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Navigating the Divide: Balancing AI's Optimal Solution with the Appropriate Solution in Chinese Construction Management

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Abstract

While Artificial Intelligence (AI) offers powerful tools for optimizing construction processes, its effective integration hinges on navigating the gap between algorithmic "optimality" and practical "appropriateness". Focusing on China's construction industry, a critical context for AI deployment, this research explores the managerial decision-making processes involved in balancing these two facets. Through a qualitative methodology involving 15 expert interviews across diverse organizational types (SOEs, private, consultancy) and thematic analysis incorporating constant comparison, this study elucidates the complex interplay between AI recommendations and human judgment. Key findings identify five interconnected themes influencing this balance: Decision Balance & Human Adjustment, Data & Technology Challenges, Human-AI Collaboration and Trust, External Constraints & Contextual Factors, and Sector-Specific Dynamics. The research highlights the proactive role of managers as "adaptive integrators" rather than passive users. Extending existing literature, this study contributes theoretically by challenging simplistic views of optimality, refining human-AI interaction concepts, and proposing an empirically grounded Adaptive Human-AI Interaction Framework that explicitly incorporates contextual modulators and managerial interpretation. The findings hold significant practical implications for developing more effective AI tools, targeted training programs, supportive organizational cultures, and nuanced policy guidelines to foster responsible and productive AI integration in construction and analogous operational fields.

Keywords : Artificial Intelligence (AI); Construction Management; China; Human-AI Interaction; Adaptive Integration

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Introduction

Background and Context

Artificial intelligence (AI) is rapidly transforming industries worldwide, redefining processes in sectors as diverse as healthcare, finance, and manufacturing (Malik et al., 2024). In particular, China's construction industry—fueled by rapid urbanization, massive infrastructure projects, and a national commitment to technological innovation (Wu, 2023; Yu et al., 2024) —has become a key focus area. In recent years, the Chinese government has introduced policies supporting high-tech and digital transformation, encouraging the adoption of AI, big data, and IoT technologies in traditional sectors. As a foundational industry, construction has responded to these policy drivers, beginning to adopt AI for functions like smart construction and safety monitoring. Consequently, the sector is positioned to become a significant adopter of AI technologies like predictive analytics, computer vision, and LLMs, which promise enhanced planning, resource allocation, risk management, and efficiency (Malik et al., 2024). Crucially, however, beneath the surface of these technological advancements lies a critical managerial challenge: reconciling the algorithmically derived "optimal" solutions proposed by AI with the nuanced, context-dependent "appropriate" adjustments required for practical, real-world application. This fundamental tension between algorithmic potential and managerial practice, situated at the intersection of technology adoption, decision-making theory, and organizational practice, remains largely underexplored.

Problem Statement

Despite substantial research demonstrating AI's technical potential to improve design accuracy, forecast delays, and streamline workflows (Kokala, Abhilash, 2024), a significant gap persists. Much of the existing literature centers on the technical performance of AI systems in construction, often overlooking the pivotal role of managerial judgment in mediating their implementation. In practice, managers must interpret AI recommendations—frequently based on idealized assumptions—

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and adapt them to navigate practical constraints such as regulatory requirements, resource limitations, labor dynamics, and stakeholder expectations (Kinney et al., 2024). How managers navigate this critical space between AI's "optimal" outputs and the "appropriate", actionable solutions remains insufficiently understood, particularly within the complex and dynamic environment of China's construction sector. In this study (Ni et al., 2024), an "optimal" solution is defined as the algorithmically derived output based solely on quantitative data and efficiency metrics, while an "appropriate" solution refers to the adaptation of that output through managerial judgment, which incorporates contextual, regulatory, and practical considerations.

Research Objectives and Research Question

This study aims to bridge the gap between AI's technical capabilities and its practical managerial application by examining how managers in China's construction industry interpret and balance AI-driven recommendations with real-world operational constraints. The specific objectives are:

1. To investigate the decision-making processes managers employ when evaluating AI-generated "optimal" solutions.
2. To explore the contextual factors (regulatory, labor, stakeholder pressures) influencing the adaptation of AI recommendations into "appropriate" solutions.
3. To identify best practices and challenges in human-AI collaboration within construction management.
4. To contribute to theoretical discussions on AI, management, and decision-making by illuminating the interplay between algorithms and human judgment.

Accordingly, the research question guiding this study is:

How do managers in China's construction industry interpret and balance AI's optimal solutions with appropriate, practical solutions?

Significance of the Study

This research holds significant implications for theory, practice, and policy. By focusing on the nuanced interplay between AI outputs and managerial discretion, it contributes to a more holistic understanding of AI integration in operational settings. The findings are expected to:

1. Advance academic knowledge by extending literature on human-AI interaction and technology adoption, particularly within the unique constraints of construction management.
2. Inform industry practice by highlighting the indispensable role of human judgment and the need for training and collaborative strategies for effective AI use.
3. Guide policy formulation by illustrating how regulatory and socio-political contexts shape AI adoption, supporting the development of adaptive policies that foster innovation while ensuring safety and sustainability.

Given China's global leadership in both construction and AI deployment, insights from this study may offer valuable lessons for other regions and industries grappling with similar integration challenges.

Structure of the Article

This article proceeds as follows: Chapter 2 reviews the relevant literature on AI in construction and managerial decision-making. Chapter 3 details the research methodology employed. Chapter 4 presents the findings derived from the data analysis. Chapter 5 discusses the implications of these findings in relation to existing literature and theory. Finally, Chapter 6 concludes the study, summarizing key insights and suggesting future research directions.

Literature Review

This chapter critically reviews the existing literature pertinent to the intersection of AI adoption, managerial challenges, and decision-making processes within the construction industry. It synthesizes research across three core areas: (1) the current landscape of AI applications in construction; (2) the identified managerial challenges hindering effective AI integration; and (3) the conceptual tension between algorithmically "optimal" solutions and managerially determined "appropriate" actions. By critically examining these interconnected themes, this review establishes the theoretical foundation for the study and sharpens the focus on the central research gap: understanding how managers navigate the practical realities of balancing AI potential with operational constraints, particularly in the Chinese context.

AI Applications in Construction: Potential and Limitations

The integration of AI into the construction industry has shown considerable promise across various operational phases. Key applications include:

1. **Predictive Analytics:** AI algorithms analyze historical project data to forecast potential risks, cost overruns, and schedule delays (F. Afzal et al., 2019; Gondia et al., 2020). While valuable, such studies often focus on predictive accuracy under controlled data conditions. This research seeks to investigate how managers grapple with AI predictions when data quality is variable in situ, potentially challenging the direct applicability of optimal forecasts derived from idealized data, a nuance often overlooked.
2. **Building Information Modeling (BIM) Enhancement:** AI complements BIM by automating design checks, optimizing layouts, and improving clash detection (Abdulfattah et al., 2023; M. Afzal et al., 2023). However, integrating AI insights

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seamlessly into existing BIM workflows often requires significant technical expertise and process adaptation. Furthermore, the optimistic integration scenarios presented often underplay the socio-technical hurdles (Pan & Zhang, 2023; Tran et al., 2024). By examining managerial resistance documented by Salimimoghadam et al. (2025), this study aims to provide empirical evidence on the specific adaptive strategies managers employ, moving beyond technical potential to explore the practical realities of AI-BIM interaction as mediated by human actors.

3. **Large Language Models (LLMs):** LLMs are emerging as tools for contract analysis, communication streamlining, and knowledge management (Saparamadu et al., 2025; Zafar et al., 2024). Their application is still nascent, and challenges remain regarding domain-specific accuracy and contextual understanding within complex construction projects. Although nascent, their inclusion is relevant as they represent a rapidly emerging category of AI poised to influence communication and knowledge-based decision-making, raising pertinent questions even now about how managers will vet and integrate their potentially opaque outputs into established workflows.
4. **Computer Vision:** AI-powered image recognition is used for site monitoring, safety compliance checks, and progress tracking (Musarat et al., 2024). Deployment can be hindered by variable site conditions (e.g., lighting, weather) and the need for robust data infrastructure.

These applications demonstrate technical potential, the literature often emphasizes technological capabilities over the socio-technical challenges of implementation. A critical gap exists in understanding how managers interact with these tools not just as technical outputs, but as inputs into complex decision-making processes constrained by real-world factors.

Managerial Challenges in AI Implementation

The effective adoption of AI in construction is impeded by several interrelated managerial challenges that directly impact how AI-driven “optimal” solutions are evaluated and adapted:

1. **Data Quality and Availability:** The construction industry notoriously suffers from fragmented, inconsistent, and often incomplete data (Kazmi et al., 2023; Riazi et al., 2020). This directly undermines the reliability of AI predictions and complicates managerial trust in “optimal” outputs, often necessitating significant human oversight and adjustment.
2. **Regulatory and Compliance Hurdles:** Navigating complex building codes, safety regulations, and contractual obligations requires nuanced human judgment (Yazdi et al., 2024). AI solutions, while potentially optimizing for specific parameters, may not fully account for these multifaceted regulatory landscapes, forcing managers to intervene and ensure compliance, thereby modifying the “optimal” suggestion.
3. **Algorithm Aversion and Trust:** Managers may exhibit skepticism or reluctance (“algorithm aversion”) towards AI recommendations, especially when they contradict intuition or experience (Turel & Kalhan, 2023). Building trust requires transparency in AI processes and demonstrable reliability, yet the “black box” nature of some algorithms complicates this, leading managers to favor familiar, albeit potentially less “optimal”, approaches.
4. **Organizational Culture and Skills Gap:** Successful AI integration requires a supportive organizational culture and a workforce equipped with the necessary digital literacy (Cetindamar et al., 2024; Tursunbayeva & Chalutz-Ben Gal, 2024). Resistance to change and skill deficits can lead managers to underutilize AI or override its suggestions due to a lack of understanding or confidence, impacting the translation from “optimal” potential to “appropriate” action.

These challenges collectively highlight that AI implementation is not merely a technical problem but a complex socio-technical process where managerial interpretation and adaptation are crucial. How managers weigh these challenges against the perceived benefits of AI’s “optimal” solutions is central to this study.

The Tension: Optimal vs. Appropriate Solutions

The core theoretical tension explored in this research lies in the divergence between the “optimal” solutions generated by AI algorithms and the “appropriate” solutions deemed necessary by human managers operating within specific contexts. AI often optimizes for quantifiable metrics based on available data (e.g., minimizing cost, maximizing speed) (Surianarayanan et al., 2023). However, managerial decision-making involves balancing these quantifiable metrics against less tangible factors like stakeholder relations, long-term strategic goals, ethical considerations, and unforeseen site-specific issues. This reflects principles of bounded rationality (Hunt et al., 2024), where managers make decisions within cognitive and contextual limits, often relying on heuristics or “satisficing” rather than pure optimization. It also aligns with naturalistic decision-making, which emphasizes how experts operate under time pressure and uncertainty using experience-based intuition (Lawani et al., 2023), factors often contrasting with the data-driven logic of AI.

This necessitates a process of “human adjustment” where managers interpret, validate, and often modify AI outputs (X. Wang et al., 2022). The literature suggests that effective human-AI collaboration involves leveraging AI's analytical power while retaining human oversight for context, ethical judgment, and strategic alignment (Celestin & Vanitha, 2020; Joseph et al., 2024). Yet, *how* this balance is practically struck in the high-stakes environment of construction, particularly when faced with the managerial challenges outlined above, remains inadequately explored. Existing models often focus on either the technology or the human element in isolation, rather than their dynamic interplay in shaping the final “appropriate” decision.

Research Gap and Contextual Focus

Synthesizing the literature reveals a clear gap: while AI’s potential in construction and the associated managerial challenges are acknowledged, there is limited empirical research exploring the specific decision-making processes managers use to reconcile AI's "optimal" recommendations with the practical need for "appropriate", context-sensitive solutions. This research gap suggests that more research based on field data is needed to explore the actual methods and strategies used by managers when integrating AI decision-making into specific project contexts. Furthermore, much of the existing research originates from Western contexts, understanding this dynamic within Chinese construction firms is crucial for both localized insights and broader comparative understanding. This study directly addresses this gap by investigating the nuanced interplay between AI optimality and managerial judgment within this specific, significant context.

Methodology

This chapter details the methodological approach employed to address the research question: ***How do managers in China's construction industry interpret and balance AI's optimal solutions with appropriate, practical solutions?*** Given the exploratory nature of the inquiry and the need to understand complex managerial decision-making processes within their specific context—considering project background, resource conditions, organizational culture, and on-site realities—a qualitative research design was deemed most appropriate. Because it is necessary to comprehensively consider the specific background, resource conditions and management experience of the project. This balance involves not only quantitative data, but also qualitative factors such as organizational culture, teamwork, experience judgment and actual on-site conditions. Therefore, the use of qualitative research design can better reveal the complex process of managers making decisions in specific situations and help understand how they achieve this balance in theory and practice. This chapter outlines the research philosophy, methodological choices, data collection procedures, analytical strategy, ethical considerations, and methodological limitations.

Research Philosophy and Approach

An interpretivist philosophical stance underpins this research, acknowledging that understanding human actions, like managerial decision-making, requires interpreting the meanings individuals ascribe to their experiences (Cuthbertson et al., 2020). This aligns with the study's focus on the subjective processes managers use to balance objective AI outputs with subjective contextual factors. Consequently, an exploratory qualitative approach was adopted. This approach is particularly suited for investigating phenomena that are not yet fully understood, allowing for in-depth exploration of participants' perspectives and the identification of emergent themes related to the optimal versus appropriate decision-making dynamic (Lim, 2024).

Theoretical Underpinning: Thematic Analysis and Grounded Theory Elements

The primary analytical framework employed is Thematic Analysis (TA), following the steps outlined by (Braun & Clarke, 2023). TA provides a flexible yet rigorous method for identifying, analyzing, and reporting patterns (themes) within qualitative data, making it well-suited to uncovering the core strategies managers use when interacting with AI.

To further enhance the analysis, particularly in understanding the *process* of adaptation and the development of managerial strategies, elements of Grounded Theory (GT) were incorporated, specifically techniques like constant comparison (Timonen et al., 2018). Constant comparison involves continually comparing data segments (e.g., interview transcripts) with emerging codes and themes. This iterative process helps refine thematic definitions and allows for the development of a nuanced understanding of *how* managers actively negotiate between AI recommendations and practical constraints, thereby directly addressing the dynamic nature implied in the research question. This blended approach leverages the structural clarity of TA while incorporating the process-oriented insights facilitated by GT techniques.

Contextual Focus: China's Construction Industry

The study is specifically situated within China's construction industry due to its unique characteristics: rapid AI adoption, significant state influence, large-scale projects, and distinct regulatory and cultural contexts (Yan et al., 2023; Yu et al., 2024). This specific focus allows for a rich, context-dependent understanding of the research problem, acknowledging that managerial practices are deeply embedded within their operational environment.

Data Collection

As shown in Figure 1, we adopted a multifaceted data collection strategy to ensure richness and achieve triangulation. Figure 1 illustrates the iterative flow from purposive sampling to thematic analysis, highlighting the triangulation process that enhances data robustness—a visual aid to the multifaceted strategy described. The flowchart depicts stages including purposive sampling (targeting state-owned enterprises, private firms, consultancies), semi-structured interviews, data familiarization, open coding (using NVivo), axial/thematic coding (using NVivo, Braun & Clarke approach), and validation/triangulation (inter-coder checks, member checking, secondary data), highlighting iterative refinement based on constant comparison.

Primary Data: Expert Interviews:

1. **Sampling:** Purposive sampling targeted 15 experts. This initial range (12-20) was informed by common practices in qualitative exploratory research within management studies aiming for thematic depth. (a final number achieved through iterative recruitment) with direct experience in managing construction projects involving AI applications in China. Participants included senior project managers, technology leads, and department heads.

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2. **Diversity:** Efforts were made to include participants from state-owned enterprises (SOEs), private companies, and consulting firms to capture diverse organizational perspectives.
3. **Protocol:** Semi-structured interviews allowed for flexibility while ensuring key topics were covered, focusing on experiences with AI tools, decision-making processes when evaluating AI outputs, encountered challenges, and strategies for balancing "optimal" versus "appropriate" solutions. Interviews were conducted remotely via secure video conferencing, audio-recorded with consent, and transcribed verbatim. Participants were selected based on criteria including a minimum of 10 years' experience in construction management, direct involvement in AI-supported projects (e.g., predictive analytics or BIM enhancement), and representation across organizational types (SOEs, private firms, consultancies). Recruitment ceased at 15 participants because thematic saturation was demonstrably reached; interviews 14 and 15 yielded no new significant concepts or themes related to the core research question, confirming the adequacy of the sample size for capturing the phenomenon under investigation.

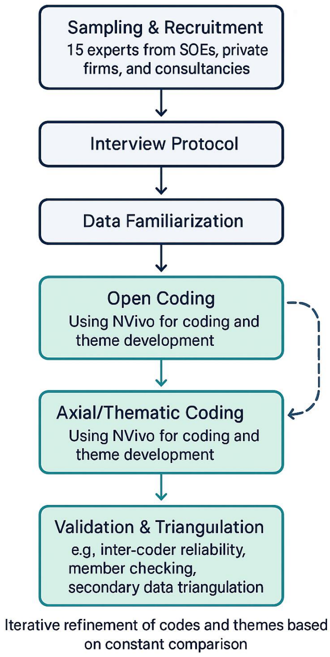

Figure 1 Qualitative Research Methodology Flowchart

Secondary Data:

1. **Sources:** Publicly available data from the National Bureau of Statistics of China, relevant government policy documents (e.g., AI development plans), industry association reports, and company publications were collected.
2. **Purpose:** This data served to contextualize interview findings, triangulate emergent themes (e.g., verifying reported industry trends), and provide a broader backdrop of AI adoption patterns and challenges in the Chinese construction sector.

Data Analysis Process

The analysis followed a systematic process integrating TA and GT elements, facilitated by NVivo software. NVivo was selected for its robust capacity to handle large qualitative datasets and support iterative coding. Specifically, it enabled efficient organization of transcripts, systematic application of open and axial codes, visualization of relationships between codes through mapping features, and execution of complex queries to support the constant comparison technique borrowed from grounded theory, thereby enhancing analytical rigor. Its tagging and query functions enabled efficient theme development across 15 transcripts and secondary sources.

1. **Familiarization:** Repeated reading of transcripts and secondary data to gain deep understanding.
2. **Initial Coding:** Systematically coding interesting features across the entire dataset ("open coding").
3. **Theme Development:** Collating codes into potential themes, examining relationships between codes and themes ("axial coding" inspiration from GT). Constant comparison was used here to refine code definitions and ensure themes accurately reflected the data related to the optimal/appropriate balancing act.
4. **Reviewing Themes:** Checking if themes work in relation to coded extracts and the entire dataset, generating a thematic map.
5. **Defining and Naming Themes:** Ongoing analysis to refine specifics of each theme, generating clear definitions and names.
6. **Validation:** Rigor was enhanced through:

A. Inter-coder reliability: A. Inter-coder reliability: A subset of transcripts (e.g., 20% of the data) was independently coded by a second researcher. Initial agreement yielded a Cohen's Kappa of [Insert Value, e.g., 0.78], indicating substantial agreement. Subsequent discussion resolved discrepancies, leading to consensus on code application and refinement of the codebook.

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B. Member checking: Key findings and interpretations were shared with select participants to verify their resonance with lived experiences.
C. Triangulation: Comparing findings from interviews with secondary data sources.

Ethical Considerations

Ethical conduct was paramount throughout the research process:

1. **Informed Consent:** Participants received detailed information about the study's purpose, procedures, risks, benefits, and their right to withdraw before providing written consent.
2. **Anonymity and Confidentiality:** Participant and organizational identities were anonymized using pseudonyms in transcripts and reports. Data was stored securely on encrypted devices.
3. **Data Security:** Adherence to institutional data protection guidelines was maintained.

Methodological Limitations

1. **Generalizability:** As a qualitative study focused on a specific context, findings may not be directly generalizable to all construction sectors or geographic regions. The aim is analytical generalization – contributing theoretical insights applicable elsewhere.
2. **Potential for Bias:** Self-reported data from interviews may be subject to recall bias or social desirability bias. Triangulation with secondary data aimed to mitigate this.
3. **Dynamic Field:** AI technology and its adoption are rapidly evolving, meaning findings reflect a specific point in time.

These limitations were considered during data interpretation and are acknowledged in the discussion of findings.

Results

This chapter presents the findings derived from the thematic analysis of interview data, triangulated with secondary sources, concerning how managers in China's construction industry navigate the balance between AI-driven "optimal" solutions and practically "appropriate" decisions. The analysis involved systematic coding and theme development, including open and axial coding facilitated by NVivo. (Detailed steps, coding examples, and the constant comparison process are provided in Table 1 and Table 2.) Following familiarization with the data, the analysis identified five core themes that illuminate the complexities of this balancing act (shown in Figure 2) : (1) Decision Balance & Human Adjustment; (2) Data & Technology Challenges; (3) Human-AI Collaboration and Trust; (4) External Constraints & Contextual Factors; and (5) Sector-Specific Dynamics. These themes emerged from a systematic analytical process involving deep familiarization with interview and secondary data, rigorous open and axial coding facilitated by NVivo software, and iterative refinement using constant comparison techniques derived from grounded theory. Inter-coder reliability checks and member checking were employed to enhance validation. (Further details on the coding process and preliminary code examples can be found in Appendix A). The following sections elaborate on each of the five core themes identified.

This preliminary analysis reveals that AI integration in construction across SOEs, private enterprises, and consultancies involves a consistent tension between "optimal" AI solutions and "appropriate" real-world adaptations. Key challenges include data quality and integration, regulatory compliance, and the need for human oversight, while strategies differ by organizational type—SOEs emphasize policy-driven validation, private firms focus on cost and innovation, and consultancies prioritize ethical customization. These insights lay the groundwork for deeper thematic analysis in subsequent research phases.

Theme 1: Decision Balance & Human Adjustment

This theme encapsulates the core process observed: managers actively weighing AI recommendations against their own experience and contextual knowledge to arrive at actionable decisions. Participants consistently described AI outputs not as final directives, but as valuable inputs requiring human interpretation and adaptation.

1. Managers emphasized their role in validating AI outputs against practical realities. As Manager[A] (SOE) stated, "***The system might suggest the theoretically fastest schedule [optimal], but it doesn't know about the specific ground conditions we found last week. We have to adjust [appropriate].***" This highlights the need to integrate real-time, site-specific knowledge that AI models might lack.

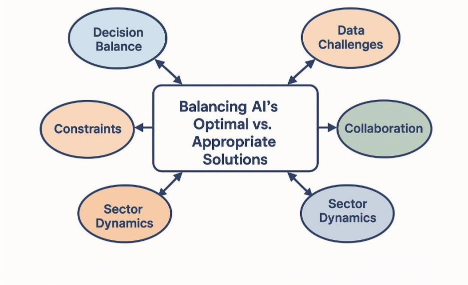

Figure 2 Thematic Map of AI Solution Balancing

2. Experience and intuition were frequently cited as crucial counterbalances. Manager[B] (Private Firm) explained, "*AI recommended a material allocation based purely on cost [optimal]. But my experience tells me that for this specific application, a slightly costlier but more durable material is better long-term [appropriate]. The algorithm doesn't capture that nuance.*"
3. The "human adjustment" often involved simplifying or modifying AI's complex outputs to make them understandable and implementable for site teams. This iterative process of balancing algorithmic suggestions with practical feasibility was central to decision-making.

Theme 2: Data & Technology Challenges

This theme addresses the significant practical hurdles related to data quality and technological limitations that directly influence managers' ability and willingness to rely on AI's "optimal" solutions. Poor data inputs were seen as directly compromising the reliability of AI outputs.
1. Data fragmentation and inconsistency were major concerns. "*Garbage in, garbage out,*" stated Technology Lead[C] (Consultancy). "*If the initial data from subcontractors isn't standardized or accurate, the AI analysis [optimal] is fundamentally flawed. We spend more time cleaning data than using the insights.*" This resonates with industry reports indicating variable levels of data maturity across firms. For instance, while BIM adoption is increasing, its effective integration for data consistency remains a challenge. Studies indicate varied implementation levels; for example, a 2019 study found BIM utilization at ~35% among listed AEC companies over the preceding decade (Babatunde et al., 2020), while others noted low project-level adoption rates and persistent difficulties with data exchange, thereby limiting the quality of data available for AI (Sang et al., 2020).
2. Technological limitations, such as the inability of some AI tools to process unstructured data or adapt to rapidly changing site conditions, also necessitated managerial intervention. This often led managers to favour less "optimal" but more robust traditional methods when AI reliability was questionable.

Theme 3: Human-AI Collaboration and Trust

This theme explores the evolving relationship between managers and AI systems, focusing on the development of trust and the nature of collaboration. Trust was not automatic but had to be earned through consistent performance and transparency.
1. Building trust required AI systems to demonstrate tangible benefits and reliability over time (as shown in Figure 3). Manager[D] (SOE) noted, "*Initially, we were skeptical. But after the scheduling AI correctly predicted several potential delays [demonstrating value], we started trusting its recommendations more, using them as a strong baseline [collaboration].*"
2. Transparency was key. *"If we don't understand why the AI suggests a certain approach [optimal], it's hard to trust it fully,"* said Manager[E] (Private Firm). *"Black box algorithms make it difficult. We prefer systems where we can interrogate the logic."* This lack of transparency often led managers to default to their own judgment, modifying the AI's suggestion.
3. Effective collaboration was described as synergistic, with AI handling complex data analysis and managers providing strategic oversight and contextual understanding.

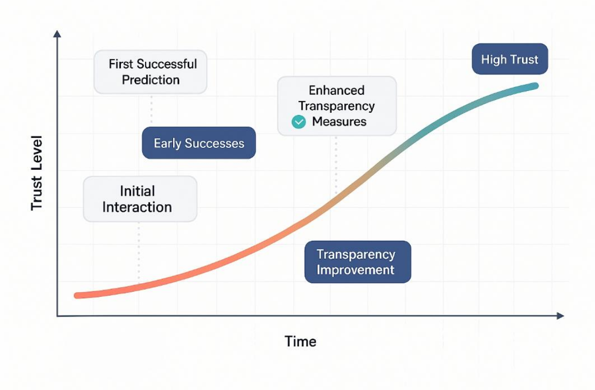

Figure 3 Trust Development in Human-AI Collaboration

Theme 4: External Constraints & Contextual Factors

This theme highlights the significant influence of the broader operational environment, including regulations, client demands, and market pressures, on the adoption and adaptation of AI solutions. These external factors often force deviations from purely "optimal" paths.
1. Regulatory compliance frequently necessitated adjustments to AI-driven plans. *"The AI might propose the most cost-effective site layout [optimal], but it doesn't always align perfectly with local safety regulations or environmental permits. Human oversight is essential to ensure compliance [appropriate],"* explained Manager[F] (SOE).
2. Client expectations and contractual obligations could also override AI recommendations. *"Sometimes the client insists on a specific supplier or method, even if the AI suggests a cheaper alternative [optimal]. We have to balance technical optimization with relationship management [appropriate],"* stated Manager[I] (Private Firm).

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3. The broader economic and policy context in China, emphasizing rapid development and technological advancement, created both pressure to adopt AI and challenges in ensuring its thoughtful, appropriate implementation amidst tight deadlines and competitive pressures.

Theme 5: Sector-Specific Dynamics

This theme acknowledges that the way managers balance optimal and appropriate solutions varies depending on the specific construction sub-sector (e.g., infrastructure, residential, commercial).

1. Large-scale infrastructure projects, often involving SOEs, showed greater propensity for adopting sophisticated AI for planning and risk management due to project complexity and scale, though bureaucratic processes could slow adaptation. As one participant noted, the anticipated productivity gains, often highlighted in government planning documents promoting AI adoption pilots, served as a key incentive for exploring these technologies, despite the complexities of implementation within established protocols (Yigitcanlar et al., 2024).
2. In contrast, smaller residential or commercial projects, often managed by private firms, might use AI more selectively, prioritizing tools with immediate, tangible benefits (e.g., cost estimation) and relying more heavily on managerial experience due to tighter budgets or less complex data environments. Manager[J] (Private Firm, Residential) commented, *"We use some AI for estimates, but for day-to-day site decisions, my gut feeling and direct observation are still primary."*

Sector-Specific Dynamics in Balancing Optimal and Appropriate Solutions

This subsection examines how different organization types in Chinese construction management balance AI's optimal solutions with appropriate, context-sensitive approaches. The following analysis draws from interview data to highlight sector-specific dynamics across SOEs, private firms, and consultancies.

Table 3 Comparison of Organizational Approaches to Balancing Optimal and Appropriate Solutions

Organization Type	Decision-Making Processes	Data Handling	Trust in AI	Response to External Constraints
SOEs	Policy-driven with multi-level approvals	Centralized, governed by strict protocols	Cautious, requiring human oversight	Prioritize regulatory compliance and social goals
Private Firms	Agile, market-oriented decisions	Flexible, cost-focused integration	Pragmatic, tied to return on investment	Adapt quickly to market and client needs
Consultancies	Client-centric, evidence-based customization	Cross-sector data synthesis, secure	Trust via expertise validation	Balance client demands with ethical/regulatory limits

Table 3 summarizes the key differences in organizational approaches, including decision-making processes, data handling, trust in AI, and responses to external constraints.

For example, SOEs emphasized regulatory compliance as a key constraint, while private firms prioritized market agility. Consultancies, meanwhile, focused on integrating client-specific needs into AI solutions. These organizational differences underscore the sector-specific dynamics of AI integration, which are further explored in the Discussion section in relation to existing literature and practical implications

Summary of Findings

The findings indicate that managers in China's construction industry engage in a complex, dynamic process of balancing AI's potential for optimization against practical realities. This involves active "human adjustment" based on experience and context, navigating significant data and technology challenges, building trust through performance and transparency, responding to potent external constraints, and adapting strategies based on sector-specific demands. AI is viewed as a valuable tool, but human judgment remains central in translating its "optimal" outputs into "appropriate" and actionable solutions within the specific operational context.

Discussion

This chapter interprets the findings presented in Chapter 4, discussing their significance in relation to the existing literature and the study's central research question regarding how managers in China's construction industry balance AI's "optimal" solutions with "appropriate" practical applications. Moving beyond a summary of results, this discussion delves into the theoretical contributions, practical implications, limitations, and future research directions stemming from the observed complexities of human-AI interaction in this specific context.

Synthesis of Findings and Connection to Literature

The findings underscore that the integration of AI in construction is not a straightforward process of adopting technically superior solutions, but rather a nuanced negotiation mediated by human judgment. The core finding—that managers actively engage in "Decision Balance & Human Adjustment" (Theme 1)—resonates with, yet significantly extends, existing literature on technology acceptance and human-computer interaction. Furthermore, these themes are interconnected. For instance, the persistent "Data & Technology Challenges" (Theme 2) directly exacerbate the need for "Decision Balance & Human Adjustment" (Theme 1), as managers must compensate for unreliable AI inputs. This unreliability, in turn, hinders the

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development of "Human-AI Collaboration and Trust" (Theme 3), particularly for less transparent systems. Simultaneously, "External Constraints" (Theme 4), such as rigid regulations, often dictate the parameters within which 'human adjustment' must occur, sometimes forcing deviations from AI optima regardless of data quality or trust levels.

This situation is analogous to architectural design, where technologies like Computer-Aided Design (CAD), while offering powerful optimisation capabilities, also function as mediators requiring significant human judgment to align outputs with specific client needs, site conditions, and regulatory contexts. Examining this parallel is valuable because it underscores a fundamental point for AI adoption in construction: the challenge lies not just in the technology itself, but in integrating its logic within the existing complex, socio-technical system of project delivery, which inherently demands negotiation and adaptation by managers. Therefore, much like in architecture, AI in construction does not eliminate the need for human expertise and contextual negotiation; rather, it reshapes how that negotiation occurs, underscoring the manager's critical role as an "adaptive integrator" rather than a passive user of technological outputs.

For this reason, the introduction of technology is actually more like a "negotiation" - in this negotiation, technical suggestions are constantly reconciled with human experience, intuition and ethical judgment to achieve the best design solution. While studies acknowledge managerial oversight (Uusitalo et al., 2024), this research illuminates the proactive and adaptive nature of this oversight in construction. Managers are not just validators; they are active sense-makers and context-weavers, translating abstract AI outputs into grounded actions.

The persistent "Data & Technology Challenges" (Theme 2) confirm known issues in the industry (Sarta et al., 2021), but this study highlights how these challenges directly fuel the need for human adjustment, often forcing managers to prioritize robustness or compliance over theoretical optimality. Similarly, the findings on "Human-AI Collaboration and Trust" (Theme 3) align with literature emphasizing trust as crucial (Shin, 2021), but add nuance by showing how trust is built incrementally through demonstrated value and contingent on transparency, particularly impacting the willingness to adopt less interpretable AI recommendations.

The strong influence of "External Constraints & Contextual Factors" (Theme 4) reinforces the importance of context stressed in socio-technical systems theory (K. Wang et al., 2023) but specifies how regulatory pressures and client demands in the Chinese construction context actively shape the definition of an "appropriate" solution, sometimes diverging significantly from an AI's "optimal" one. Finally, the "Sector-Specific Dynamics" (Theme 5) suggest that the balancing act is not uniform, adding granularity to our understanding of AI adoption patterns across different organizational types and project scales within the industry.

Theoretical Implications: Towards an Adaptive Human-AI Interaction Framework

This study offers several key theoretical contributions:

1. **Refining Human-AI Interaction Models:** Current models often portray humans as either supervisors or collaborators with AI (Sowa et al., 2021). This research suggests a more dynamic role, particularly in operational fields like construction: the manager as an adaptive integrator. This role involves not just using AI outputs but actively synthesizing them with tacit knowledge, contextual intelligence, and foresight – capabilities currently beyond typical AI.
2. **Challenging Notions of "Optimality":** The findings challenge a purely techno-centric view of "optimality". In practice, "optimal" is redefined through the lens of contextual "appropriateness". True optimization in complex environments like construction appears to be a hybrid outcome, emerging from the synergy between algorithmic calculation and situated human judgment. This calls for theoretical frameworks that explicitly incorporate contextual appropriateness alongside algorithmic efficiency.
3. **Extending the Technology Acceptance Model:** The manager as an "adaptive integrator" extends the Technology Acceptance Model by suggesting that perceived usefulness and ease of use are mediated by contextual modulators and managerial interpretation, not just individual attitudes. Similarly, the trust dynamics observed (Theme 3) align with Karhapää (2022) model, where transparency and performance reliability incrementally build trust, though this study highlights the critical role of contextual adaptation absent in their framework. This expanded framework explicitly incorporates: A. Algorithmic Input (the AI's "optimal" suggestions frequently mentioned by participants). B. Contextual Modulators (reflecting Theme 2 findings on data/tech issues and Theme 4 findings on external constraints like regulations). C. Managerial Interpretation Engine (capturing Theme 1's emphasis on experience/intuition and Theme 3 aspects related to trust/skepticism). D. Adaptive Integration Process (representing the iterative balancing and adjustment process described by managers, linking Theme 1 and Theme 5 sector dynamics). E. Appropriate Action (the final, contextually-sound decision resulting from this human-mediated process). This framework
4. **Proposing an Expanded Framework:** Based on the findings, we propose an expansion of existing technology adoption/interaction frameworks for AI in operational settings. This expanded framework should explicitly incorporate (As shown in Figure 4):

A. Algorithmic Input: The "optimal" recommendation from AI.
B. Contextual Modulators: Data reliability, technological limitations, regulatory landscape, client/stakeholder pressures, organizational culture, sector norms.
C. Managerial Interpretation Engine: Experience-based heuristics, risk assessment, ethical judgment, strategic alignment.
D. Adaptive Integration Process: The iterative cycle of evaluating, adjusting, implementing, and learning that leads to the...

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E. Appropriate Action: The final, contextually-sound decision. This framework moves beyond linear models to capture the dynamic, multi-factor negotiation central to effective AI use in practice.

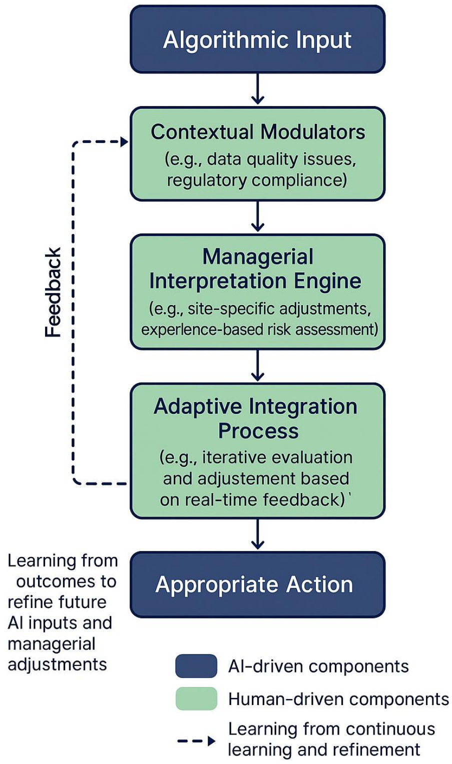

Figure 4 Adaptive Human-AI Interaction Framework

Practical Implications

The findings offer actionable insights for various stakeholders:

1. **For Construction Managers:** Recognize that human judgment is not a barrier to AI but its essential complement. Develop skills in critically evaluating AI outputs and integrating them with contextual knowledge. Foster open communication channels for sharing site-specific insights that AI might miss.
2. **For AI Developers:** Prioritize transparency and interpretability ("explainable AI") alongside predictive accuracy. Design systems that facilitate easy integration of human feedback and contextual overrides. Develop tools that are robust to imperfect data common in construction.
3. **For Organizations:** Invest in data infrastructure and standardization. Promote a culture that values both technological innovation and experiential knowledge. Provide training that focuses not just on using AI tools but on collaborating effectively with them.
4. **For Policymakers:** Develop regulations that encourage AI adoption while ensuring safety, ethical use, and accountability. Support initiatives for workforce training and data standardization within the industry. Recognize that "optimal" technological pathways may need adaptation to meet broader societal or environmental goals.
5. **For Performance Measurement:** Organizations may need to develop or adapt performance metrics. Beyond traditional Key performance indicators (cost, time, quality), new metrics might be needed to evaluate the effectiveness of the "adaptive integration" process itself and the long-term value derived from "appropriate" solutions, which might not always align with short-term "optimal" AI targets.

For managers, training should include workshops on interpreting AI outputs (e.g., understanding predictive analytics dashboards) and scenario-based exercises integrating site-specific variables. AI developers should prioritize features like real-time feedback loops allowing managers to input contextual overrides (e.g., weather disruptions) and visual explainability tools to demystify "black box" outputs. Policymakers could incentivize data standardization through tax credits for firms adopting interoperable BIM platforms.

Limitations and Future Research

While this study provides valuable insights, its limitations, detailed in Chapter 3 (qualitative nature, contextual specificity, potential biases), suggest avenues for future research:

1. **Quantitative Validation:** Complementary studies using large-scale quantitative data could assess the generalizability of these findings and potentially model the factors influencing the optimal/appropriate balance.

2. **Cross-Cultural Comparison:** Comparative studies in different national contexts could reveal how cultural and regulatory variations shape human-AI interaction in construction.
3. **Longitudinal Studies:** Tracking AI adoption and managerial adaptation over time would provide insights into evolving practices and the long-term impacts on project outcomes and organizational structures.
4. **Exploring New AI Applications:** As new AI tools (e.g., adaptive learning systems, advanced robotics) emerge, research should continue to explore how they reshape managerial roles and decision-making processes.

In conclusion, this study reveals that integrating AI into China's construction industry involves a complex adaptive process led by managers. They actively balance AI's "optimal" suggestions against a web of practical constraints and contextual factors to arrive at "appropriate" solutions. This deepens our understanding of human-AI interaction in demanding operational settings and underscores the enduring value of human judgment in the age of artificial intelligence. The theoretical and practical implications highlighted here provide a foundation for improving AI design, managerial practices, and policy formulation in construction and potentially analogous sectors.

Conclusion

Summary of Key Insights

This study investigated the critical yet underexplored process by which managers in China's construction industry interpret and balance the "optimal" solutions generated by AI with the "appropriate" actions required by practical realities. The research revealed that this is not a passive acceptance of technology but an active, dynamic negotiation. Managers engage in significant "human adjustment", leveraging their experience and contextual understanding to adapt AI recommendations. This process is heavily influenced by persistent data and technology challenges, the necessary cultivation of trust in human-AI collaboration, potent external constraints including regulatory and client pressures, and variations specific to different construction sectors. Ultimately, human judgment remains central in transforming AI's potential into effective, actionable outcomes within the complex operational landscape of construction. A key revelation is the proactive role of managers as "adaptive integrators", actively reshaping AI outputs rather than passively overseeing them, highlighting the primacy of human agency in successful technology integration.

Theoretical Contributions

Theoretically, this study contributes to a more nuanced understanding of human-AI interaction in operational settings. It challenges purely techno-centric views of "optimality" by demonstrating its practical contingency on contextual "appropriateness". By highlighting the manager's role as an "adaptive integrator", the research suggests refinements to existing technology adoption and interaction models, proposing an expanded framework that explicitly accounts for contextual modulators and the managerial interpretation engine in mediating AI use. Crucially, it identifies and emphasizes the manager's role as an "adaptive integrator", offering a more dynamic perspective than traditional supervisor/collaborator models in human-AI interaction literature.

Practical Implications

Practically, the findings offer guidance for managers (emphasizing critical evaluation skills), AI developers (prioritizing transparency and adaptability), organizations (investing in data infrastructure and collaborative culture), and policymakers (developing supportive yet realistic regulatory frameworks). These insights aim to foster more effective and synergistic human-AI collaboration within the construction industry and potentially analogous fields.

Limitations and Future Research Directions

Acknowledging the study's qualitative nature and specific contextual focus, avenues for future research include quantitative validation across broader samples, cross-cultural comparative studies, longitudinal analyses of AI adoption trajectories, and investigation into the impact of emerging AI technologies on managerial practices.

Final Remarks

This research illuminates the vital synergy required between AI's analytical power and human judgment in complex, high-stakes environments like construction. By detailing how managers in China navigate the optimal-appropriate tension, the study underscores that the successful integration of advanced digital tools hinges critically on recognizing and leveraging human expertise. As AI continues its rapid evolution, fostering this human-AI partnership—grounded in transparency, trust, and adaptability—will be paramount for realizing technological potential while ensuring practical efficacy and responsible innovation in the built environment and beyond. The path forward lies not in replacing human insight, but in augmenting it intelligently.

Conflict of Interest

The authors declare no conflict of interest.

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Appendix A: Detailed Data Analysis Procedures

1. Data Preparation

A. Organizing and Archiving: Digitization and Desensitization: All interview recordings and transcripts have been digitized. Sensitive information such as specific project names, financial figures, and personal identifiers has been anonymized to comply with research ethics and confidentiality requirements; Software Readiness: Files are stored in a format compatible with qualitative analysis tools like NVivo or Atlas.ti for subsequent coding and thematic analysis.
B. Ensuring Completeness Verification: Each transcript has been cross-checked for accuracy, including interview date, time, location, and anonymized interviewee details. Background information (e.g., project types, organizational roles) is documented to ensure traceability.

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C. Data Security: A secure storage scheme using encrypted cloud servers has been established, adhering to ethical standards and confidentiality protocols outlined in the informed consent agreements signed by interviewees.

2. Familiarization

A. Initial Observations: Recurring Keywords: “Optimal vs. appropriate solutions”, “data quality”, “human-machine collaboration”, “policy constraints”, “cost control”, “ethical considerations”.
B. Phenomena: Frequent adjustments of AI-generated “optimal” solutions to “appropriate” ones due to real-world constraints; challenges in data integration across platforms; emphasis on human oversight in decision-making.

3. Initial Coding (Open Coding)

Linear coding: For each interview, identify and mark key concepts and phenomena line by line. Table 1 shows the initial codes generated:

Table 1 Initial Coding Codes from Interview Analysis

Category	Codes
AI Recommendations and Adjustments	"AI optimal solution", "appropriate solution adjustment", "continuous operation vs. single shift", "model output vs. site conditions", "human intervention", "human-machine responsibility"
Data Issues	"insufficient data quality", "data integration difficulties", "BIM model conversion losses", "lag in real-time data updates", "data desensitization", "multi-source data integration"
Technology and Implementation	"predictive analytics", "multimodal AI", "laser radar scanning", "UWB positioning", "intelligent scheduling", "algorithm ethics", "four-dimensional validation"
Management and Decision-Making	"policy compliance review", "economic and social risks", "human experience and judgment", "approval processes", "cost-benefit trade-off"
Enterprise and Industry Characteristics	"state-owned vs. private enterprise differences", "consultancy strategies", "cross-border regulation", "industry innovation and risks"
Background Condition Codes	"prefabricated residential project", "labor shortage", "environmental pressure", "political mandate"
Technical Practice Codes	"component hoisting path optimization", "concrete curing decisions", "GPS to UWB technology transition"
Decision Trade-Off Codes	"conflict between optimal and appropriate solutions", "policy, economic, social considerations"

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4. Axial Coding

Group similar codes: Aggregate preliminary codes into higher-level categories to provide a structured framework for analysis. The categories include Table 2:

Table 2 Axial Coding Categories and Codes

Axial Coding Category	Codes / Themes
Decision Balance & Human Adjustment	"optimal solution", "appropriate solution", "human adjustment", "four-dimensional validation", "policy-economic trade-off"
Data & Technology Challenges	"data quality", "multi-platform data integration", "real-time issues", "technology implementation barriers", "model limitations"
Human-AI Collaboration and Trust	"human-machine interaction", "experience supplementing AI", "technology reliance vs. human wisdom", "training and cultural acceptance"
External Constraints & Contextual Factors	"regulatory requirements", "policy compliance", "environmental conditions", "social factors", "market demand"
Sector-Specific Dynamics	"state-owned vs. private enterprise differences", "consultancy strategies", "cross-border regulation challenges", "industry innovation and risks"

5. Constant Comparison Method

1. **Similar Scenarios**: Across interviews, AI’s “continuous operation” suggestions are adjusted for feasibility, showing a shared need for practical adaptation.
2. **Data and Tech Limitations**: SOEs and private firms both note data scarcity, but private firms use riskier acquisition methods.
3. **Differences by Context**: SOEs face stricter policy constraints, while private firms prioritize cost and brand, and consultancies navigate ethical data use.