos, 2025). As the Kingdom of Saudi Arabia dramatically accelerates its digital infrastructure to meet the ambitious software engineering and economic diversification objectives of Vision 2030, organizations are rapidly adopting GenAI platforms to maintain market competitiveness (Albaroudi et al., 2025). However, the mere organizational deployment of these technological tools does not automatically translate into operational efficiency.

Studies indicate that a lack of structured interaction with AI systems often leads professionals to feel lost on the "jagged technological frontier" (Dell'Acqua et al., 2026). In this unpredictable operational space, attempting to use GenAI platforms without formalized prompt-engineering competencies often results in suboptimal information retrieval, inconsistent outputs, and severe algorithmic hallucinations (Sahoo et al., 2024). Because the AI's processing capabilities fluctuate drastically depending on the precise phrasing and contextual framing of a query, unstructured interactions frequently lead to a breakdown in human-machine collaboration. Consequently, this friction inadvertently hinders problem-solving and critical thinking by increasing extraneous cognitive load (Nagori et al., 2025), preventing project managers from focusing on the strategic leadership and decision-making roles that GenAI is meant to facilitate (Santos, 2025).

For technical project managers operating within the Kingdom of Saudi Arabia's fast-paced Project Management Offices (PMOs), this technological friction creates a severe psychological bottleneck. When prompt engineering skills are deficient, the manager is forced into an exhausting cycle of repetitive, unstructured prompting just to extract viable, context-specific data (Debnath et al., 2024; Nagori et al., 2025). This highly inefficient interaction intrinsically consumes valuable operational time and exponentially exacerbates the user's mental strain by generating extraneous cognitive load. Instead of the GenAI system functioning as an analytical assistant that alleviates workload, it becomes an active source of extraneous cognitive burden. The project manager is thereby forced to expend vital mental energy verifying, correcting, and deciphering flawed AI outputs, which severely depletes the cognitive resources necessary for high-level strategic execution (Saito & Yamada, 2026).

This state of cognitive exhaustion directly threatens the integrity of strategic project management. Operating under immense timeline constraints and financial pressures, project managers experiencing this AI-induced mental fatigue are significantly more susceptible to "automation bias", the dangerous tendency to over-rely on automated algorithmic outputs without applying sufficient human oversight (Dell'Acqua et al., 2026). Because AI hallucinations can produce highly convincing yet fabricated text, it becomes incredibly dangerous to trust the model's outcomes in risky decision-making situations without rigorous analytical validation (Phillips-Wren & Håkansson, 2025). If left unchecked, this over-reliance poses substantial operational risks to mega projects aligned with Vision 2030 (Albaroudi et al., 2025).

Consequently, the primary issue this study aims to address is the critical empirical gap regarding how prompt engineering impacts project managers' cognitive load and practical decision-making capabilities (Afilali, 2026; Nagori et al., 2025). Although prompt engineering is increasingly recognized as a fundamental technical competency, its precise role in facilitating cognitive alignment and enhancing analytical rigor remains under-researched. This study aims to determine whether the systematic application of prompt engineering techniques can effectively reduce the extraneous cognitive load of technical project managers, thereby enabling safer, more reliable, and highly accurate strategic decisions. By investigating this human-AI dynamic within the Kingdom of Saudi Arabia, this research seeks to provide actionable insights for optimizing project management efficacy and ensuring that GenAI integration aligns safely with the nation's ambitious industrial objectives.

1.3 Significance of the Study:

The importance of this study comes in two main ways: it helps us understand things better, and it has real-world uses. Both of these ways are crucial for changing how we think about people working with artificial intelligence. Instead of just focusing on the technology, we're shifting our attention to the human skills needed to make the most of it.

1.3.1 Theoretical Significance:

Theoretically, this research addresses a pronounced empirical lacuna in contemporary literature regarding the micro-level psychological dynamics of human interaction with Generative AI. While an extensive body of research has mapped the technical capabilities and macroeconomic impacts of Large Language Models (LLMs), empirical investigations treating "prompt engineering" as a distinct, measurable operational and psychological competency remain exceedingly sparse (Debnath et al., 2024).

By conceptualizing prompt engineering not merely as a technical input in computer science, but as an indispensable form of "cognitive scaffolding" that governs the human-machine interface, this study significantly enriches the theoretical understanding of digital cognitive load (Aruleba et al., 2026). It actively challenges the oversimplified narrative that AI deployment automatically and universally reduces human workload. Instead, by integrating the concept of the "jagged technological frontier," this study provides a nuanced perspective: it proves that without structured alignment, AI introduces extraneous cognitive friction (Dell'Acqua et al., 2026). Consequently, this research advances Cognitive Load Theory within modern AI contexts by demonstrating how "lightweight prompt engineering" acts as a moderating variable that establishes "cognitive alignment" between the human operator and the machine, effectively transforming AI from a source of mental fatigue into a facilitator of germane, strategic thinking (Yaacoub et al., 2025; Nagori et al., 2025).

1.3.2 Practical Significance:

In practical terms, the findings of this study possess substantial strategic value for technology-driven organizations operating in the highly dynamic economic landscape of the Kingdom of Saudi Arabia. As KSA accelerates its digital transformation to realize the advanced software engineering and infrastructure objectives of Vision 2030, billions of dollars are being heavily invested in technological mega-projects (Albaroudi et al., 2025). Consequently, technical project managers are placed under immense operational pressure to deliver flawless outcomes on accelerated timelines.

This study provides executive leadership and decision-makers with the empirical foundation necessary to design and implement targeted AI literacy and integration programs within the Project Management Office (PMO). It demonstrates how systematic prompt engineering methodologies can accelerate the speed, accuracy, and reliability of complex decision-making, while concurrently mitigating the risks associated with automation bias and an over-reliance on algorithmic outputs (Phillips-Wren & Håkansson, 2025). Furthermore, the study outlines a practical framework for

organizations to maximize their return on investment in AI technologies. By adopting these structured approaches, companies can ensure that their AI deployments effectively augment human capabilities rather than introducing extraneous inefficiencies or operational hazards. Ultimately, the objective of this research is to facilitate the intelligent, secure, and commercially viable integration of GenAI into project management workflows (Afilali, 2026).

Furthermore, the study has critical significance for compliance and governance. The research outcomes directly support and operationalize the ethical AI directives established by the Saudi Data and AI Authority (SDAIA, 2025) and the Arab League Educational, Cultural and Scientific Organization (ALECSO, 2024). By advocating for "ethical prompt engineering," this study provides technical leaders with actionable methodologies to mitigate organizational risks associated with algorithmic biases, digital hallucinations, and data privacy breaches, ensuring that the deployment of GenAI remains transparent, reliable, and strictly aligned with national governance frameworks (Bura et al., 2025).

1.4 Objectives of the Study:

This research seeks to reframe prompt engineering from a theoretical concept in computer science to a measurable and essential skill within contemporary project management (Debnath et al., 2024). In response to gaps identified in the literature and to offer practical solutions for technical project environments, the study pursues the following objectives:

1. To assess the current skill levels of prompt engineering among technical project managers in the Kingdom of Saudi Arabia. This context will reflect the country's rapid adoption of AI and Vision 2030 initiatives (Albaroudi et al., 2025).
2. To quantitatively measure how advanced, structured prompt engineering skills help reduce operational friction and "extraneous cognitive load" that project managers face during complex technical tasks (Nagori et al., 2025; Saito & Yamada, 2026).
3. To evaluate how structured and context-aware GenAI prompting improves the quality, accuracy, speed, and reliability of project decision-making processes, thereby reducing the risk of automation bias (Dell'Acqua et al., 2026; Phillips-Wren & Håkansson, 2025).
4. To identify the main challenges and obstacles, particularly the unpredictable changes at the "jagged technological frontier," that technical project managers face when integrating Generative AI into their daily PMO workflows (Dell'Acqua et al., 2026; Sahoo et al., 2024).

To develop evidence-based, practical recommendations for technology-driven organizations. These recommendations will help design targeted training frameworks that boost human-AI collaboration within the Project Management Office (PMO). All practices will align with national AI ethics and governance guidelines (Afilali, 2026; SDAIA, 2025).

1.5 Research Questions:

To systematically operationalize the research problem and fulfill the established empirical objectives, this study translates its theoretical foundations into measurable variables. Anchored in both Cognitive Load Theory (CLT) and the Task-Technology Fit (TTF) model, this study seeks to answer the following primary, overarching research question:

"What is the measurable impact of Generative AI prompt engineering skills on reducing cognitive load and improving the quality of strategic decision-making among technical project managers operating within the Kingdom of Saudi Arabia?"

To comprehensively deconstruct and answer this central inquiry, the research is guided by the following highly specific sub-questions:

1. **Assessing Baseline Proficiency:** What is the current level of prompt engineering proficiency among technical project managers and PMO directors operating within technological sectors in KSA, given the rapid integration of Large Language Models (LLMs) into enterprise digital workflows (Debnath et al., 2024; Sahoo et al., 2024)?
2. **Evaluating Cognitive Dynamics:** How does the systematic application of structured and "lightweight prompt engineering" techniques act as "cognitive scaffolding" to mitigate extraneous cognitive load, while simultaneously optimizing the germane load experienced by project managers during complex analytical tasks (Aruleba et al., 2026; Nagori et al., 2025; Yaacoub et al., 2025)?
3. **Measuring Decision-Making Quality:** To what extent do advanced prompting competencies enhance the accuracy, reliability, and speed of strategic project decision-making, while concurrently mitigating the risks of algorithmic hallucinations and "automation bias" at the jagged technological frontier (Dell'Acqua et al., 2026; Phillips-Wren & Håkansson, 2025)?
4. **Analyzing Demographic Variances:** Are there statistically significant differences at the level of ($\alpha \leq 0.05$) in the perceived impact of prompt engineering on cognitive load and decision-making quality attributed to demographic and professional variables (e.g., years of experience, age, geographic location, and frequency of GenAI usage) (Afilali, 2026; Santos, 2025)?

1.6 Research Hypotheses:

To empirically investigate the research problem and provide a robust statistical answer to the primary research questions, this study formulates three core hypotheses. These hypotheses translate the study's theoretical paradigms Cognitive Load Theory (CLT) and the Task-Technology Fit (TTF) model into measurable, testable variables. By examining how human-centric skills dictate algorithmic, outcomes at the "jagged technological frontier" (Dell'Acqua et al., 2026), the study tests the following hypotheses, presented in both their null (H0) and alternative (H1) states:

Hypothesis 1: The Impact of Prompt Engineering on Cognitive Load

- **Theoretical Rationale:** Grounded in Cognitive Load Theory (CLT), this hypothesis projects that advanced prompting skills act as "cognitive scaffolding." By structuring AI interactions, project managers can filter out algorithmic hallucinations and significantly reduce the mental fatigue associated with processing complex GenAI outputs (Aruleba et al., 2026; Nagori et al., 2025; Saito & Yamada, 2026).
- **Null Hypothesis (H01):** There is no statistically significant inverse correlation at the level of ($\alpha \leq 0.05$) between a technical project manager's proficiency in prompt engineering and their perceived extraneous cognitive load.
- **Alternative Hypothesis (H1):** There is a statistically significant inverse (negative) correlation at the level of ($\alpha \leq 0.05$) between a technical project manager's proficiency in prompt engineering and their perceived extraneous cognitive load. (Meaning: As prompt engineering skills increase, cognitive load decreases.)

Hypothesis 2: The Impact of Prompt Engineering on Decision-Making Quality

- **Theoretical Rationale:** Grounded in the Task Technology Fit (TTF) model, this hypothesis posits that precise prompt engineering guarantees a strict "fit" between the GenAI's raw output and the specific, high-risk demands of engineering projects. This alignment actively mitigates "automation bias" and enhances the reliability of executive choices (Anam, 2025; Debnath et al., 2024; Dell'Acqua et al., 2026; Phillips-Wren & Håkansson, 2025).
- **Null Hypothesis (H02):** There is no statistically significant direct correlation at the level of ($\alpha \leq 0.05$) between a technical project manager's prompt engineering proficiency and the quality, speed, and reliability of their strategic decision-making outcomes.
- **Alternative Hypothesis (H2):** There is a statistically significant direct (positive) correlation at the level of ($\alpha \leq 0.05$) between a technical project manager's prompt engineering proficiency and the quality, speed, and reliability of their strategic

decision-making outcomes. (Meaning: As prompt engineering skills increase, decision-making quality improves.)

Hypothesis 3: Demographic and Professional Variances

- **Theoretical Rationale:** This hypothesis tests the universality of human-AI collaboration challenges across the Saudi technological ecosystem. It seeks to determine if external variables such as an organization's maturity, a manager's seniority, or the specific complexities of Saudi Vision 2030 mega projects alter how AI impacts the user (Afilali, 2026; Albaroudi et al., 2025; Santos, 2025).
- **Null Hypothesis (H03):** There are no statistically significant differences at the level of ($\alpha \leq 0.05$) in the perceived impact of prompt engineering on cognitive load and decision-making quality based on demographic and professional characteristics (e.g., years of experience, geographic location, age, and frequently of GenAI usage).
- **Alternative Hypothesis (H3):** There are statistically significant differences at the level of ($\alpha \leq 0.05$) in the perceived impact of prompt engineering on cognitive load and decision-making quality based on demographic and professional characteristics.

1.7 Scientific Theory Adopted for the Research:

To provide a rigorous analytical framework for this empirical investigation, the study adopts a dual-theoretical approach. By integrating modern adaptations of Cognitive Load Theory (CLT) with the Task Technology Fit (TTF) Model, this research establishes a comprehensive socio-technical paradigm that explains both the internal psychological mechanisms and the external operational outcomes of human-AI collaboration (Anam, 2025).

1.7.1 Cognitive Load Theory (CLT) in Human-AI Interaction:

Originally established as a foundational psychological framework explaining the strict limitations of human working memory, CLT has been recently recontextualized by contemporary scholars to analyze human-computer interactions in the generative AI era (Nagori et al., 2025). In the context of this study, the theory posits that human cognitive capacity is finite and divided into intrinsic, extraneous, and germane loads.

When a technical project manager interacts with GenAI at the unpredictable "jagged technological frontier" without structured instructions, the model frequently produces ambiguous, hallucinated, or irrelevant outputs (Dell'Acqua et al., 2026). Processing these flawed outputs exponentially inflates the user's "extraneous cognitive load", the mental effort wasted on navigating poor instructional design and filtering bad data (Nagori et al., 2025; Saito & Yamada, 2026). Conversely, this study theorizes that mastering prompt engineering acts as a vital form of "cognitive scaffolding" (Aruleba et al., 2026). By systematically structuring the input parameters, the project manager externalizes the task's structural complexity, thereby drastically minimizing extraneous load. This psychological relief directly optimizes the "germane cognitive load," allowing the manager's finite mental capacity to be fully redirected toward high-level strategic analysis, complex problem-solving, and risk mitigation.

1.7.2 Task-Technology Fit (TTF) Model for AI Augmented Decisions:

While Cognitive Load Theory explains the internal psychological relief afforded by prompt engineering, the Task Technology Fit (TTF) model links this relief to external, practical project outcomes. The fundamental premise of the TTF model argues that the mere organizational availability of an advanced technological tool does not guarantee performance improvement. Rather, it is the precise "fit" between the technology's output and the specific requirements of the managerial task that drives operational value (Anam, 2025).

Large Language Models are inherently generalist technologies. However, technical project management requires extreme specificity and contextual accuracy. Within this study, prompt engineering is theorized as the critical moderating variable that enforces "cognitive alignment" between the human operator and the machine (Yaacoub et al., 2025). By using advanced prompting frameworks, project managers compel generalized GenAI technology to align precisely with the complex, rigorous task requirements of engineering ecosystems. This engineered alignment ensures the extraction of highly

contextualized, data-driven insights, thereby directly elevating the accuracy, speed, and reliability of the resulting strategic decisions (Phillips-Wren & Håkansson, 2025).

Chapter Two: Literature Review

2.1 Introduction:

This chapter introduces the study's theoretical framework by systematically discussing the core research variables: prompt engineering skills, the reduction of extraneous cognitive load, and the enhancement of strategic decision-making quality in project management. Grounded in Cognitive Load and the Task-Technology model, this chapter comprehensively reviews previous empirical studies related to these variables. Furthermore, it discusses the key contributions of the reviewed literature and highlights the specific empirical gaps that distinguish the current study from prior research.

2.2 Theoretical Framework:

This section discusses the study variables, which are prompt engineering skills, the reduction of extraneous cognitive load, and strategic decision-making quality in project management. It reviews the main concepts for each variable and discusses how they contribute to the effective application of Generative Artificial Intelligence in project management. The section begins with prompt engineering skills, followed by the reduction of extraneous cognitive load, and finally, strategic decision-making quality.

2.2.1 Prompt Engineering Skills:

Prompt engineering has become an essential skill with the rapid development of Generative Artificial Intelligence (GenAI). As Large Language Models (LLMs) are increasingly used across various domains, the quality of AI-generated output is significantly impacted by the quality of the prompts provided by users. Therefore, prompt engineering focuses on designing and refining prompts that enable AI systems to generate accurate, relevant, and reliable responses (Sahoo et al., 2024).

According to Schulhoff et al. (2024), prompt engineering is a systematic strategy that includes various prompting techniques and best practices for improving AI model performance. Their study developed a comprehensive taxonomy of prompt engineering, organizing prompting techniques and practical applications to help users in selecting appropriate strategies for various tasks and improving AI-generated outputs.

Similarly, Debnath et al. (2024) presented a comprehensive survey of prompt engineering techniques for Large Language Models. The study systematically categorized prompting techniques according to their methodological foundations and application domains, emphasizing that selecting appropriate prompting strategies enhances reasoning, decision-making, knowledge synthesis, and the reliability of AI-generated outputs.

In addition, Federiakin et al. (2024) described prompt engineering as a twenty-first-century skill that supports effective communication between humans and AI systems. The authors proposed four dimensions of prompt engineering skills: prompt structure comprehension, prompt literacy, prompting methods, and critical online reasoning. These dimensions represent the knowledge and abilities required to interact effectively with GenAI.

Prompt Structure Comprehension Is the ability to understand how prompts should be structured to enhance AI responses by clearly describing the task, giving suitable context, and specifying the expected output to improve AI responses (Federiakin et al., 2024).

Prompt Literacy refers to the ability to write clear, specific, and well-structured prompts that accurately communicate users' intentions to AI systems (Federiakin et al., 2024).

Prompting Methods involve selecting appropriate prompting techniques according to the task requirements. Common techniques include zero-shot prompting, few-shot prompting, chain-of-thought prompting, retrieval-augmented generation, and self-consistency prompting, all of which are designed to improve AI performance in different situations (Debnath et al., 2024; Sahoo et al., 2024; Schulhoff et al., 2024).

Critical Online Reasoning refers to the ability to critically evaluate AI-generated information before applying it in academic or professional contexts, ensuring that AI outputs to be accurate, reliable, and appropriate for the intended purpose (Federiakin et al., 2024).

2.2.2 Reduction of Extraneous Cognitive Load:

The reduction of extraneous cognitive load plays a pivotal role in improving users' ability to process information and perform complex analytical tasks when interacting with Generative AI. Studies have highlighted the significant contribution of prompt engineering to minimizing cognitive friction and facilitating more effective human–AI interaction.

Nagori et al. (2025) investigated the impact of prompt engineering skills on cognitive load during complex data analysis. The study found that effective prompt engineering reduced intrinsic and extraneous cognitive load while enhancing germane cognitive load, enabling users to analyze complex information more efficiently.

Similarly, Saito and Yamada (2026) reported that users with higher confidence in interacting with AI experienced lower cognitive load and greater satisfaction, suggesting that effective human–AI interaction can actively reduce mental effort during task completion.

Furthermore, Aruleba et al. (2026) found that structured prompts improved the clarity and quality of AI-generated learning materials, enabling users to process information more efficiently while reducing unnecessary cognitive effort. The study concluded that prompt engineering can serve as a vital cognitive support strategy—or "cognitive scaffolding"—that enhances learning and improves interaction with AI systems.

2.2.3 Decision-Making Quality in Project Management:

Strategic decision-making is a fundamental process in project management, as project managers continuously execute critical choices related to planning, scheduling, budgeting, risk management, communication, and resource allocation. The quality of

these decisions directly influences project performance and the successful achievement of project objectives (PMI, 2021).

Decision-making quality refers to the ability to make accurate, effective, and timely decisions based on reliable information and the appropriate evaluation of available alternatives. High-quality decisions significantly enhance project outcomes, whereas suboptimal choices frequently precipitate schedule delays, budget overruns, and overall project failure.

Studies have highlighted the growing role of Artificial Intelligence in supporting managerial decision-making. Albashrawi (2025) found that Generative AI improves decision-making by increasing efficiency, accuracy, and personalization through rapid information analysis and recommendation generation. However, the study also emphasized the importance of addressing ethical issues, transparency, and bias when using AI in decision-making.

Similarly, Sirch (2026) reported that structured prompting strategies improve the quality of AI-generated outputs, making them significantly more useful during managerial decision-making. The findings showed that effective prompt engineering enables managers to obtain clearer and more organized information, supporting a better evaluation of available alternatives.

Several studies have also demonstrated the immense value of AI in project management ecosystems. Obana (2024) and Arjun (2025) concluded that AI improves project efficiency and supports project managers by automating routine activities and facilitating highly informed decision-making.

Despite these advantages, previous studies consistently emphasize that Artificial Intelligence should strictly support, rather than replace, project managers. Human judgment remains absolutely essential for evaluating AI-generated recommendations, considering broader organizational objectives, and making final strategic decisions in complex project environments (Sabir & Ghimire, 2024; Santos, 2025).

2.3 Literature Review:

This section reviews studies related to the variables of the current study. The studies are classified into three categories based on the three main variables: Prompt Engineering Skills, the Reduction of Extraneous Cognitive Load, and Decision-Making Quality in Project Management. The review aims to identify the major findings of previous research, highlight existing research gaps, and provide the theoretical and empirical foundation for the current study.

2.3.1 Studies Related to Prompt Engineering Skills:

Federiakin et al. (2024) examined prompt engineering as a twenty-first-century competency and proposed four dimensions of prompt engineering skills: prompt structure comprehension, prompt literacy, prompting methods, and critical online reasoning. The study emphasized that developing these competencies enables users to interact more effectively with Generative Artificial Intelligence systems and critically evaluate AI-generated outputs.

Sahoo et al. (2024) conducted a systematic survey to review prompt engineering techniques for Large Language Models and Vision-Language Models. The study proposed a comprehensive taxonomy of prompting techniques and discussed their applications, strengths, limitations, and future research directions. The findings indicated that appropriate prompting techniques improve the quality and effectiveness of AI-generated outputs.

Schulhoff et al. (2024) presented a comprehensive taxonomy of prompt engineering by classifying prompting techniques, evaluation methods, and practical applications. The study identified a broad range of prompting strategies and best practices that support effective interaction with AI systems and improve the quality of generated responses.

Debnath et al. (2024) conducted a comprehensive survey of prompt engineering techniques for (LLM). The study organized prompting strategies into categories based on their methodological foundations and application domains, including zero-shot prompting, few-shot prompting, chain-of-thought reasoning, retrieval-augmented generation, and self-consistency mechanisms. The study found that well-designed prompts improve reasoning, decision-making, knowledge synthesis, and the reliability of AI-generated outputs. The study also provided a structured framework to help researchers and practitioners in selecting appropriate prompting techniques according to different tasks and application contexts.

2.3.2 Studies Related to the Reduction of Extraneous Cognitive Load:

Nagori et al. (2025) investigated the impact of prompt engineering skills on cognitive load during complex data analysis. Using Cognitive Load Theory as the theoretical foundation, the study found that effective prompt engineering reduced intrinsic and extraneous cognitive load while enhancing germane cognitive load, enabling participants to analyze complex data more efficiently.

Saito and Yamada (2026) explored the relationship between AI self-efficacy, cognitive load, and user satisfaction during AI-assisted image generation. The findings showed that users with higher AI self-efficacy experienced lower cognitive load and greater satisfaction, indicating that confidence in interacting with AI systems contributes to reducing mental effort.

Aruleba et al. (2026) examined the effectiveness of prompt engineering in AI-assisted learning. The study found that structured prompts improved the clarity and quality of AI-generated learning materials, reduced unnecessary cognitive effort, and supported more effective learning experiences.

2.3.3 Studies Related to Decision-Making Quality in Project Management:

Sagri and Ghimire (2024) examined the impact of Artificial Intelligence on project management practices. The study emphasized that AI should complement rather than replace project managers, highlighting the continuing importance of human judgment in complex project environments.

Obana (2024) investigated the use of Artificial Intelligence in project management. The findings showed that AI improves productivity by automating routine project management tasks, allowing project managers to focus on strategic and value-added activities.

Albashrawi (2025) investigated the role of Generative Artificial Intelligence in decision-making across different domains. The study found that Generative AI enhances decision-making by improving efficiency, accuracy, and personalization while emphasizing the importance of addressing ethical concerns, transparency, and bias.

Arjun (2025) examined the role of Artificial Intelligence in modern project management. The study concluded that AI enhances project planning, forecasting, communication, and decision-making while improving project efficiency throughout the project life cycle.

Santos (2025) explored the integration of Generative Artificial Intelligence into project management practices. The findings indicated that AI automates repetitive project management activities and supports project managers in making timely and informed decisions, enabling them to devote greater attention to leadership and strategic responsibilities.

Sirch (2026) investigated the effect of prompt engineering on managerial decision-making. The study reported that structured prompting strategies improved the quality, clarity, and organization of AI-generated outputs, supporting managers in making more informed decisions.

Anghel and Cioara (2026) explored the application of Generative Artificial Intelligence in project management. The study found that Generative AI supports project planning, communication, documentation, scheduling, and decision-making, contributing to improved project performance.

2.4 Summary of Previous Studies:

The previous studies contributed to identifying the research variables, developing the conceptual framework, selecting the research methodology, and identifying the research gap. They also provided guidance for developing the study instrument.

The current study differs from other studies by examining the relationship between prompt engineering skills, the reduction of extraneous cognitive load, and decision-making quality within the context of project management through a single conceptual framework.

Chapter Three: Methodology

3.1 Introduction:

This chapter delineates the comprehensive methodological framework employed to empirically investigate the central research problem. It acts as the critical scientific bridge between the theoretical paradigms established in Chapter Two, specifically Cognitive Load Theory (CLT) and the Task Technology Fit (TTF) model, and their practical, real-world application within modern project environments (Nagori et al., 2025; Yaacoub et al., 2025). While the preceding chapters mapped the conceptual boundaries of human-AI collaboration, this chapter establishes the empirical blueprint needed to translate theoretical propositions about Generative Artificial Intelligence (GenAI) and prompt engineering into quantifiable, measurable, and statistically verifiable outcomes.

To achieve this transition, the chapter meticulously details the selected research design, justifying the adoption of a quantitative descriptive correlational approach as the optimal mechanism for measuring the complex psychological and operational variables at play (Anam, 2025). It outlines the psychometric data-collection instruments, specifically tailored to capture the nuances of intrinsic, extraneous, and germane cognitive load, as well as metrics for decision-making quality. Furthermore, it defines the specific statistical procedures and analytical software to be used to rigorously test the study's hypotheses and validate the correlations between prompt-engineering proficiency and executive performance.

Beyond the mechanics of data collection, this chapter explicitly defines the target population, specifically targeting technical project managers and Project Management Office (PMO) directors operating within the Kingdom of Saudi Arabia's rapidly evolving technological sectors. It details the sampling strategy engineered to capture a representative cross-section of professionals currently navigating the unpredictable "jagged technological frontier" (Afilali, 2026; Dell'Acqua et al., 2026). To maintain a strict empirical focus and prevent scope creep, the chapter rigorously establishes the study's objective, spatial, temporal, and human limits, ensuring the research remains highly contextualized within the software engineering and technological innovation objectives of Saudi Vision 2030 (Albaroudi et al., 2025).

Crucially, this methodology is constructed to ensure absolute and unwavering alignment with the stringent academic, legal, and ethical standards required for applied research in the Kingdom of Saudi Arabia. Investigating cognitive interactions with AI requires collecting sensitive professional data. Therefore, this chapter systematically incorporates the ethical AI directives established by the Saudi Data and AI Authority (SDAIA, 2025). Furthermore, it embeds the digital integration guidelines formulated by the Digital Government Authority (DGA, 2024) and the scientific integrity frameworks mandated by the Arab League Educational, Cultural and Scientific Organization (ALECSO, 2024). By adhering to these institutional guardrails, this chapter ensures that the empirical investigation of human-AI collaboration upholds the highest possible standards of data privacy, operational transparency, and scientific rigor, ultimately ensuring that the study's findings are both credible and actionable.

3.2 Methodology and Research Methods:

To effectively answer the primary research questions and empirically measure the impact of prompt-engineering skills on cognitive load and decision-making quality, this study employs a Quantitative Descriptive Correlational Research Design. This methodological choice is highly appropriate for investigating human-computer interaction paradigms, as it allows for both the systematic observation of current behaviors and the statistical testing of predictive relationships among defined variables (Anam, 2025).

3.2.1 Research Approach:

The selected quantitative research design operates on two interconnected analytical levels to ensure a comprehensive evaluation:

- **The Descriptive Component:** This facet of the methodology is utilized to systematically assess and baseline the current proficiency levels of prompt engineering among technical project managers in the Kingdom of Saudi Arabia. Given the rapid digital transformation driven by Saudi Vision 2030, this component maps the current operational landscape and quantifies how frequently and effectively GenAI is utilized within PMOs (Afilali, 2026; Albaroudi et al., 2025).
- **The Correlational Component:** This facet is designed to statistically identify the strength and direction of the relationships between the independent variable (prompt-engineering proficiency) and the dependent variables (cognitive load and decision-making quality). By employing correlational analysis, the study moves beyond mere observation to empirically test hypotheses derived from Cognitive Load Theory and the Task-Technology Fit model, determining whether structured prompting serves as a reliable mechanism for reducing psychological friction (Nagori et al., 2025; Saito & Yamada, 2026).

3.2.2 Data Collection Instrument:

To facilitate scalable and standardized data collection across diverse technological sectors, the primary method is a structured, electronically administered questionnaire. The questionnaire is meticulously designed using validated psychometric scales adapted from recent human-AI interaction studies to ensure high construct validity and reliability (Yaacoub et al., 2025).

The instrument is divided into four highly specific sections:

- **Demographic and Professional Profile:**

Collecting data geographical location, years of experience, Age, and frequently of GenAI usage to test for demographic variances and operational contexts (Hypothesis 3).

- **Prompt Engineering Proficiency:**

Measuring the participant's familiarity with and utilization of advanced prompting strategies (e.g., zero-shot, chain-of-thought, role-prompting) to establish the independent variable (Debnath et al., 2024).

- **Perceived Cognitive Friction:**

Utilizing adapted cognitive load indexes to measure the respondent's perceived intrinsic, extraneous, and germane load when interacting with GenAI, explicitly targeting the mental fatigue caused by algorithmic hallucinations (Nagori et al., 2025; Saito & Yamada, 2026).

- **Decision-Making Outcomes:**

Evaluating the perceived accuracy, speed, and strategic reliability of AI-augmented decisions, as well as the participant's susceptibility to automation bias (Dell'Acqua et al., 2026; Phillips-Wren & Håkansson, 2025).

3.2.3 Ethical Methodology and Data Security:

- Investigating corporate decision-making and algorithmic interactions inherently involves sensitive professional data. Therefore, this research methodology is governed by a strict ethical and legal compliance framework:
- Academic Consent: The study adheres comprehensively to the regional academic standards outlined in the Arab Guidelines for Scientific Research Ethics and Artificial Intelligence (ALECSO, 2024). Before accessing the questionnaire, an electronic "Informed Consent" gateway must be completed. This mechanism explicitly informs participants of the study's academic purpose, the voluntary nature of their participation, and their absolute right to withdraw at any stage without professional repercussions.

Data Anonymization and Privacy: To ensure strict alignment with the National AI Ethics Principles established by the Saudi Data and AI Authority (SDAIA, 2025) and the Kingdom's Personal Data Protection Law (PDPL), the methodology employs absolute data anonymization. No direct personal identifiers, IP addresses, or specific corporate email domains are collected (Digital Government Authority, 2025).

3.3 Research Population and Sampling Strategy:

The empirical validity, reliability, and ultimate generalizability of any applied quantitative study rely fundamentally on the precise delineation of its research population. To accurately measure the psychological and operational impacts of GenAI, the selected participants must be actively engaged in high-stakes human-AI collaboration. Therefore, this section strictly defines the demographic targeted for this research and outlines the purposive sampling strategy engineered to ensure targeted and representative data collection.

In defining this cohort, although the final sample size comprised 63 respondents, this number is considered methodologically sufficient and highly representative given the highly specialized and niche nature of the target population and also, the time limitation for the study. The study specifically targets technical project managers and PMO directors within the Saudi technology sector, an elite professional cohort characterized by its limited size and high operational demands, making the sample collection process significantly challenging. Furthermore, the high degree of professional and contextual homogeneity among these practitioners reduces the statistical necessity for a massive sample size to achieve variance representation. Statistically, a sample size of ($N = 63$) strictly satisfies the parametric requirements for conducting Pearson correlation and One-Way ANOVA tests with robust statistical power and reliability.

3.3.1 Target Population the Demographic:

The target population for this study consists exclusively of Technical Project Managers, Agile Scrum Masters, and Project Management Office (PMO) Directors operating in technology-driven sectors in the Kingdom of Saudi Arabia.

Academic and Strategic Justification: This specific professional cohort was deliberately selected for three critical reasons:

- **Organizational Shift:** Contemporary literature indicates that PMO structures are currently undergoing the most rapid and disruptive integration of AI tools across the corporate landscape. As PMOs transition from traditional administrative centers into predictive, AI-driven intelligence hubs, project managers sit at the absolute epicenter of this digital transformation (Afilali, 2026; Sabir & Ghimire, 2024).
- **The Vision 2030 Context:** Because technical project managers in KSA are tasked with executing the highly complex software engineering and infrastructure mega projects mandated by Saudi Vision 2030, they are the primary professionals experiencing the acute cognitive friction of the "jagged technological frontier" (Albaroudi et al., 2025; Dell'Acqua et al., 2026).
- **The Human in the Loop:** They are the ultimate decision-makers who must constantly evaluate, verify, and strategically apply GenAI outputs. This makes

their prompt-engineering proficiency and the resulting cognitive load the perfect independent and dependent variables for an empirical study (Obana, 2024).

3.3.2 Sampling Strategy Methodological Choice:

Given the elite and highly specialized nature of the study population, and to ensure the acquisition of accurate, representative data reflecting actual empirical practice, this research adopted a purposive sampling approach. The study instrument was specifically directed toward subject matter experts, technical project managers. This strategy mitigates undirected randomness and ensures that all responses are derived from active practitioners utilizing the technology within real-world operational environments, thereby reinforcing the reliability and statistical validity of the research findings. The population is stratified across three primary dimensions:

- **Managerial Experience Levels:** As AI readiness and cognitive adaptability often intersect with professional seniority (Santos, 2025), the sample captures varying levels of experience (ranging from junior to senior/director roles) to evaluate how prompt engineering impacts professionals at different stages of their cognitive development (Arjun, 2025).
- **Age Demographics:** The sample encompasses a diverse range of age groups. This dimension was captured to rigorously test whether generational differences inherently influence the adoption rate or the cognitive impact of GenAI tools in project management.
- **Geographical Distribution (City):** To capture a truly national perspective that aligns with the macroeconomic goals of Vision 2030, the sample includes technical project managers operating across the Kingdom's primary technological and economic hubs (e.g., Riyadh, Jeddah, and Dammam).
- **Frequency of GenAI Usage:** Crucially, the sample profiles the behavioral frequency of AI interaction among respondents. Given the rapidly evolving nature of the technological frontier, tracking how often managers utilize these tools provides the definitive metric for measuring true AI maximization and operational integration.

By capturing these multidimensional profiles within a purposive sampling framework, the study ensures that the final sample accurately reflects the structural composition of KSA's technical project management workforce. This rigorous demographic profiling guarantees that the subsequent inferential statistical tests (e.g., One-Way ANOVA conducted in Chapter Four) possess robust statistical power and yield highly valid, context-specific findings.

3.4 Research Delimitations:

To maintain strict academic rigor, ensure high internal construct validity, and prevent unintended methodological scope creep, the boundaries of this empirical research are explicitly defined across four distinct dimensions. These delimitations are designed to isolate the variables of human-AI collaboration from broader, confounding organizational factors.

3.4.1 Thematic Delimitations:

The Boundary: Thematically, this study is exclusively confined to measuring the impact of Prompt Engineering skills applied to Generative Artificial Intelligence. The research focuses solely on measuring two precise psychological and operational outcomes: Cognitive Load (divided into intrinsic, extraneous, and germane dimensions) and Strategic Decision-Making Quality (measured by accuracy, speed, and the mitigation of automation bias).

Academic Justification: This strict thematic boundary is drawn to isolate human-cognitive interaction from general project metrics. Consequently, this study excludes the evaluation of other forms of artificial intelligence (e.g., predictive machine learning, deep learning analytics, or physical robotics) and deliberately does not measure traditional, macro-level project management KPIs such as overall budget variance or schedule performance indices (Arjun, 2025; Nagori et al., 2025; Phillips-Wren & Håkansson, 2025).

3.4.2 Spatial Delimitations:

The Boundary: Geographically, the empirical data collection is strictly restricted to the Kingdom of Saudi Arabia (KSA). The distribution of the research instrument primarily targets the Kingdom's major technological and commercial hubs: Riyadh, Jeddah, and Dammam.

Academic Justification: Concentrating on these specific metropolitan regions ensures a statistically representative sample of the nation's rapidly expanding digital ecosystem. It guarantees that the data reflects the authentic, high-stress environments where the advanced software engineering and digital infrastructure mega-projects of Saudi Vision 2030 are currently being executed (Albaroudi et al., 2025).

3.4.3 Demographic and Professional Delimitations:

The Boundary: Demographically, the study targets exclusively active Technical Project Managers .

Academic Justification: These specific professionals are targeted because they hold direct strategic decision-making authority and are most heavily exposed to the cognitive friction of the "jagged technological frontier" (Dell'Acqua et al., 2026). The study deliberately excludes project sponsors, end-users, and software developers. While those groups utilize AI, their cognitive interactions serve entirely different operational purposes (e.g., coding

vs. managing) and do not involve the same level of overarching strategic project oversight required for this investigation (Santos, 2025).

3.4.4 Temporal Delimitations:

The Boundary: Temporally, this research, including data collection and analysis, is conducted and finalized during the 2026–2027 academic year.

Academic Justification: This temporal boundary is exceptionally critical for contextualizing the findings. Generative AI capabilities, prompt engineering frameworks, and national regulatory policies, most notably the AI Ethics Principles and Guidelines issued by the Saudi Data and AI Authority (SDAIA), are evolving at an unprecedented pace. Therefore, the empirical findings of this thesis represent a highly accurate, yet strictly time-bound snapshot of the technological landscape and human-AI collaborative maturity during this specific academic period.

Chapter Four: Results and Recommendations

4.1 Introduction:

This chapter of the scientific study presents the empirical findings; the results will be analyzed and discussed. The hypotheses of the applied study will be tested, and appropriate recommendations will be made to address weaknesses related to cognitive load and decision-making quality.

Data was collected from a targeted sample of 63 valid respondents. The chapter is structured to sequentially present the descriptive statistics and hypothesis testing using parametric analyses.

This chapter will analyze and discuss descriptive statistics, test hypotheses, and examine the relationship of the results to the established theoretical frameworks.

4.2 Data Analysis and Descriptive Statistics:

After collecting data from the target sample of 63 eligible respondents, the SPSS analysis program was used to ensure data integrity and accuracy. The research sample was analyzed using reliability analysis to verify internal consistency in the areas of command engineering skills, cognitive load reduction, and decision-making quality improvement.

Moreover, the demographic characteristics of the sample were analyzed, including gender, age, work experience, geographical distribution, and use of command engineering.

4.2.1 Reliability Analysis:

To analyze the reliability of the main axes using SPSS software, Cronbach's alpha coefficient was calculated according to the following table:

Table 1: Internal Consistency Analysis of the Main Variables (Prompt Engineering Skills, Cognitive Load Reduction, and Improving Decision-Making Quality).

Code	Construct	Number of Items	Cronbach's Alpha	Reliability
PE	Prompt Engineering Skills	5	0.885	Good
CL	Cognitive Load Reduction	5	0.850	Good
DM	Improving Decision-Making Quality	5	0.738	Acceptable
Total		15	0.894	Good

The Cronbach's alpha coefficient for the Prompt Engineering Skills dimension was 0.885, for the Cognitive Load Reduction dimension it was 0.850, and for the Improving Decision-Making Quality dimension it was 0.738.

The overall reliability of the instrument, calculated using Cronbach's alpha coefficient, was 0.894, a good level of reliability that far exceeds the acceptable academic threshold of 0.70. This confirms that the measures of these main variables possess high reliability.

4.2.2 Demographic Characteristics:

The following tables and figures demonstrate the diversity of the sample in terms of demographic characteristics, showing the number and percentage of each category.

Table 2: The Demographic Variable of Gender.

Demographic Variable	Category	Frequency (N)	Percentage (%)
Gender	Male	40	63.49
	Female	23	36.51
Total		63	100.00

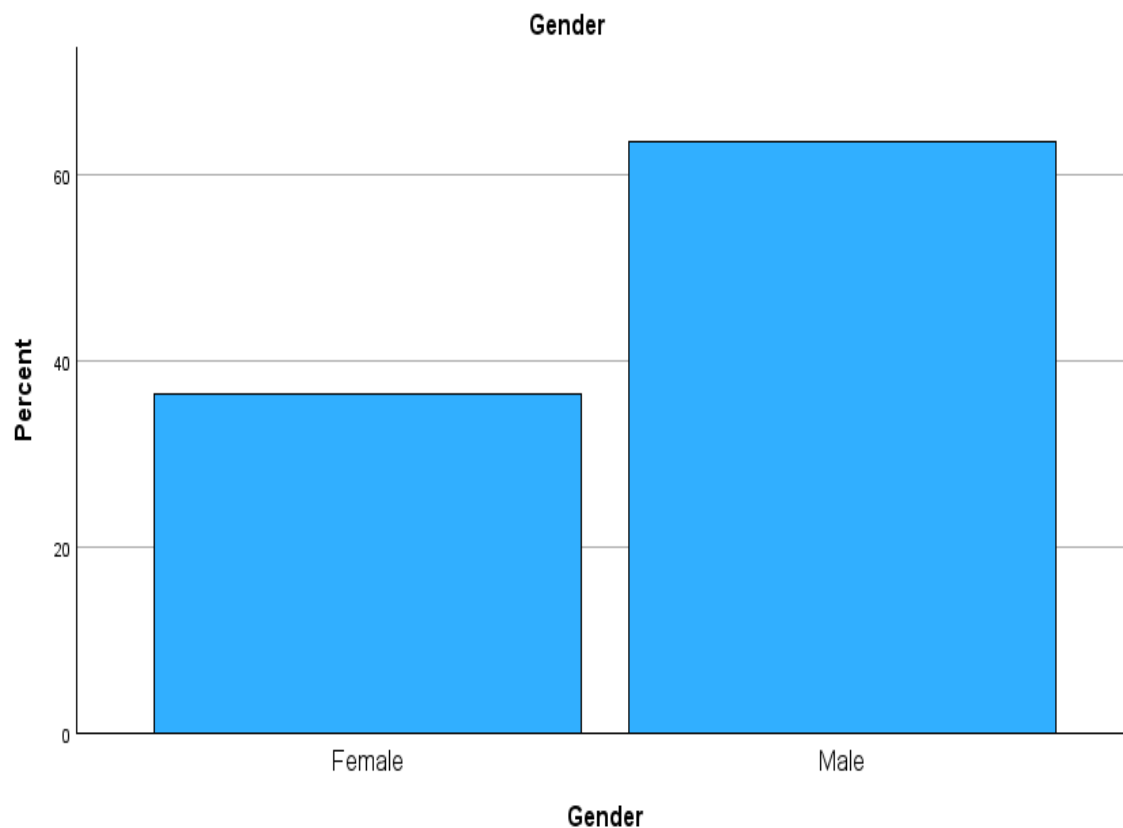


Figure 1: The Demographic Variable of Gender

We observe that the demographic variable of gender shows that the percentage of males is 63.49%, while the percentage of females is 36.51%. The percentage of males in the sample for this demographic variable was 26.98% higher.

Regarding the age demographic variable of the Age:

Table 3: Demographic Variable of Age.

Demographic Variable	Category	Frequency (N)	Percentage (%)
Age	More than or equal 50 years	2	3.17
	20-30 years	3	4.76
	31-39 years	38	60.32
	40-49 years	20	31.75
Total		63.00	100.00

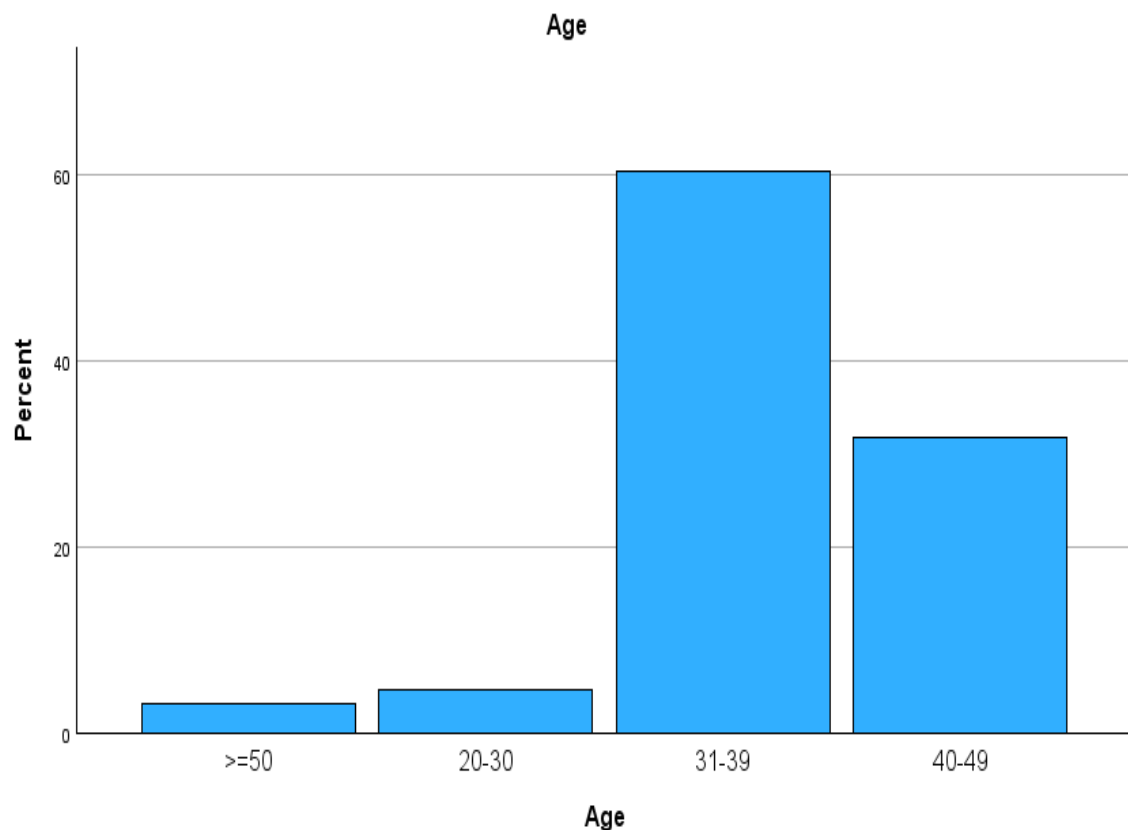


Figure 2: The Demographic Variable of Age

We observe that the age demographic variable is divided into four categories. The percentage of those aged 50 years and older was 3.17%, while the percentage of those aged 20-30 years was 4.76%, the percentage of those aged 31-39 years was 60.32%, and the percentage of those aged 40-49 years was 31.75%. The percentage of those aged 31-39 years was the highest among the categories, while the percentage of those aged 50 years and older was the lowest.

Regarding the demographic variable of years of experience for the sample:

Table 4: Demographic Variable of Years of Experience.

Demographic Variable	Category	Frequency (N)	Percentage (%)
Years of Experience	Less than 5 years	13	20.63
	More than 20 years	7	11.11
	11-20 years	21	33.33
	5-10 years	22	34.92
Total		63	100.00

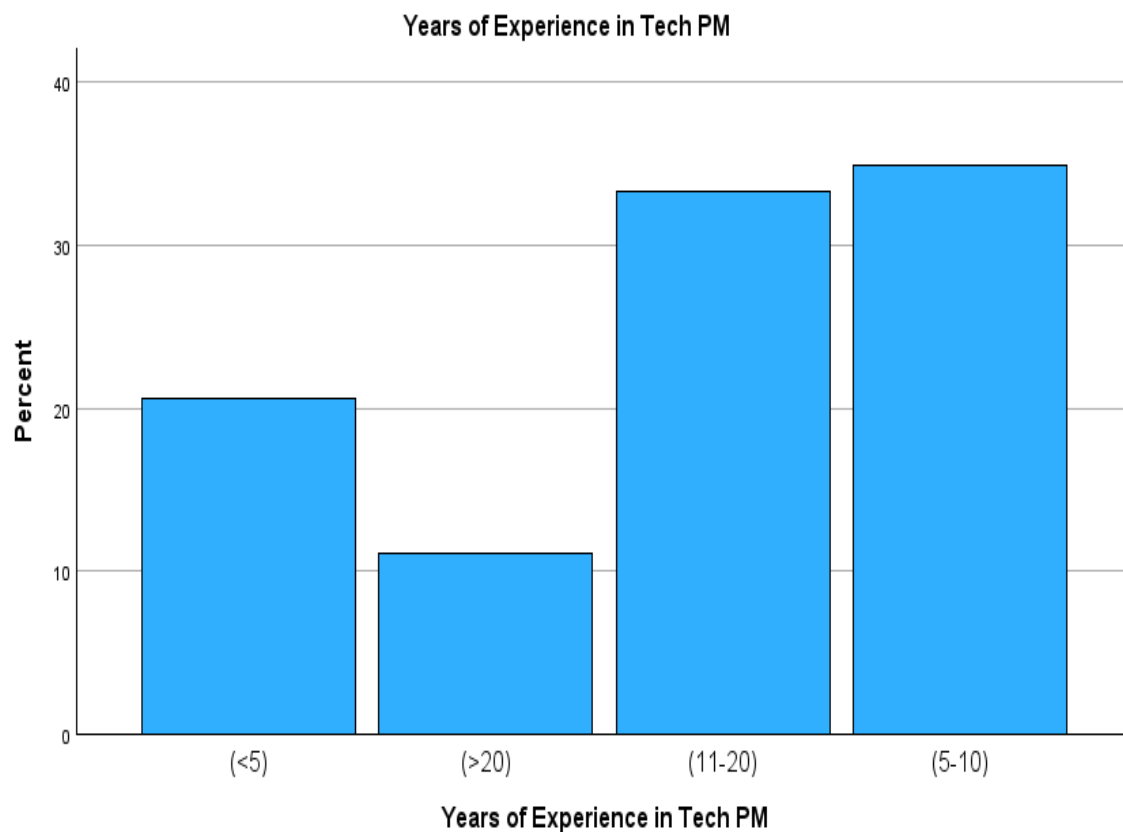


Figure 3: Demographic Variable of Years of Experience

We observe that the demographic variable of years of experience is divided into four categories. The percentage of those with less than 5 years of experience was 20.63%, while the percentage of those with more than 20 years of experience was 11.11%, the percentage of those with between 11 and 20 years of experience was 33.33%, and the percentage of those with between 5 and 10 years of experience was 34.92%. The percentage of those with between 5 and 10 years of experience was the highest among the categories, while the percentage of those with more than 20 years of experience was the lowest.

Regarding the demographic variable of the current city of work:

Table 5: Demographic Variable of the Current City of Work.

Demographic Variable	Category	Frequency (N)	Percentage (%)
Current City of Work	Dammam	4	6.35
	Jeddah	9	14.29
	Riyadh	50	79.37
Total		63	100.00

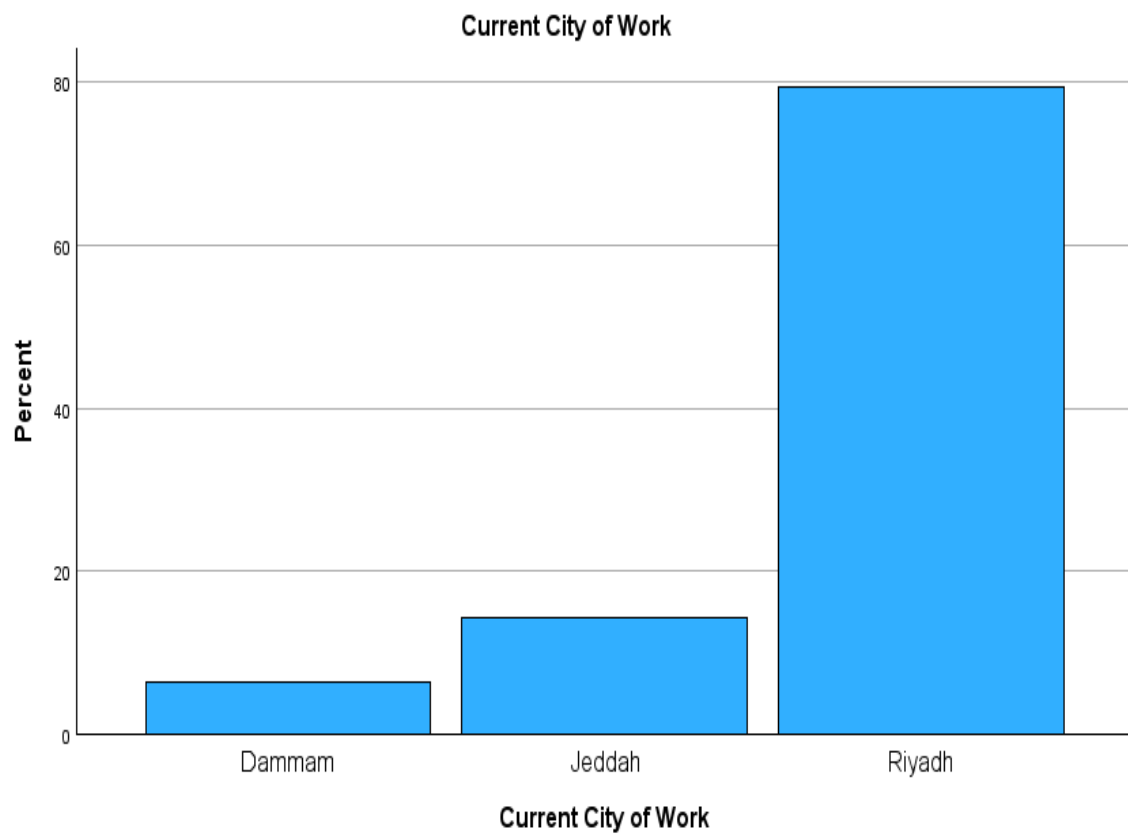


Figure 4: Demographic Variable of the Current City of Work

We observe that the demographic variable of the current city of work is divided into three categories: Dammam (6.35%), Jeddah (14.29%), and Riyadh (79.37%). Riyadh had the highest percentage, while Dammam had the lowest.

Regarding the demographic variable of Frequency GenAI usage:

Table 6: Demographic Variable of Frequently GenAI Usage.

Demographic Variable	Category	Frequency (N)	Percentage (%)
Frequency of GenAI Usage	Daily	39	61.90
	Never	1	1.59
	Rarely	6	9.52
	Weekly	17	26.98
Total		63	100.00

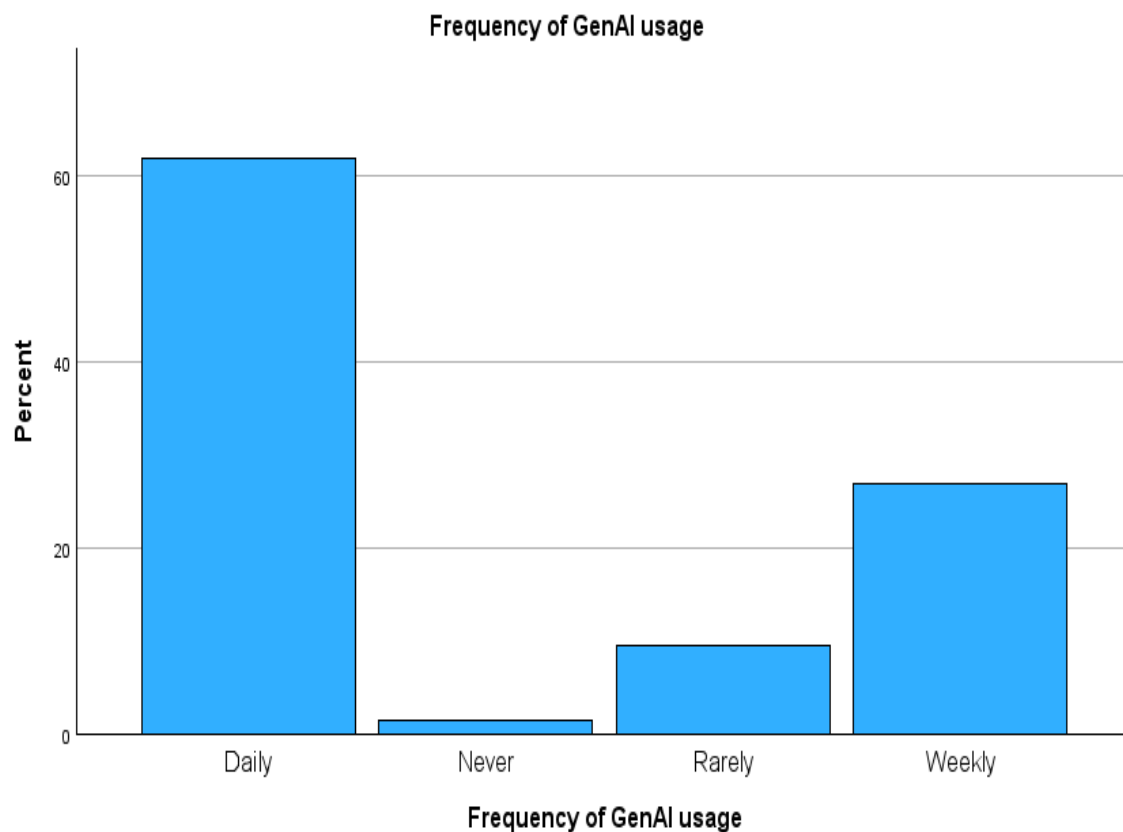


Figure 5: Demographic Variable of Frequently GenAI Usage

We observe that the demographic variable of GenAI usage rate is divided into four categories: Daily (61.90%), Never (1.59%), Rare (9.52%), and Weekly (26.98%). Daily usage had the highest percentage, while Never had the lowest.

4.2.3 Descriptive Statistics:

The descriptive statistical analysis of the main variables presents data such as the arithmetic mean, standard deviation, and other descriptive data, calculated on a five-point Likert scale from 1 to 5, where 1 means strongly disagree and 5 means strongly agree.

Table 7: Descriptive Analysis of Main Variables.

Code	Construct	Arithmetic Mean	Standard Deviation	Relative Weight	Level	Rank
PE	Prompt Engineering Skills	4.07	0.765	81.3%	High	2
CL	Cognitive Load Reduction	4.12	0.648	82.5%	High	1
DM	Improving Decision-Making Quality	3.91	0.604	78.2%	High	3
Total		4.03	0.67	80.7%	High	

By observing the data in the table for the main variables, we note that the overall level of the main variables is high, with a mean of 4.03 and a percentage of 80.7%. The arithmetic means of the main variables ranged from 3.91 to 4.12, representing percentages of 78.2% and 82.5%, respectively. The highest value, ranking 1, was "cognitive load reduction" with a mean of 4.12, while the lowest value, ranking 3, was "Improving the quality of decision-making" with a mean of 3.91.

To detail the results of the descriptive analysis for each main variable across all items, based on the sample members' ratings:

Prompt Engineering Skills:

The descriptive statistical analysis of the main variable, Prompt Engineering Skills, reveals the mean, standard deviation, and other descriptive data for each item, according to the sample members' ratings.

Table 8: Descriptive Analysis of the Main Variable - Prompt Engineering Skills.

Construct 1: Prompt Engineering Skills						
Code	Statement	Arithmetic Mean	Standard Deviation	Relative Weight	Level	Rank
PE1	I ensure to provide a detailed and clear project context to the AI when requesting task analysis	4.13	0.907	82.6%	High	2
PE2	I use role-playing techniques for the AI	3.89	0.935	77.8%	High	5

	model to obtain highly specialized results					
PE3	I have the ability to break down complex administrative problems into a series of iterative prompts	4.06	0.982	81.2%	High	3
PE4	I accurately specify the desired output format (e.g., tables, critical analysis) when writing the prompt	4.19	0.780	83.8%	High	1
PE5	I set clear constraints to prevent the model from providing information outside the project's scope	4.06	0.998	81.2%	High	4
Total		4.07	0.920	81.3%	High	

By observing the data in the table for the main variable, Prompt Engineering Skills, we note that the overall level is high, with a mean of 4.07 and a percentage of 81.3%. The mean scores for the items related to the main variable ranged from 3.89 to 4.19, representing 77.8% of the total. The highest-scoring item, ranking 1, was PE4, with a mean of 4.19, while the lowest-scoring item, ranking 5, was PE2, with a mean of 3.89.

Cognitive Load Reduction:

The descriptive statistical analysis of the core variable cognitive load reduction, reveals the mean, standard deviation, and other descriptive data for each item, as estimated by the sample members.

Table 9: Descriptive Analysis of the Core Variable – Cognitive Load Reduction.

Construct 2: Cognitive Load Reduction						
Code	Statement	Arithmetic Mean	Standard Deviation	Relative Weight	Level	Rank
CL1	Effective use of prompt engineering reduces the mental fatigue associated with processing massive amounts of project data	4.22	0.750	84.4%	Very High	1
CL2	Precisely targeted prompts help me organize scattered thoughts and reduce	4.19	0.759	83.8%	High	2

	mental distraction during planning					
CL3	Fast AI outputs contribute to saving my mental energy to focus on strategic tasks	4.06	0.780	81.3%	High	4
CL4	Using prompt engineering alleviates the psychological stress I feel as project deadlines approach	4.02	0.975	80.3%	High	5
CL5	Accurate querying reduces the time spent writing reports, limiting daily strain	4.13	0.813	82.5%	High	3
Total		4.12	0.816	82.5%	High	

By observing the data in the table for the core variable, cognitive load reduction, we note that the overall level is high, with a mean of 4.12 and a percentage of 82.5%. The mean scores for the items related to the core variable ranged from 4.02 to 4.22, representing 80.3% to 84.4%. The highest-scoring item, ranking 1, was CL1, with a mean of 4.22, indicating a very high level. The lowest-scoring item, ranking 5, was CL4, with a mean of 4.02.

Improving Decision-Making Quality:

The descriptive statistical analysis of the core variable, improving decision-making quality, reveals the mean, standard deviation, and other descriptive data for each item, as estimated by the sample members.

Table 10: Descriptive Analysis of the Main Variable - Improving the Quality of Decision-Making.

Construct 3: Improving Decision-Making Quality						
Code	Statement	Arithmetic Mean	Standard Deviation	Relative Weight	Level	Rank
DM1	Professionally crafted text prompts provide me with multiple alternatives and options that contribute to more	3.79	0.845	75.9%	High	5

	accurate risk assessment					
DM2	Prompt engineering helps reduce personal biases during the technical decision-making process	3.84	0.827	76.8%	High	4
DM3	Accurate information extracted increases my confidence in decisions made for project resource allocation	4.11	0.805	82.2%	High	1
DM4	Effective prompts enable me to extract predictive data that supports proactive decisions	3.95	0.869	79.0%	High	2
DM5	Thanks to generative AI, I now respond to urgent technical problems with greater speed and efficiency	3.86	0.965	77.1%	High	3
Total		3.91	0.862	78.2%	High	

By observing the data in the table for the main variable, Improving the Quality of Decision-Making, we note that the overall level is high with an arithmetic mean of (3.91) and a percentage of (78.2%). The arithmetic means of the items related to the main variable were between (4.11 - 3.79) and a percentage of (82.2% - 75.9%), where the highest item, which obtained rank 1, was item DM3 with an arithmetic mean of (4.11), while the lowest item, which obtained rank 5, was item DM with an arithmetic mean of (3.79).

4.3 Results:

Based on the statical tests that answers the research questions utilizing a significance level of ($\alpha \leq 0.05$):

4.3.1 Hypothesis 1 - Prompt Engineering Skills and Cognitive Load Reduction:

For this hypothesis we used Pearson Correlation Coefficient.

Table 11: Pearson Correlation Coefficient for Testing Hypothesis 1.

Variable	Pearson Correlation	Sig
Prompt Engineering Skills	0.516	<0.001
Cognitive Load Reduction		

Based on the result in Table 11 shows that there is a strong positive correlation because Sig value <0.001 and the type of this of this correlation is inverse correlation but Pearson Correlation value is 0.516. This positive value obtained between Prompt Engineering Skills and Cognitive Load Reduction should be interpreted in light of the questionnaire positive phrasing. Cognitive Load items were designed to measure the contribution to reducing mental effort. A higher proficiency score naturally aligns with higher agreement on load reduction. Thus, this positive statistical correlation provides direct empirical support for the inverse correlation.

The null hypothesis H01 is rejected. As a technical project manager's ability structure prompts increases, their perceived mental fatigue and cognitive load decrease significantly.

The alternative hypothesis H1 is accepted.

4.3.2 Hypothesis 2: Prompt Engineering Skills and Improve Decision-Making Quality:

For this hypothesis we used Pearson Correlation Coefficient.

Table 12: Pearson Correlation Coefficient for Testing Hypothesis 2.

Variable	Pearson Correlation	Sig
Prompt Engineering Skills	0.348	0.005
Improving Decision-Making Quality		

Based on the result in Table 12 shows that there is a positive correlation because Sig value is 0.005 and Pearson Correlation value is 0.348 which is positive with moderate relationship.

The findings confirm that the prompt engineering skills directly enhances the speed and accuracy project decisions. The null hypothesis H02 is rejected and we will accept the alternative hypothesis H2.

4.3.3 Hypothesis 3: Demographic Variances:

For testing this hypothesis, we used one Way ANOVA.

Table 13: One Way ANOVA for Testing Hypothesis 3.

One Way ANOVA - Demographic Variances							
Demographic Variances	Dependent Variable	Source of Variation	Sum of Squares	df	Mean Square	F	Sig. ^a
Age	Cognitive Load Reduction	Between Groups	0.56	3.00	0.19	0.43	0.73
		Within Groups	25.47	59.00	0.43		
		Total	26.03	62.00			
	Improving Decision-Making Quality	Between Groups	0.34	3.00	0.11	0.30	0.83
		Within Groups	22.29	59.00	0.38		
		Total	22.62	62.00			
City	Cognitive Load Reduction	Between Groups	0.30	2.00	0.15	0.34	0.71
		Within Groups	25.74	60.00	0.43		
		Total	26.03	62.00			
	Improving Decision-Making Quality	Between Groups	0.80	2.00	0.40	1.10	0.34
		Within Groups	21.82	60.00	0.36		
		Total	22.62	62.00			
Years of Experience	Cognitive Load Reduction	Between Groups	1.87	3.00	0.62	1.53	0.22
		Within Groups	24.16	59.00	0.41		
		Total	26.03	62.00			
	Improving Decision-Making Quality	Between Groups	1.43	3.00	0.48	1.33	0.27
		Within Groups	21.19	59.00	0.36		
		Total	22.62	62.00			
Frequency of GenAI Usage	Cognitive Load Reduction	Between Groups	3.98	3.00	1.33	3.54	0.02
		Within Groups	22.06	59.00	0.37		
		Total	26.03	62.00			
	Improving Decision-Making Quality	Between Groups	1.75	3.00	0.58	1.65	0.19
		Within Groups	20.87	59.00	0.35		
		Total	22.62	62.00			

Table 13 shows that there were no statistically significant differences ($P > 0.05$) in the impact of the prompt engineering skills with cognitive load reduction and improve decision making quality based on the demographic variances (Age, City, Years of Experience). That's indicate to the cognitive and strategic of GenAI are equally in these demographic variances by all technical project managers. Also, the fourth demographic variance which is (frequency of GenAI usage) with improving decision making quality. However, there was one notable exception emerged. The demographic variance frequency of GenAI usage with the main variable cognitive load reduction. It shows statistically significant difference with sig value 0.02 and F value 3.54. After checking the frequency of GenAI usage items, the highest category in rank 1 with arithmetic mean value equal 4.28 and it was related to who uses daily GenAI.

The null hypothesis H03 is largely accepted with minor rejection.

The alternative hypothesis H3 is largely rejected with minor acceptance.

4.4 Discussion of Findings:

We will discuss the experimental results obtained through statistical analysis within the framework of the theoretical framework, specifically cognitive load theory and the task-fitness model for technology. The main objective is to measure the impact of command engineering skills for generative artificial intelligence on reducing mental load and improving the quality of decision-making among technical project managers in Saudi Arabia.

The results confirm that command engineering is not merely human-machine interaction, but rather a strategic and cognitive competency essential for overcoming technical challenges.

4.4.1 Basic Competency Level of Command Engineering Skills Among Technical Project Managers in Saudi Arabia:

This study, based on the descriptive analysis of prompt engineering skills, reveals a high basic competency level among technical project managers in Saudi Arabia.

4.4.2 Cognitive Support and Technical Challenges:

The first finding of this study confirms the inverse relationship between command engineering skills and cognitive load reduction, despite the advantages offered by artificial intelligence models. Unstructured human-machine interaction often produces algorithmic illusions or inaccurate data and information, which increases mental fatigue. However, the correlation in the first hypothesis confirms the validity of the cognitive load theory.

Advanced prompt engineering techniques act as effective cognitive supports by clearly organizing AI outputs.

Highly skilled technical project managers with prompt engineering skills filter out digital noise, enabling them to direct their cognitive resources toward critical analysis and problem-solving.

4.4.3 Strategic Alignment and Mitigating Automation Bias:

The positive correlation in the results related to the second hypothesis supports the task-technology fit model. This model is characterized by its high sensitivity and the rarity of AI raw outputs perfectly matching requirements.

The results clearly show that command engineering skills are the link that achieves this fit.

Effective interaction between technical project managers and AI is crucial, as it significantly mitigates automation bias by requiring AI to justify or analyze constraints through advanced guidance. This greatly improves the accuracy, speed, and reliability of the decision-making process.

4.4.4 The Overall Benefit of Artificial Intelligence vs. the Necessity of Effective Practice:

Perhaps the most significant finding of this study, in analyzing demographic variations, is found in the results of the third hypothesis analysis.

The absence of statistical significance between demographic variables, such as age, years of experience, and city, was clearly evident.

This demonstrates that the cognitive and strategic advantages of artificial intelligence are not limited to age, major cities, or extensive experience. Rather, AI technologies represent a general democratic force.

Nevertheless, this variation regarding the frequent use of AI highlights a crucial aspect.

It indicates that behavioral practice determines success in using AI, as command engineering is an experience-based ability.

Repeated interaction, which cognitive psychologists call "schema automation," allows frequent users to quickly and intuitively create highly useful commands with minimal mental effort.

Therefore, the full potential of AI in managing technical projects depends less on administrative hierarchies and more on continuous practice.

4.4.5 Challenges and Obstacles in Generative AI Integration:

To comprehensively address the fourth objective of this research, it is necessary to delineate the operational challenges and structural obstacles encountered by technical project managers when integrating Generative AI (GenAI) into daily Project Management Office (PMO) workflows. The inferential analysis, particularly the broad acceptance of the third null hypothesis, provides critical insight into these barriers. The data indicate that traditional demographic variables such as age, location, or years of experience do not present significant impediments to AI adoption. Rather, the empirical evidence identifies the lack of routine practice and insufficient organizational infrastructure as the primary challenges.

This finding carries substantial implications within the context of the "accelerating technological frontier" or the "jagged frontier" (Dell'Acqua et al., 2026). The primary challenge for project managers is not the intrinsic complexity of Large Language Models

(LLMs), but rather the lack of comprehensive institutional support. Reliance on fragmented, informal, and individual prompting efforts fails to produce sustainable strategic value and increases the risk of automation bias and algorithmic hallucinations.

The central challenge is the transition from individual experimentation to scaled, institutionalized governance. Project managers encounter difficulties due to the lack of centralized, peer-reviewed prompt repositories and formal corporate training. Additionally, as the technological frontier evolves unpredictably, utilizing these tools without a structured ethical framework introduces operational risks. Addressing these integration challenges requires organizations to promote a culture of consistent AI utilization and to develop standardized prompt libraries that align with national regulatory frameworks, such as the Saudi Data and AI Authority (SDAIA) ethical guidelines.

4.5 Recommendations:

Based on the findings and the theoretical synthesized in this study, the following actionable recommendations are proposed for technical project managers in Kingdom of Saudi Arabia:

- **Develop Standardized Prompt Libraries:** Providing a library of pre-built command templates for technical project managers helps reduce their cognitive load.
- **Encouraging GenAI Usage:** Encouraging the responsible use of GenAI tools, as prompt engineering skills are behavioral skills acquired through experience and practice.
- **Prompt Engineering Training:** Providing training sessions for prompt engineering skills that related to technical project management.
- **Align with SDAIA Ethical Frameworks:** As increasingly rely on GenAI for decision-making, prompts must be engineered to exclude sensitive data, ensuring strict compliance with the Saudi Personal Data Protection Law (PDPL) and SDAIA's AI Ethics Principles (2025).

4.6 Future Research Directions:

While this study provides significant empirical evidence regarding the impact of prompt engineering on project management, the rapid evolution of Generative AI opens several avenues for future academic exploration:

- **Longitudinal Studies on Schema Automation:**

This study utilized a cross-sectional design to capture a snapshot of current proficiencies. Future research should employ a longitudinal approach to track project managers over several years. This would help determine if the reduction in cognitive load is sustained over time as LLMs evolve, and how long it takes for a project manager to achieve complete "schema automation" when interacting with AI.

- **Qualitative and Mixed-Methods Approaches:**

The quantitative data supported the theory well, but future studies could use interviews or observations. Looking at the specific ways, project managers write prompts in real time could give a better understanding of how people and AI work together.

- **Comparative Analysis of Specific GenAI Models:**

This study assessed GenAI as a broad technological concept. Future research could isolate and compare the Task-Technology Fit (TTF) of different models (e.g., OpenAI's GPT-4 vs. Google's Gemini vs. open-source enterprise models) to determine which specific architecture is most optimal for highly technical project management tasks.

- **Expansion Beyond the Technical/Engineering Sector:**

Because this study focused on technical project managers within the Saudi Vision 2030 ecosystem, future researchers should replicate this model in other vital sectors, such as healthcare administration, finance, or public policy. Comparing these sectors would further test the universality of the demographic findings discovered in this research.

- **The Impact of AI on Project Team Dynamics:**

While this study focused on the individual project manager's cognitive load and decision-making, future research should explore how the integration of prompt engineering affects team cohesion, delegation, and overall project team dynamics.

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Appendices:

Questionnaire:

MIDOCEAN UNIVERSITY

RESEARCH TOPIC | عنوان البحث

أثر مهارات هندسة الأوامر للذكاء الاصطناعي التوليدي في تقليل العبء الذهني وتحسين جودة اتخاذ القرار: دراسة تطبيقية على مديري المشاريع التقنية في المملكة العربية السعودية

The Impact of Prompt Engineering Skills for Generative AI in Reducing Cognitive Load and Improving Decision-Making Quality: An Applied Study on Technical Project Managers in the Kingdom of Saudi Arabia

كتيب الاستبانة البحثية

QUESTIONNAIRE BOOKLET

الباحث | Researcher

رائد نقاش

عزيزي المشارك / عزيزتي المشاركة،

أقوم حالياً بإجراء دراسة ميدانية كجزء من متطلبات الحصول على درجة الماجستير، بعنوان: "أثر مهارات هندسة الأوامر للذكاء الاصطناعي التوليدي في تقليل العبء الذهني وتحسين جودة اتخاذ القرار: دراسة تطبيقية على مديري المشاريع التقنية في المملكة العربية السعودية".

أرجو منكم التكرم والموافقة على المشاركة في هذه الدراسة من خلال الإجابة على فقرات هذه الاستبانة التي تعكس واقع تجاربكم المهنية.

مشاركتم تطوعية تماماً، وتُعد إسهاماً قيماً في إثراء البحث العلمي وتطوير ممارسات الإدارة التقنية.

أؤكد لكم التزامي التام بأخلاقيات البحث العلمي، حيث سوف تعامل جميع الإجابات بسرية تامة، ولن يُطلب منكم الإفصاح عن هويتكم أو اسم جهة عملكم.

البيانات المُجمّعة ستُستخدم حصرياً للأغراض الأكاديمية والتحليل الإحصائي الشامل ولن يتم مشاركتها مع أي أطراف تجارية أو وظيفية.

يحق لكم التوقف عن تعبئة الاستبانة والانسحاب في أي وقت دون إبداء الأسباب.

شكراً جزيلاً لتعاونكم ووقتكم الثمين.

الباحث: رائد نقاش

البريد الإلكتروني: raed93359@gmail.com

المشرفون:

د. الفيصّل عبد الحميد محمد

د. فايز على جرّاد

Dear Participant,

I am currently conducting a field study as part of the requirements for a Master's degree, titled: **"The Impact of Prompt Engineering Skills for Generative AI in Reducing Cognitive Load and Improving Decision-Making Quality: An Applied Study on Technical Project Managers in the Kingdom of Saudi Arabia."**

I kindly request your participation in this study by answering the items in this questionnaire, which reflects your professional experiences. Your participation is entirely voluntary and is a valuable contribution to enriching scientific research and developing technical management practices.

I assure you of my complete commitment to scientific research ethics. All responses will be treated with absolute confidentiality, and you will not be asked to disclose your identity or your organization's name. The collected data will be used exclusively for academic purposes and comprehensive statistical analysis, and will not be shared with any commercial or functional parties. You have the right to stop filling out the questionnaire and withdraw at any time without providing a reason.

Thank you very much for your cooperation and valuable time.

Researcher: Raed Naqqash

Email: raed93359@gmail.com

Supervisors:

Dr. Al-faisal Abdelhameed Mohamed

Dr. Fayez Ail Jrad

القسم الأول: البيانات الديموغرافية والوظيفية | Section One: Occupational Data and Demographic

يرجى التفضل بوضع علامة ✓ بجانب الإجابة المناسبة / Please select the appropriate answer

1. Gender	1. الجنس
☐ ذكر Male ☐ أنثى Female	
2. Age	2. العمر
☐ 20 - 30 سنة years 20 - 30 ☐ 31 - 39 سنة years 31 - 39 ☐ 40 - 49 سنة years 40 - 49 ☐ 50 سنة فأكثر years and over 50	
3. Years of Experience in Tech PM	3. سنوات الخبرة في إدارة المشاريع التقنية
☐ أقل من 5 سنوات Less than 5 years ☐ 5 - 10 سنوات years 5 - 10 ☐ 11 - 20 سنة years 11 - 20 ☐ أكثر من 20 سنة More than 20 years	
4. Current City of Work	4. منطقة العمل الحالية
☐ الرياض Riyadh ☐ جدة Jeddah ☐ الدمام Dammam ☐ أخرى (يرجى التحديد) Other:	
5. Industrial Sector of your Company	5. قطاع الشركة الصناعية التي تعمل بها
☐ التقنيات الصناعية والأتمتة Automation ☐ الصناعات التحويلية Manufacturing ☐ سلاسل الإمداد Supply Chain ☐ أخرى Other	
6. Frequency of GenAI usage	6. معدل استخدامك لأدوات الذكاء الاصطناعي
☐ يومياً Daily ☐ عدة مرات أسبوعياً Weekly ☐ نادراً Rarely ☐ لا أستخدمها Never	

القسم الثاني: محاور الدراسة الأساسية | Section Two: Main Study Constructs

يرجى تحديد درجة موافقتك أو عدم موافقتك على العبارات التالية بناءً على المقياس الخماسي التالي:

Please indicate your level of agreement or disagreement with the following statements based on this 5-point scale:

• (1) غير موافق بشدة | Strongly Disagree

• (2) غير موافق | Disagree

• (3) محايد | Neutral

• (4) موافق | Agree

• (5) موافق بشدة | Strongly Agree

المحور الأول: مهارات هندسة الأوامر | Construct 1: Prompt Engineering Skills

الرمز Code	العبارة (Statement)	(1) غير موافق بشدة Strongly Disagree	(2) غير موافق Disagree	(3) محايد Neutral	(4) موافق Agree	(5) موافق بشدة Strongly Agree
PE1	أحرص على توفير سياق مفصل وواضح للذكاء الاصطناعي عند طلب تحليل مهام المشروع. I ensure to provide a detailed and clear project context to the AI when requesting task analysis					
PE2	أستخدم أسلوب تعيين الأدوار لنموذج الذكاء الاصطناعي للحصول على نتائج أكثر تخصصية. I use role-playing techniques for the AI model to obtain highly specialized results					
PE3	أمتلك القدرة على تجزئة المشكلات الإدارية المعقدة إلى سلسلة من الأوامر المتدرجة I have the ability to break down complex administrative problems into a series of iterative prompts					
PE4	أحدد صيغة المخرجات المطلوبة بدقة (مثل: جداول، تحليل نقدي) عند كتابة الأمر. I accurately specify the desired output format (e.g., tables, critical analysis) when writing the prompt					
PE5	أضع قيوداً واضحة لمنع النموذج من تقديم معلومات خارج نطاق المشروع. I set clear constraints to prevent the model from					

الرمز Code	العبارة (Statement)	(1) غير موافق بشدة Strongly Disagree	(2) غير موافق Disagree	(3) محايد Neutral	(4) موافق Agree	(5) موافق بشدة Strongly Agree
	providing information outside the project's .scope					

المحور الثاني: تقليل العبء الذهني والإدراكي | Construct 2: Cognitive Load Reduction

الرمز Code	العبارة (Statement)	(1) غير موافق بشدة Strongly Disagree	(2) غير موافق Disagree	(3) محايد Neutral	(4) موافق Agree	(5) موافق بشدة Strongly Agree
CL1	الاستخدام الفعال لهندسة الأوامر يقلل من الإرهاق الفكري المرتبط بمعالجة كميات هائلة من بيانات المشروع. Effective use of prompt engineering reduces the mental fatigue associated with processing .massive amounts of project data					
CL2	تساعدني الأوامر الموجهة بدقة في تنظيم الأفكار المتناثرة وتخفيف التشوش الذهني أثناء التخطيط. Precisely targeted prompts help me organize scattered thoughts and reduce mental distraction during .planning					
CL3	تساهم مخرجات الذكاء الاصطناعي السريعة في توفير طاقتي الذهنية للتركيز على المهام الاستراتيجية. Fast AI outputs contribute to saving my mental energy to focus .on strategic tasks					

الرمز Code	العبارة (Statement)	(1) غير موافق بشدة Strongly Disagree	(2) غير موافق Disagree	(3) محايد Neutral	(4) موافق Agree	(5) موافق بشدة Strongly Agree
CL4	استخدام هندسة الأوامر يخفف من الضغط النفسي الذي أشعر به عند اقتراب المواعيد النهائية. Using prompt engineering alleviates the psychological stress I feel as project deadlines approach					
CL5	يقلل الاستعلام الدقيق من الوقت المستغرق في كتابة التقارير، مما يحد من الإجهاد اليومي. Accurate querying reduces the time spent writing reports, limiting daily strain					
CL-C	سؤال رقابي: لضمان جودة البيانات، يرجى اختيار 'غير موافق' (2) لهذه العبارة. Control Question: To ensure data quality, please select 'Disagree' (2) for this item					

المحور الثالث: تحسين جودة اتخاذ القرار | Construct 3: Improving Decision-Making Quality

الرمز Code	العبارة (Statement)	(1) غير موافق بشدة Strongly Disagree	(2) غير موافق Disagree	(3) محايد Neutral	(4) موافق Agree	(5) موافق بشدة Strongly Agree
DM1	الأوامر النصية المصاغة باحترافية توفر لي بدائل وخيارات متعددة تسهم في تقييم المخاطر بشكل أدق. Professionally crafted text prompts provide me with multiple alternatives and options that contribute to more accurate risk assessment					
DM2	تساهم هندسة الأوامر في الحد من التحيزات الشخصية أثناء عملية اتخاذ القرارات التقنية.					

الرمز Code	العبارة (Statement)	(1) غير موافق بشدة Strongly Disagree	(2) غير موافق Disagree	(3) محايد Neutral	(4) موافق Agree	(5) موافق بشدة Strongly Agree
	Prompt engineering helps reduce personal biases during the technical decision-making process.					
DM3	المعلومات الدقيقة المستخرجة تزيد من ثقتي في القرارات التي أتخذها لتخصيص موارد المشروع. Accurate information extracted increases my confidence in decisions made for project resource allocation.					
DM4	تمكنني الأوامر الفعالة من استخراج بيانات تنبؤية تدعم القرارات الاستباقية. Effective prompts enable me to extract predictive data that supports proactive decisions.					
DM5	بفضل الذكاء الاصطناعي التوليدي، أصبحت أستجيب للمشكلات التقنية الطارئة بسرعة وكفاءة أعلى. Thanks to generative AI, I now respond to urgent technical problems with greater speed and efficiency.					

القسم الثالث: الأسئلة المفتوحة (اختياري) | Section Three: Open-Ended Questions (Optional)

Q1. من خلال خبرتك الإدارية في السوق السعودي، ما هي أبرز التحديات التي تواجهك عند صياغة الأوامر للذكاء الاصطناعي للحصول على مخرجات دقيقة؟

Based on your managerial experience in the Saudi market, what are the most prominent challenges you face when formulating prompts for AI to obtain accurate outputs

.....

Q2. هل لديك أي تعليقات أو مقترحات إضافية ترغب في إضافتها لتطوير هذه الدراسة؟

Do you have any additional comments or suggestions you would like to add to improve this study

.....

رسالة شكر وتقدير | Note of Thanks and Appreciation

نتقدم لك بخالص الشكر والامتنان على تخصيص جزء من وقتك الثمين للإجابة على هذه الاستبانة.
مساهمتك تعني لنا الكثير، وهي حجر الزاوية في إنجاح هذا البحث العلمي.

We extend our sincere thanks and gratitude for dedicating part of your valuable time to answering this questionnaire. Your contribution means a lot to us and is the cornerstone for the success of this scientific research.

مع خالص التقدير والاحترام | With sincere appreciation and respect

الباحث | The Researcher

One Way ANOVA Result for Testing Hypothesis by Using SPSS:

```

CORRELATIONS
/VARIABLES=Prompt_Engineering_Skills Cognitive_Load_Reduction
/PRINT=TWOTAIL NOSIG FULL
/MISSING=PAIRWISE.

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→ Correlations

Correlations

		Prompt Engineering Skills	Cognitive Load Reduction
Prompt Engineering Skills	Pearson Correlation	1	.516***
	Sig. (2-tailed)		<.001
	N	63	63
Cognitive Load Reduction	Pearson Correlation	.516***	1
	Sig. (2-tailed)	<.001	
	N	63	63

***. Correlation is significant at the 0.001 level (2-tailed).

```

CORRELATIONS
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→ Correlations

Correlations

		Prompt Engineering Skills	Improving Decision-Making Quality
Prompt Engineering Skills	Pearson Correlation	1	.348**
	Sig. (2-tailed)		.005
	N	63	63
Improving Decision-Making Quality	Pearson Correlation	.348**	1
	Sig. (2-tailed)	.005	
	N	63	63

**. Correlation is significant at the 0.01 level (2-tailed).

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ONEWAY Cognitive_Load_Reduction Improving_Decision_Making_Quality BY Age_Num
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/POSTHOC=TUKEY ALPHA(0.05) .

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		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig. ^a
Cognitive Load Reduction	Between Groups	.561	3	.187	.433	.730
	Within Groups	25.473	59	.432		
	Total	26.034	62			
Improving Decision-Making Quality	Between Groups	.337	3	.112	.297	.827
	Within Groups	22.285	59	.378		
	Total	22.622	62			

a. Confidence Interval: 95%

```

ONEWAY Cognitive_Load_Reduction Improving_Decision_Making_Quality BY City_Num
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/STATISTICS DESCRIPTIVES
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		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig. ^a
Cognitive Load Reduction	Between Groups	.295	2	.148	.344	.710
	Within Groups	25.739	60	.429		
	Total	26.034	62			
Improving Decision-Making Quality	Between Groups	.803	2	.402	1.105	.338
	Within Groups	21.819	60	.364		
	Total	22.622	62			

a. Confidence Interval: 95%

```

ONEWAY Cognitive_Load_Reduction Improving_Decision_Making_Quality BY Experience_Num
/ES=OVERALL
/STATISTICS DESCRIPTIVES
/MISSING ANALYSIS
/CRITERIA=CILEVEL(0.95)
/POSTHOC=TUKEY ALPHA(0.05) .

```

		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig. ^a
Cognitive Load Reduction	Between Groups	1.874	3	.625	1.526	.217
	Within Groups	24.160	59	.409		
	Total	26.034	62			
Improving Decision-Making Quality	Between Groups	1.429	3	.476	1.326	.275
	Within Groups	21.193	59	.359		
	Total	22.622	62			

a. Confidence Interval: 95%

```

ONEWAY Cognitive_Load_Reduction Improving_Decision_Making_Quality BY GenAIUsage_Num
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/STATISTICS DESCRIPTIVES
/MISSING ANALYSIS
/CRITERIA=CILEVEL(0.95)
/POSTHOC=TUKEY ALPHA(0.05) .

```

		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig. ^a
Cognitive Load Reduction	Between Groups	3.975	3	1.325	3.544	.020
	Within Groups	22.059	59	.374		
	Total	26.034	62			
Improving Decision-Making Quality	Between Groups	1.750	3	.583	1.649	.188
	Within Groups	20.872	59	.354		
	Total	22.622	62			

a. Confidence Interval: 95%

Midocean University

College of Management

Master of Project Management



**The Impact of Prompt Engineering Skills for Generative AI in Reducing Cognitive Load and
Improving Decision-Making Quality: An Applied Study on Technical Project Managers in the
Kingdom of Saudi Arabia**

Prepared by:

Raed Ahmed Naqqash

253002775

Supervised by:

Dr. Al-faisal Abdelhameed Mohamed

Dr. Fayez Ali Jrad

Year:2026