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AI-Driven Compensation Transparency and Human Capital Accounting Disclosure: A Framework for Manufacturing Organizations in Emerging Economies

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ABSTRACT

Purpose: This study investigated the relationship between AI integration in compensation systems and the quality of human capital accounting disclosure (HCAD) among manufacturing organizations in Thailand's Eastern Economic Corridor (EEC), and developed and validated an integrated framework that links AI-driven compensation analytics to human capital disclosure practices.

Design/Methodology/Approach: A cross-sectional, exploratory sequential explanatory mixed-methods design was employed, combining quantitative survey data from 400 manufacturing organizations across Chonburi, Rayong, and Chachoengsao with qualitative thematic analysis of three open-ended questions embedded in the same survey instrument. Quantitative analysis used correlation analysis, Cronbach's alpha reliability testing, and subgroup moderation testing through Fisher's z-test. Qualitative analysis followed Braun and Clarke's (2021) six-phase thematic method, with quantitative and qualitative findings integrated through a joint display (Fetters et al., 2013). Confirmatory factor analysis, bootstrapped mediation testing, and inferential moderated regression are committed to the next research phase.

Findings: AI integration in compensation systems demonstrated moderate-to-high levels ($M = 4.73$), while human capital disclosure quality remained persistently low ($M = 2.98$), producing a data-to-disclosure gap of 1.75 points. The direct relationship between AI integration and HCAD quality was not supported (H1: $r = -0.075$, $p = .132$), nor was mediation by integration protocols (H2) or moderation by organizational size (H4). Pay transparency was confirmed as a significant positive moderator (H3: $z = 2.25$, $p = .024$), demonstrating that organizational transparency culture — rather than technological capability alone — conditions disclosure outcomes. Qualitative themes (organizational readiness, governance, ethical legitimacy) provided convergent evidence from an independent methodological lens. A tiered AI–Human Capital Accounting Disclosure (AI-HCAD) implementation framework was developed and validated across organizational segments. Barrier–enabler analysis revealed that technical constraints ($M = 3.67$) and weak external support structures ($M = 2.45$) sustain the gap between AI capability and disclosure practice.

Practical Implications: Manufacturing organizations must invest simultaneously in AI infrastructure and in an internal transparency culture to translate data capabilities into stakeholder-accessible disclosures. Policymakers and industry bodies should strengthen external enablers through regulatory guidance and technical assistance frameworks.

Originality/Value: This study provides the first empirically grounded framework that integrates AI-driven compensation systems with human capital accounting disclosure in emerging-economy manufacturing. The findings reframe AI integration as a necessary but not sufficient condition for disclosure quality — institutional readiness, embodied in pay transparency, is the enabling mechanism that translates technological capability into stakeholder-accessible reporting. By demonstrating that institutional readiness, not technological capacity, conditions disclosure outcomes, the study advances theory across AI transparency, human capital accounting, and organizational disclosure behavior.

Keywords: Human capital accounting, AI compensation systems, pay transparency, financial disclosure, manufacturing organizations, emerging economies, Thailand EEC, workforce analytics

INTRODUCTION

Background and Rationale

Three developments are transforming how organizations manage, value, and report human capital, yet have evolved along separate trajectories: the rapid integration of artificial intelligence (AI) into compensation and payroll systems, the global expansion of pay-transparency legislation, and heightened expectations for human capital disclosure.

AI and machine learning are fundamentally transforming payroll management, enabling automated processing, compliance monitoring, anomaly detection, workforce analytics, and predictive decision-making (Meenugu, 2025c), allowing HR professionals to shift from routine administrative processing to strategic workforce planning (Patel, 2025). Predictive analytics now enables pay equity monitoring and forward-looking workforce planning beyond traditional payroll systems (Arulappan, 2025).

Concurrent with these technological advances, pay transparency regulations are rapidly expanding across jurisdictions, driven by a growing commitment to addressing workplace compensation inequities. Both the United States and European Union are implementing comprehensive pay transparency measures (Avdul et al., 2023; Lahuerta et al., 2024). The European Union's Pay Transparency Directive (Directive 2023/970), requiring full implementation by June 2026, establishes harmonized disclosure requirements across member states, aiming to strengthen the principle of equal pay through transparency and enforcement mechanisms (Križan, 2025). In the United States, states such as California, Colorado, Washington, and New York have enacted legislation requiring salary-range disclosure in job postings, reflecting a broader national movement toward pay openness (Cullen, 2023). These developments reflect a strategic approach to reducing compensation disparities, with researchers noting that pay transparency can help close pay gaps, reduce employee turnover, and elevate trust in organizations (Avdul et al., 2023).

Despite regulatory momentum, the SEC's 2020 principles-based mandate for human capital reporting has produced inconsistent results. Corporate disclosures have varied widely in length, tone, and numerical content, with language becoming increasingly generic over time (Demers et al., 2022). Quantitative metrics increased following the regulation but were primarily limited to diversity and turnover information (Bourveau et al., 2025), and disparities in disclosure attributes persist across companies (Pandit, 2023). While disclosure length increased, informativeness remained limited, suggesting the regulatory approach has not yet achieved its intended transparency goals (Batish et al., 2021).

These challenges are particularly acute in emerging economies. Manufacturing organizations in Thailand and similar economies face significant challenges in human capital reporting and transparency within global value chains. While technology adoption is widespread, persistent limitations exist in logistics automation, and funding for advanced equipment (Voraseyanont & Amali, 2020), and business pressures alone do not enhance technological readiness without intermediary support (Vong et al., 2025). These technological gaps compound reporting difficulties: human capital disclosure remains underdeveloped in emerging market firms, with few companies reporting comprehensive workforce metrics (Natsagdorj et al., 2025). Although sustainable HR practice frameworks have been identified as potential paths to improved transparency (Napathorn, 2025), the evidence collectively points to a critical need for standardized reporting mechanisms and regulatory support.

Despite their interdependence, technological innovation, pay transparency regulation, and human capital disclosure have mainly evolved in isolation. Technology vendors emphasize automation and compliance; regulators focus on transparency and equity; accounting standard-setters prioritize investor information needs. This fragmentation carries significant consequences: technological and regulatory divergence in accounting information systems leads to inefficiencies in allocation, operations, and error detection (Vasarhelyi, 2012). The absence of an integrated framework not only perpetuates inconsistent reporting but also represents missed opportunities to examine the conditions under which AI-generated data may contribute to enhanced transparency and disclosure. Addressing this gap requires cross-domain collaboration; developing a comprehensive mapping of human capital components could provide the foundation for such an integrated framework (Saba et al., 2024).

Statement of the Problem

This study addresses the lack of an integrated framework connecting AI-driven compensation systems with human capital accounting disclosure requirements. Four interrelated problems emerge within this gap.

1. A data-to-disclosure disconnect. AI payroll systems generate detailed workforce data — such as pay structures, compensation trends, compliance indicators, and anomaly detections — yet firms lack guidance on translating these analytics into standardized external disclosures. Current accounting standards do not specify how AI-enabled insights can be incorporated into financial reporting (Demers et al., 2022). Importantly, this disconnect may persist even when AI capability is fully present, because translation from data to disclosure also depends on organizational conditions — particularly internal transparency culture — that determine whether technological outputs are converted into stakeholder-accessible information. The data-to-disclosure relationship is therefore likely conditional rather than direct, motivating the study's examination of moderating factors alongside the direct technological effect.

2. Fragmented and inconsistent compliance. Pay transparency regulations create significant compliance challenges due to substantial cross-jurisdictional variations and industry-specific complexities. Approximately 71% of OECD countries have enacted pay transparency policies, each with distinct requirements and enforcement mechanisms (Cullen, 2023). Transparency requirements differ dramatically between industries (Kirby, 2023), and multi-jurisdictional environments compound compliance difficulties for organizations operating across borders (Olajide et al., 2024). The lack of regulatory harmonization leads to duplicated effort and inconsistencies in reporting across jurisdictions (Challapalli, 2023), undermining the core objectives of pay transparency and exposing organizations to compliance risk.

3. Outdated theoretical frameworks. Traditional human resource accounting models are increasingly inadequate for capturing the potential of contemporary AI-enabled analytics and real-time workforce data. Predictive analytics has become crucial for understanding human capital investments, with businesses leveraging business intelligence to transform workforce management (Fitz-enz, 2010). This shift extends beyond traditional metrics like headcount; companies now use analytics to predict future talent needs and optimize workforce planning (Worth, 2011), supported by analytic infrastructures that enable improved workforce insight (Sumtotal Systems, 2009). The transformative potential of these data-driven methods underscores the limitations of pre-AI accounting frameworks.

4. Contextual complexity in emerging economies. Manufacturing firms in emerging economies face significant challenges integrating AI compensation systems while meeting multinational transparency expectations, with institutional complexity and uneven digital capabilities creating substantial barriers. AI adoption in these contexts is hindered by infrastructural deficiencies and skill shortages, limiting the foundation for advanced compensation systems (Borines et al., 2024). Even among multinational firms that have progressed further, a substantial compliance gap persists: while 65% have implemented AI governance frameworks, only 30% fully comply with international standards (Nakajima, 2024). Cultural factors add further complexity, as compensation practices in emerging markets are often relation-based rather than market-based, complicating efforts to implement transparent AI-driven systems (Luo, 2013). Addressing these challenges requires HR to play a critical role in fostering employee trust by protecting privacy and ensuring the ethical use of AI algorithms (Nyberg et al., 2023).

Research Objectives

This research pursues five interrelated objectives, contributing theoretical understanding and practical guidance for organizations, regulators, and researchers.

The first objective is to examine the current state of AI integration in compensation systems among manufacturing organizations in emerging economies, documenting the types of AI technologies deployed, the scope of their application across compensation functions, and the data outputs generated. Understanding the technological baseline is essential for assessing the feasibility of enhanced disclosure practices and identifying gaps between available capabilities and current utilization.

The second objective is to identify gaps between AI-generated compensation data and existing human capital disclosure requirements, mapping the information produced by AI compensation systems against regulatory requirements, voluntary disclosure frameworks, and stakeholder information needs. The analysis will reveal where current systems generate potentially useful data that goes unreported, and where disclosure requirements exceed current data-generation capabilities.

The third objective is to develop an integrated framework specifying the conditions under which AI compensation analytics can contribute to human capital accounting disclosures. The framework will specify the components necessary for effective integration — data generation protocols, validation processes, reporting formats, and governance mechanisms — grounded in established theoretical perspectives while remaining practically implementable across organizations with varying technological sophistication.

The fourth objective is to propose standardized disclosure practices suitable for manufacturing contexts with varying levels of technological maturity. Because organizations differ in their AI adoption and analytical capabilities, the research develops tiered recommendations enabling progressive improvement in disclosure quality as organizations advance their technological infrastructure.

The fifth objective is to validate the framework through empirical testing in Thailand's Eastern Economic Corridor manufacturing sector, assessing applicability across manufacturing subsectors, organization sizes, and ownership structures represented in the EEC, and identifying refinements needed for broader application.

Research Questions

The study addresses four research questions:

RQ1: How do manufacturing organizations in emerging economies utilize AI-driven compensation systems, and what data outputs do these systems generate?

This question establishes the technological foundation on which enhanced disclosure must be built — both adoption patterns and the analytics outputs produced.

RQ2: What gaps exist between AI-generated compensation data and current human capital disclosure practices?

This question examines the disconnect between data availability and reporting, identifying why valuable information remains undisclosed and the barriers that prevent organizations from leveraging AI capabilities to achieve transparency.

RQ3: What framework elements and organizational conditions are needed to integrate AI compensation analytics with human capital accounting disclosure?

This question drives the theoretical contribution by requiring the synthesis of technological, regulatory, and accounting perspectives into a coherent integration model.

RQ4: How can standardized disclosure practices be adapted for organizations with varying technological maturity?

This question addresses practical implementation; one-size-fits-all approaches are unlikely to succeed given the diversity of capabilities across emerging-economy manufacturing.

Scope and Delimitations

This research focuses specifically on manufacturing organizations operating within Thailand's Eastern Economic Corridor, encompassing the provinces of Chonburi, Rayong, and Chachoengsao. The geographic focus provides a coherent regulatory and economic context while capturing diversity across manufacturing subsectors, including automotive, electronics, petrochemicals, and food processing. Organizations with fifty or more employees are included to ensure sufficient scale for meaningful AI implementation and disclosure requirements.

The research addresses compensation-related human capital disclosure rather than the full scope of human capital management. While human capital encompasses recruitment, training, development, engagement, and retention, the study concentrates on compensation transparency and its accounting implications. This focus aligns with regulatory momentum on pay transparency and enables deeper analysis within a defined domain.

Several delimitations bound the research scope. First, the study examines disclosure to external stakeholders through financial reporting mechanisms rather than internal management accounting applications. Second, the research addresses formal employment relationships and does not extend to gig workers or informal labor arrangements. Third, the framework development prioritizes voluntary disclosure enhancement within existing accounting standards rather than proposing fundamental changes to standard-setting processes. Fourth, the study employs a cross-sectional, single-source survey design, in which data are collected from organizational respondents at a single point in time. This design is appropriate for examining associations among AI integration, pay transparency, and disclosure quality, but does not support causal inference. Longitudinal designs and content analysis of objective disclosure outputs are recommended for subsequent research (Sections 3.2, 5.10.1).

Significance of the Study

This research holds significance for academic understanding and professional practice across multiple stakeholder groups.

From an academic research perspective, this study represents the first integrated treatment of AI-powered compensation systems, compensation transparency requirements, and human capital accounting disclosures. It contributes to AI-disclosure theory by demonstrating that AI integration is a necessary but not sufficient condition for high-quality human capital disclosure, with pay transparency as the enabling institutional mechanism. By linking previously fragmented literature streams, the research opens new opportunities for theoretical development and empirical validation, and the validated measurement instruments may serve as methodological tools for future research across contexts.

For manufacturing organizations, this research provides practical guidance on leveraging AI capabilities to enhance disclosure quality while addressing regulatory compliance. A tiered implementation model accommodating varying levels of digital readiness facilitates continuous improvement rather than requiring immediate, comprehensive adoption. Grounded in the EEC manufacturing context, the framework is relevant to organizations facing similar challenges in other emerging economies.

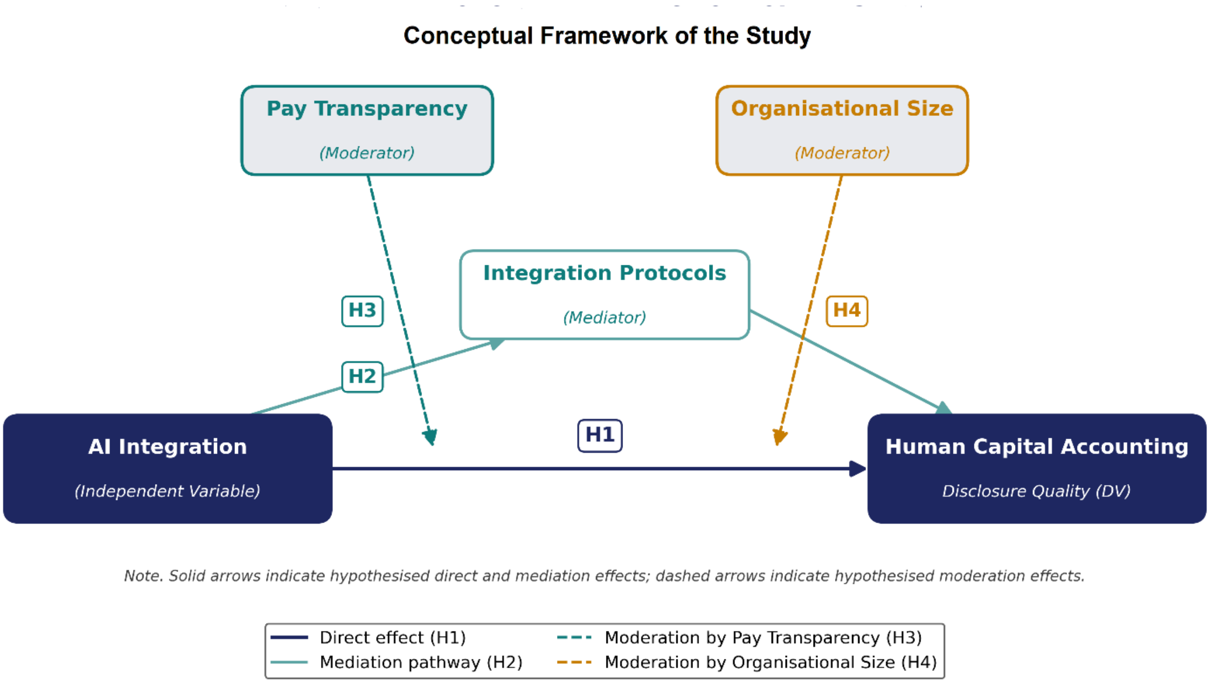
For regulatory bodies and standard-setters, the study provides evidence on current organizational capabilities and practices to inform policy development. Understanding the data AI systems can generate — and the obstacles to disclosing it — supports the design of realistic and effective regulation. Findings on varying technological readiness may inform consideration of phased implementation or tiered compliance requirements.

For investors and other stakeholders, improved human capital disclosure could enhance the decision-making information environment. Research consistently shows that turnover rates, workforce stability measures, and compensation structures correlate with financial performance, and more accessible disclosure could support more efficient resource allocation and stakeholder engagement.

Hypotheses and Conceptual Framework

Four hypotheses translate the research problem into empirically examinable relationships, grounded in the literature reviewed in Section 2 and operationalized in Section 3.

Figure 1. Conceptual Framework of the Study



The first hypothesis examines the direct relationship between AI integration and the quality of human capital accounting disclosures. Drawing on the technological-translation perspective, which posits that advanced AI capabilities should enable richer and more standardized disclosures, the study tests whether this direct effect holds in the emerging-economy manufacturing context.

H1: AI integration in compensation systems is positively associated with human capital accounting disclosure quality.

The second hypothesis examines whether the relationship between AI integration and disclosure quality operates through integration protocols—the formalized data-management and reporting procedures that link AI-generated outputs to external disclosure processes. This mediation pathway represents the operational mechanism through which technological capability is conventionally expected to translate into disclosure outcomes.

H2: Integration protocols mediate the relationship between AI integration and the quality of human capital accounting disclosures.

The third hypothesis introduces the central conditional argument of the study. Drawing on institutional theory and the pay transparency literature, the study tests whether the AI–disclosure relationship depends on the level of organizational pay transparency. This hypothesis reflects the theoretical proposition that AI integration is a necessary but not sufficient condition for disclosure quality, requiring an enabling institutional environment to translate technological capability into disclosure outcomes.

H3: Pay transparency moderates the relationship between AI integration and human capital accounting disclosure quality, such that the relationship is stronger in organizations with higher levels of pay transparency.

The fourth hypothesis examines whether organizational size moderates the AI–disclosure relationship, recognizing that larger organizations may possess greater resources, formalization, and reporting infrastructure to translate AI capabilities into disclosure outcomes.

H4: Organizational size moderates the relationship between AI integration and human capital accounting disclosure quality, with the relationship stronger in larger organizations.

Together, these four hypotheses constitute the conceptual framework: AI integration as the central independent variable, human capital accounting disclosure quality as the dependent variable, integration protocols as a mediator, and pay transparency and organizational size as moderators. The framework deliberately tests both direct and conditional pathways, allowing the study to determine whether AI capability alone explains disclosure outcomes or whether organizational and institutional conditions are required to activate that capability.

Definition of Key Terms

AI-Driven Compensation Systems.

AI-driven compensation systems are advanced payroll technologies that apply artificial intelligence to compensation management through intelligent automation and strategic decision support. These systems utilize machine learning algorithms, natural language processing, and predictive analytics to automate complex compensation processes (Meenugu, 2025c). They extend beyond basic calculation to provide sophisticated capabilities, including automated and augmented compensation tasks and strategic decision support (Marler, 2024).

Human Capital Accounting Disclosure.

Human capital accounting disclosure is a comprehensive reporting practice that provides external stakeholders with detailed insights into an organization's workforce through financial statements and annual reports. Disclosures include metrics on employee skills, training, development, workplace safety, and diversity. While such disclosure remains mainly voluntary, it provides valuable information about organizational human capital investments and potential value creation (Bourveau et al., 2025).

Pay Transparency.

Pay transparency is a multidimensional organizational practice involving the disclosure of compensation information across three key dimensions: pay-outcome transparency, pay-process transparency, and pay-communication transparency (Bamberger, 2021). This area is rapidly evolving, with governments and employees increasingly demanding greater compensation transparency, particularly among younger workforce generations (Avdul et al., 2023).

Manufacturing Organizations.

Manufacturing organizations are enterprises engaged in the physical or chemical transformation of materials into new products, specifically classified under the manufacturing division and registered under Thailand's Factory Act. This definition aligns with the core concept of manufacturing as the physical transformation of goods (Waldman et al., 2025). Within the Thai context, manufacturing organizations typically operate for 10–15 years, are predominantly Thai-owned, and rely on financial institutions for funding (Sawangrat, 2024).

Emerging Economies.

Emerging economies are developing market economies characterized by rapid economic transformation, ongoing institutional reforms, and increasing global economic integration. These markets are defined as economies with low- to middle-income per capita, representing approximately 80% of the global population but only 20% of the world's economies (Athukorala et al., 2007). Key features include economic liberalization, market-oriented policy transformations, and aspirations to increase global economic contributions (Marinov, 2017). Thailand exemplifies this classification, having achieved emerging-market status through prudent fiscal and monetary policies (Karim & Rahman, 2023).

Eastern Economic Corridor (EEC).

The Eastern Economic Corridor is Thailand's strategically designed special economic zone spanning Chonburi, Rayong, and Chachoengsao provinces, designed to drive the country's economic transformation. Announced in 2016, the initiative forms a central component of Thailand's "Thailand 4.0" economic policy, targeting advanced manufacturing and innovation-driven industries (Lewlomphaisarl et al., 2023; Tontisirin & Anantsuksomsri, 2021). The EEC aims to help Thailand escape the "middle-income trap" by providing investment incentives and developing critical infrastructure (Thongsawang, 2024; Tontisirin & Anantsuksomsri, 2021). As a centrally driven development strategy, the project focuses on transforming the eastern seaboard into a high-productivity economic zone, with emphasis on sectors such as automation, robotics, and digital technologies (Kamnuansilpa et al., 2023).

REVIEW OF RELATED LITERATURE

Introduction

The literature review covers three interconnected domains: the integration of artificial intelligence into compensation and payroll systems, pay transparency legislation and organizational practices, and human capital accounting and disclosure frameworks. The review establishes the current state of knowledge in each domain. It identifies the gaps at their intersection that this study addresses and concludes with the conceptual framework that guides the empirical investigation.

Artificial Intelligence Integration in Compensation Systems

Evolution of AI in Payroll and Compensation Management

Payroll and compensation management have evolved progressively from manual calculations to intelligent, integrated systems. The 1970s–1980s marked the initial phase of computerization, when electronic processing replaced manual calculation, reducing errors and processing time (Meenugu, 2025a). The 1990s saw the emergence of Enterprise Resource Planning (ERP) systems, which integrated payroll with broader HR and financial modules and enabled centralized data management (Pokala, 2025). This evolution reflects a systematic shift from transactional processing to strategic, technology-driven workforce management (Meenugu, 2025b).

Contemporary developments represent a fundamental shift from automation to intelligence. Modern AI-enabled payroll systems apply machine-learning techniques to identify patterns in historical workforce data, generate forecasts, and support compensation decision-making (Meenugu, 2025c). Advances in cloud computing and the digitization of big data have created competitive opportunities in compensation management (Marler, 2024), with AI now delivering strategic value through predictive workforce planning, pay equity monitoring, and compensation benchmarking at scale (Arulappan, 2025).

AI is rapidly transforming compensation management, with significant adoption already underway and academic scholarship still emerging. AI integration in compensation management is transitioning from a differentiating capability to an operational requirement (Chowdhury et al., 2024). However, academic literature remains limited, with most studies focusing on technical capabilities rather than organizational implementation (Parasa, 2024). Key challenges include determining how to automate compensation tasks, improve fairness, explain AI-recommended changes, and strategically leverage AI solutions (Marler, 2024). The adoption trajectory is promising, but the literature calls for more comprehensive studies of practical implementation and human-capital implications.

Capabilities of Contemporary AI Compensation Systems

Contemporary AI-enabled compensation systems apply machine learning algorithms to improve processing accuracy and efficiency, transforming how organizations manage payroll processes (Meenugu, 2025c). Organizations leveraging these capabilities have experienced significant improvements in processing accuracy, with AI handling complex scenarios such as shift differentials and leave management (Sirangula, 2025). AI-driven solutions can reduce processing times by 47.2% and increase budgetary allocation accuracy by 31.4% (Devaraju, 2024). The research consistently highlights AI's potential to execute complex payroll calculations with high precision, integrating multiple variables including overtime rules, incentive payments, and tax withholdings.

A second core capability domain concerns regulatory compliance. AI-driven compliance engines transform regulatory monitoring from reactive to proactive, intelligent workflows. AI systems leverage machine learning and natural language processing to automate regulatory monitoring with real-time data streams and semantic analysis (Essien et al., 2025), and these capabilities extend across complex international financial ecosystems (Eyinade et al., 2025). One compliance framework reduced manual audit effort by 74% and detected 98% of policy violations preemptively (Sardana et al., 2024). Researchers caution about ongoing challenges in data integration, cybersecurity, and ethical AI governance.

Predictive analytics is transforming workforce management by enabling AI-powered forecasting of payroll expenditures, turnover, and compensation risks. Organizations leverage integrated data ecosystems and machine learning to anticipate workforce needs and optimize human capital investments (Pathoori, 2025; Verma, 2025), enabling improved workforce planning, talent management, and data-driven decisions (John & Hajam, 2024). The literature consistently highlights the potential of predictive analytics to revolutionize HR management through more precise forecasting and strategic insight (Nwaimo et al., 2024).

AI-powered machine learning algorithms are increasingly effective at detecting financial fraud through continuous monitoring of transaction streams and anomaly identification. These systems detect duplicate payments, unauthorized rate changes, and fictitious employee entries (Antwi et al., 2024; Veldurthi, 2025), and by processing entire datasets, they identify subtle patterns that traditional methods miss (Kantheti & Bvuma, 2024). AI systems generate audit trails, exception logs, and risk-scoring reports that enhance governance oversight. Despite these monitoring capabilities, such analytics rarely appear in external human-capital reporting, indicating a significant gap between technological capability and public disclosure.

Data Outputs and Analytical Potential

AI-enabled compensation platforms possess advanced analytical capabilities that significantly exceed traditional payroll systems, yet organizations are not fully leveraging these technological insights for external reporting. Cloud computing and digitized big data create substantial competitive opportunities in compensation management (Marler, 2024), and over 80% of corporate value now comprises intangibles, with machine learning enabling more sophisticated analysis of human capabilities (Zhu et al., 2024). Despite these advances, a significant reporting gap persists: most human capital disclosures lack meaningful quantitative metrics even with new SEC requirements in place (Batish et al., 2021), and quantitative measures are missing for 60–90% of social metrics across leading ESG rating providers (Atz & Whelan, 2023).

Advanced AI compensation platforms integrate multidimensional data analytics into comprehensive human-capital dashboards, leveraging predictive analytics to provide real-time insights into labor costs, productivity, and workforce dynamics (Arulappan, 2025). Key capabilities include automated compliance, performance trend identification, and support for strategic decision-making (Marler, 2024). Critical challenges persist in standardizing these analytics into recognized financial reporting formats (Pasigai et al., 2025), alongside data integration complexity, ethical considerations, and the need for robust governance frameworks.

Implementation Challenges and Limitations

AI offers significant potential to streamline payroll operations, but complete automation remains challenging because contextual human judgment is required for complex compensation scenarios. AI effectively automates standardized payroll activities, but critical tasks still require human oversight (Marler, 2024). Machine learning algorithms handle routine processes effectively, yet nuanced decision-making remains a challenge (Islam, 2024). Tasks involving atypical compliance scenarios, international tax treaty interpretation, and sensitive employee issues specifically require human expertise (Meenugu, 2025c). Beyond these functional limitations, organizations face implementation challenges, including data quality concerns, security considerations, and the need for explainable AI systems. The future of payroll management lies in hybrid systems that combine AI efficiency with human strategic insight.

Data quality constraints significantly limit AI compensation capabilities; successful implementation requires a robust, consistent data infrastructure and multi-year historical records. Data fragmentation drives up AI modeling costs and restricts comprehensive implementation (Wings & Härkönen, 2023). Effective AI-driven HR systems demand consistent data-collection protocols and harmonized HR information systems (Nawaz et al., 2024), and structural barriers emerge when organizations have fragmented systems, inconsistent data-coding practices, or limited archival records (Wings & Härkönen, 2023). These constraints explain why advanced AI implementations are predominantly concentrated among larger enterprises with mature data environments (Tasleem et al., 2025).

AI-driven compensation systems present complex ethical and governance challenges that demand multifaceted regulatory approaches. Four critical challenges have been identified: automating compensation tasks, improving equity, explaining algorithmic recommendations, and strategically implementing AI solutions (Marler, 2024). Of particular concern is how algorithmic biases can emerge from flawed training data, necessitating robust data ethics frameworks (Bahangulu & Owusu-Berko, 2025). To mitigate discriminatory outcomes, organizations must implement bias detection, ensure transparency, and develop explainable AI models (Sridhar, 2025).

Pay Transparency Legislation and Organizational Practices

Global Regulatory Landscape

Transparency has emerged as a critical regulatory strategy across advanced economies to address persistent gender pay inequities and enhance organizational accountability. Pay transparency legislation has been introduced in many OECD countries to reduce pay information asymmetries (Lahuerta et al., 2024), with significant potential: a study of approximately 100,000 US academics found that pay transparency led to substantial increases in pay equity and equality (Obloj & Zenger, 2022). Core obligations typically include publishing salary ranges, providing employee access to pay-structure information, and submitting pay-data reports to regulators. Concerns persist about the disclosure of sensitive data and potential cost burdens, particularly for smaller enterprises (Lahuerta, 2022).

The United States has developed pay transparency regulations primarily through state-level action, producing a fragmented legal landscape. By late 2025, approximately 16 states had enacted salary-range disclosure statutes, beginning with Colorado in 2021 and extending through California, New York, and Washington (2023) to Illinois and Minnesota (2025). State frameworks differ substantially in employer thresholds, definitions of advertisements, disclosure content, and enforcement mechanisms (Lahuerta et al., 2024). Separate state-level anti-pay-secrecy statutes show limited practical effectiveness; nearly half of workers in covered states still encounter workplace pay secrecy rules (Rosenfeld et al., 2023).

By contrast, the EU Pay Transparency Directive (transposition deadline June 2026) imposes harmonized disclosure obligations across member states and empowers workers with enforcement mechanisms (Lahuerta et al., 2024; Križan, 2025; Tsvetkov, 2025). For multinational enterprises, this creates a unified compliance structure that supersedes fragmented national approaches, though implementation imposes substantial administrative and financial adjustments.

Thailand's pay transparency framework remains limited, with only partial legal requirements that create both regulatory challenges and constraints on organizational flexibility. The legal landscape mandates core compensation disclosures in employment contracts and workplace minimum wage displays, but stops short of comprehensive transparency. Employers are not legally required to disclose salary ranges in job advertisements or to submit detailed pay data reports (Zaini et al., 2018). The framework reflects an incremental approach typical of emerging economies, in which pay transparency evolves gradually through selective mandates rather than through a comprehensive overhaul.

Organizational Responses to Transparency Requirements

Organizational responses to pay transparency mandates are complex and strategically diverse, reflecting significant variations in implementation approaches. Pay transparency is not a one-size-fits-all approach but a strategic decision shaped by organizational context, culture, and objectives, with each transparency dimension carrying distinct implications (Bamberger, 2021). Implementation varies based on internal factors such as variable pay systems and external pressures from regulators and stakeholders (Arnold et al., 2023). Many organizations remain in the early stages of implementing pay transparency strategies, with current efforts focused on manager training and employee education (McMullen & Dahle, 2024). While pay transparency can yield benefits such as closing pay gaps and reducing turnover, it can also create confusion and adverse outcomes if poorly implemented (Avdul et al., 2023).

Pay transparency has nuanced, multidimensional effects, with strong evidence of reducing gender pay disparities but mixed implications for broader workplace dynamics. Research in Denmark found a 7% reduction in the gender pay gap relative to the pre-legislation mean, achieved primarily by slowing male wage growth (Bennedsen et al., 2022), and Canadian universities anticipating scrutiny respond more aggressively to improve gender pay equality (Lyons & Zhang, 2023). However, consequences extend beyond pay equity. Pay transparency produces beneficial outcomes, such as enhanced performance and reduced pay discrepancies, alongside problematic effects, such as increased envy and potential pay compression (Bamberger, 2021). While transparency can narrow wage gaps, it may also lead to more aggressive employer bargaining and lower average wages (Cullen, 2023).

Younger generations, particularly Generation Z, are driving significant changes in expectations for pay transparency. Generational differences are increasingly important in compensation management as younger cohorts challenge traditional approaches to salary discussions (Avdul et al., 2023). These employees are more comfortable discussing compensation and demand greater organizational disclosure (Stofberg et al., 2022), creating new pressures for transparency (Malik & Musah, 2024) and prompting organizations to adapt their reward communication strategies (McMullen & Dahle, 2024).

Integration with Financial Reporting

The integration of pay-transparency compliance mechanisms with external financial reporting remains fragmented. Most pay transparency regulations focus narrowly on HR and recruitment, leading organizations to maintain separate reporting mechanisms. Significant challenges persist in integrating alternative reporting approaches, including inconsistent standards and limited technological infrastructure (Dasila, 2025), and the endogenous nature of governance mechanisms related to financial transparency further complicates integration (Armstrong et al., 2016). Current practice allows organizations to disclose salary ranges in job advertisements while providing minimal compensation information in financial statements, potentially confusing stakeholders and reducing reporting efficiency.

Current human capital reporting systems lack a coordinated framework for leveraging compliance-oriented data infrastructure, thereby limiting the comprehensiveness of workforce reporting in financial statements. Research on SEC-mandated human capital disclosures reveals that such disclosures have been extremely limited relative to those of other asset classes, with reporting highly variable across firms and lacking numerical intensity (Demers et al., 2022). Rather than merely complying with reporting requirements, organizations should focus on measuring for the sake of managing to derive strategic value from workforce data (Zyl, 2022). Board size and diversity positively influence human capital disclosure, suggesting potential pathways for more integrated reporting (Raimo et al., 2020). However, the current landscape remains fragmented, with no standardized framework for transforming compliance data into strategic human capital insight within financial reporting.

Human Capital Accounting and Disclosure Frameworks

Historical Development of Human Resource Accounting

Human Resource Accounting (HRA) emerged in the 1960s as an approach challenging traditional accounting's treatment of human resources as period expenses. The concept traces its origins to Rensis Likert, who first used the term "human assets" in the late 1950s, arguing that human resources should be viewed as investments generating future economic value (Gogoi & Marwadikumbhar, 2024). HRA's initial objective was to improve corporate financial reporting by accounting for human assets and increasing the representational validity of financial statements (Flamholtz & Wollman, 1978). Traditional accounting methods fail to capture the economic value of human resources, resulting in significant book–market value discrepancy (Mohiuddin & Banu, 2017). By capitalizing human resource investments, organizations can more accurately reflect the strategic importance of their workforce, transforming human capital from a cost center to a measurable economic asset.

HRA has produced multiple valuation approaches — historical cost, replacement cost, present value, and opportunity cost (Abderraouf, 2020) — but each faces theoretical immaturity, weak integration with corporate culture, and limited talent-construct development (Li, K., 2024). Replacement cost appears most defensible as a surrogate for personnel valuation, though no single method is fully adequate (Carper & Posey, 1976).

Despite decades of development, HRA remains largely theoretical owing to significant implementation barriers. Difficulties arise from valuation uncertainty and the lack of specific accounting standards (Islam et al., 2013); while human resources are critical organizational assets, no legal regulations govern comprehensive human resource accounting (Cherian & Farouq, 2013). Multiple independent studies identify similar barriers, yet research remains predominantly conceptual with limited empirical validation.

Current State of Human Capital Disclosure

The SEC's 2020 principles-based human capital disclosure rules have produced highly variable corporate reporting. In the first year of implementation, disclosures were extremely heterogeneous in length, numerical intensity, and tone (Demers et al., 2022). Disparities in disclosure attributes persist across companies, with a notable lack of quantitative detail (Pandit, 2023). Quantitative metrics in 10-K filings increased from 40% to 73% post-regulation. However, the additions primarily focused on diversity and turnover metrics (Bourveau et al., 2025), and most disclosures remain generic and lack meaningful quantitative information, thereby compromising investor interpretability (Batish et al., 2021).

The SEC's Investor Advisory Committee's 2023 call for standardized human-capital disclosure is supported by empirical evidence linking workforce metrics to corporate performance. Employee turnover is negatively associated with future financial performance, with stronger effects in small and young firms (Li et al., 2021). Substantial reporting gaps persist, with only 20% of social metrics decision-useful and 60–90% of quantitative measures missing across rating providers (Atz & Whelan, 2023). These findings validate the Committee's recommendation for mandatory, structured reporting of workforce composition and turnover metrics to provide investors with more reliable, consistent information about a company's human capital.

International Developments and Frameworks

ISO 30414 represents a milestone in standardizing global human capital reporting, offering a comprehensive voluntary framework across eleven domains. The standard helps reduce information asymmetry between organizations and stakeholders (Choi et al., 2025), and reflects a broader shift toward integrating human capital disclosure with organizational transparency (Luthia et al., 2025). Its voluntary nature allows organizations flexibility while promoting consistency across reporting practices, with practical applications demonstrating use across corporate contexts (Magau, 2024). ISO 30414 thus represents a significant step toward a globally recognized approach to human capital reporting.

The European Union has shifted human capital disclosure from voluntary to mandatory practice. The Non-Financial Reporting Directive (NFRD) initiated mandatory sustainability disclosure (Hummel & Jobst, 2021); the Corporate Sustainability Reporting Directive (CSRD) expanded both the scope and depth (Fornasari & Traversi, 2024). Reporting now covers working conditions, diversity, and workplace practices (Vaio et al., 2020), with measurable improvements in disclosure quality and depth across European companies.

Global policy organizations increasingly recognize human capital as a strategic asset, with frameworks emerging to quantify workforce investment, though significant adoption challenges persist. A strategic shift toward human capital disclosure is underway (Luthia et al., 2025), but widespread implementation remains limited by theoretical immaturity, integration issues, and cautious disclosure practice (Kang, 2024). Framework complexity and limited regulatory endorsement continue to impede comprehensive adoption.

Theoretical Foundations

Institutional Theory

Institutional theory provides a framework for understanding organizational technology adoption through three interconnected pressures driving institutional isomorphism: coercive, mimetic, and normative. All three significantly predict adoption intentions, though their relative influence varies by context (Teo et al., 2003). Mimetic forces are most critical under uncertainty, coercive forces become significant with government incentives, and normative forces continuously shape adoption decisions (Sherer et al., 2016). The strength and impact of these pressures differ across settings: in Brazilian firms, normative pressures were the primary driver, contradicting some prior findings (Santos et al., 2020). Temporal dynamics also matter — mimetic pressures remain significant over time, while coercive pressures tend to be short-term and normative long-term in their effects (Jeyaraj & Zadeh, 2020).

Institutional theory suggests organizational technology adoption, including AI compensation systems, is driven by legitimacy-seeking rather than pure technical optimization. Positive relationships exist between normative and coercive pressures and digital transformation outcomes (López-Morales et al., 2022), and mimetic and normative mechanisms are particularly influential in driving organizational disclosure practices (Wukich et al., 2023). Organizations are embedded in institutional networks where external expectations and peer behaviors play crucial roles.

Institutional forces shape disclosure choices by creating complex pressures that organizations interpret and respond to differently, despite facing comparable environmental conditions. Firms under similar institutional pressures can adopt heterogeneous management practices due to differences in organizational characteristics (Delmas & Toffel, 2010), and national institutional environments create nuanced differences in sustainability disclosure across six Southeast Asian countries (Tran & Beddewela, 2020). Institutional theory thus serves as a nuanced lens for understanding selective interpretation and response, rather than as a deterministic framework.

Stakeholder Theory

Stakeholder theory provides a framework for understanding organizational accountability by emphasizing the diverse information needs of multiple constituencies beyond traditional shareholder interests. The framework complements institutional theory by examining influences on sustainability reporting across organizational levels (Herold, 2018). Stakeholders have high expectations for human capital disclosures, though corporate reporting practices often fall short (Sahari et al., 2018). Human capital disclosure positively impacts organizational performance, indicating that responding to stakeholder information needs creates tangible benefits (Lin et al., 2012). The theory is particularly suitable for organizations in developing countries, as it offers a mechanism for managing diverse stakeholder pressures (Omran & Ramdhony, 2015).

Stakeholders have fundamentally different and potentially conflicting information needs regarding human capital, making comprehensive disclosure simultaneously critical and challenging. Human capital disclosure varies with market demand: firms in competitive environments disclose more information (Haslag et al., 2021). Marked differences exist between internally collected and externally disclosed human capital information, and organizations are concerned about compromising their competitive advantage (Beattie & Smith, 2010). Stakeholders also interpret disclosures differently — equity investors respond positively to human capital information, while bond markets react negatively to specific disclosure categories (Arif et al., 2022). These findings underscore the challenge of developing approaches that satisfy diverse stakeholder needs without excessive reporting burden.

Stakeholder salience theory provides a robust framework for understanding how organizations prioritize stakeholder groups in sustainability reporting and corporate social responsibility disclosure. The theory holds that stakeholders are prioritized according to three key attributes: power, legitimacy, and urgency (Mitchell et al., 1997). Employees, community, and media stakeholders most significantly influence sustainability disclosure decisions (Majdi et al., 2023), and stakeholder legitimacy primarily drives corporate social responsibility disclosure, with power and urgency playing indirect roles (Thijssens et al., 2015). In manufacturing contexts, stakeholder salience varies systematically with ownership structures, customer dependencies, and supply-chain dynamics, indicating that complex stakeholder interactions dynamically shape disclosure strategies.

Resource-Based View

Human capital can be a source of sustained competitive advantage when it meets the strategic criteria of value, rarity, inimitability, and non-substitutability (Barney, 1991). Firm-specific investments in skills, knowledge, and organizational capabilities create unique human capital, generating this advantage (Wright et al., 1994). However, human capital resources are valuable only when directly linked to performance behaviors specific to a firm's strategy (Ployhart, 2021). Investments in firm-specific human capital significantly improve learning and performance, with time-compression diseconomies protecting these resources from imitation (Hatch & Dyer, 2004). The strength of human capital lies not just in its existence but in its strategic deployment and alignment with firm-specific performance outcomes.

The Resource-Based View (RBV) provides theoretical and empirical support for human capital as a strategic asset that can generate competitive advantage through targeted HR practice. Strategic HR configurations enhance organizational performance by creating firm-level employee-based resources (Collins, 2020). HR practices are not simple levers, but complex mechanisms that shape employee mobility and organizational capability (Delery & Roumpi, 2017). Best practices can create value, but their implementation and strategic fit are critical to realizing competitive benefit (Gerhart & Feng, 2021).

Organizations face a strategic tension between transparency demands and the need to protect competitive advantage (Callery, 2020). Detailed disclosure of workforce composition, compensation, and capability development can expose proprietary strategic assets (Grant, 1991), and the inimitability that makes human capital a competitive resource also raises the consequence of disclosure choices, requiring careful calibration of transparency against strategic protection.

Organizational Conditions as Enabling Mechanisms

Beyond institutional, stakeholder, and resource-based perspectives, an emerging literature stream emphasizes that the effectiveness of advanced technologies in producing organizational outcomes depends on internal enabling conditions. Organizational culture, leadership commitment, and information-transparency norms are increasingly recognized as the conditions that translate technological capability into observable performance and reporting outcomes (Pasigai et al., 2025; Sohani et al., 2025). Research on AI adoption demonstrates that technological investment alone rarely produces strategic value; organizational readiness — leadership orientation, employee engagement, and transparency-supportive cultural norms — moderates the realized impact of AI capabilities (Uren & Edwards, 2023). This conditional view aligns with broader theoretical developments that question direct technology-outcome relationships and emphasize the institutional and cultural conditions under which technology becomes effective.

Organizational culture is consistently identified as a critical enabling condition for transparency, ethical reporting, and disclosure-oriented behavior. Cultural orientations supportive of openness, accountability, and information-sharing positively influence disclosure quality across financial and non-financial reporting domains (Hofstede et al., 2010; Naranjo-Valencia et al., 2016). Cultures characterized by high power distance and information asymmetry tend to suppress voluntary disclosure, while those emphasizing transparency and stakeholder dialogue enhance it (Tran & Beddewela, 2020). For AI-driven systems, transparency-supportive cultures determine whether organizations treat AI-generated workforce data as legitimate input for external reporting or as internal management information that should not be disclosed. This cultural distinction carries substantial implications for whether technological investments are translated into stakeholder-accessible disclosures.

Leadership commitment functions as a second enabling mechanism by establishing the priorities, resources, and accountability structures necessary to translate AI capability into disclosure outcomes. Leadership commitment to transparency, ethics, and digital transformation drives sustainable AI integration and strengthens reporting practices (Bahangulu & Owusu-Berko, 2025; Sira, 2025). Leaders who actively endorse transparency shape organizational priorities, allocate resources to disclosure infrastructure, and create the accountability structures necessary for AI-generated data to flow into external reporting (Singh et al., 2025). Without such commitment, AI systems may operate as isolated capabilities generating sophisticated analytics but contributing little to public disclosure. Together, organizational culture and leadership commitment represent the institutional and behavioral conditions determining whether technological investment translates into transparent reporting outcomes — conditions that operate alongside pay transparency and organizational size as moderating mechanisms in the AI–human capital disclosure relationship and warrant systematic empirical examination in this and future studies.

Research Gap Analysis

The literature confirms substantial fragmentation across AI-enabled compensation, regulatory, and accounting domains, with limited cross-disciplinary integration. AI in human resource management suffers from insufficient cross-fertilization across disciplines, leading to a fragmented body of knowledge (Pan & Froese, 2023). AI-based technology research remains limited and fragmented, particularly in understanding how different organizational domains interact (Budhwar et al., 2022). Four key challenges have been identified in using AI for compensation management, while calls for strengthened regulatory frameworks and collaborative effort underscore the need for multidisciplinary integration (Alboré et al., 2025; Marler, 2024). More integrated, multidisciplinary approaches are critically needed to understand technological, regulatory, and accounting developments together.

The first gap: A critical gap exists in linking AI-generated compensation analytics to human capital reporting requirements, underscoring the need for more comprehensive, integrative frameworks. Despite 78% of organizations adopting AI, only 1% achieve mature implementation, with substantial gaps across strategic alignment (80%), technology integration (70.75%), and human capital development (16.67%) (Sira, 2025). Integrated AI frameworks incorporating data forecasting, automation, and organizational performance are essential for addressing these challenges (Lalitha et al., 2025). These sources validate the existence of integration challenges but do not directly address the specific linkage between compensation analytics and human capital reporting, indicating an opportunity for targeted frameworks that bridge these domains.

The second gap: Human capital disclosure research is disproportionately concentrated in developed markets, with significant underrepresentation of perspectives from emerging economies. North American (30%) and European (43%) affiliations account for 73% of author appearances, while Asian affiliations represent only 7.9% (Jain, 2022), and research on voluntary disclosure in emerging countries remains limited (Zaini et al., 2018). This gap is particularly significant given the unique challenges of emerging markets, including skills gaps in advanced manufacturing (Melguizo & Perea, 2016) and the need for context-specific human capital measurement frameworks (Mpofu & Sebele-Mpofu, 2023).

The third gap: Existing AI reporting frameworks presume high organizational data maturity without providing staged guidance for firms at earlier stages of adoption. A persistent disconnect exists between AI service providers' capabilities and end-users' actual needs (Dong et al., 2023), and successful AI adoption requires readiness across people, processes, data, and technology dimensions, not just technological capability (Uren & Edwards, 2023). These findings underscore the need for differentiated, progressive disclosure models accommodating varying organizational AI maturity.

The fourth gap: A methodological gap exists in AI measurement, with existing studies suffering from inconsistent, unvalidated operationalizations that impede comparative research. Researchers are adapting, reusing, or developing measures in an ad hoc manner without systematic validation (Tolsdorf et al., 2025), and traditional measurement methods suffer from bias, subjectivity, and an excessive focus on disclosure quantity rather than quality (Mechta et al., 2025). Promising developments include the Artificial Intelligence Measurement of Disclosure (AIMD), a computerized technique for quantifying disclosure intensity (Grüning, 2011), and a validated AI literacy measurement instrument with five dimensions and 13 items (Pinski & Benlian, 2023). Developing rigorous, standardized measurement frameworks is a crucial next step.

The fifth gap: Existing AI–human capital disclosure research treats the AI–disclosure relationship as a direct, technology-driven effect, with insufficient attention to the organizational and institutional conditions that may moderate it. Studies have predominantly examined whether AI adoption improves reporting quality while neglecting the conditional nature of this effect—specifically, whether technology produces disclosure outcomes only when accompanied by enabling institutional and cultural mechanisms (Naveed et al., 2025; Pasigai et al., 2025). The few studies incorporating organizational moderators tend to focus narrowly on size and resource availability, leaving culture, leadership commitment, pay transparency, and regulatory readiness under-theorized as conditional factors (Raimo et al., 2020; Singh et al., 2025). This concentration on direct effects has produced a fragmented evidence base in which inconsistent findings cannot be reconciled because the conditions under which AI capabilities translate into disclosure outcomes remain unspecified. Bridging this gap requires research designs that explicitly test moderating mechanisms alongside direct effects, treating AI integration as a necessary but not sufficient condition for disclosure quality and identifying the organizational and institutional conditions that activate technological capability into stakeholder-accessible reporting.

Conceptual Framework

The AI–Human Capital Accounting Disclosure (AI-HCAD) Framework integrates AI-generated compensation analytics with human capital disclosure through a multi-theoretical lens drawing on institutional theory, stakeholder theory, and the resource-based view (Singh et al., 2025). These complementary perspectives explain the drivers of adoption, information needs, and strategic considerations in AI–human capital integration (Chowdhury et al., 2024; Sohani et al., 2025).

The Data Generation Layer represents a technological infrastructure that uses AI to transform human capital data into strategic insight. AI and digital tools are reshaping human capital management through advanced analytics (Pasigai et al., 2025), with AI-based models predicting employee performance and workforce contribution (Sawant et al., 2025). The layer's sophistication depends on organizational investment in HRIS infrastructure, data quality, and AI maturity. AI can significantly improve core HR functions, particularly in performance management, recruitment, and workforce optimization (Muridzi et al., 2024). Key outputs include payroll analytics, workforce cost projections, pay equity metrics, compliance monitoring, and fraud-detection signals.

The Integration Layer transforms AI-generated data into structured human capital accounting information through a comprehensive data management approach that includes rigorous validation procedures, standardization protocols, and quality-assurance processes (Zhu et al., 2024). These mechanisms ensure data completeness, accuracy, and comparability across reporting units (Anantharaman et al., 2023). The Integration Layer bridges operational analytics with external reporting requirements, addressing the growing need for transparent and reliable AI-driven financial information (Almaqtari, 2024). By establishing robust translation mechanisms, the layer enables organizations to convert complex AI-generated insight into meaningful human capital accounting constructs.

The Disclosure Layer standardizes human capital reporting across channels and regulatory requirements. It specifies reporting formats aligned with regulatory mandates, stakeholder expectations, and voluntary best-practice frameworks, integrating mandatory requirements with recognized standards to develop comprehensive reporting templates (Choi et al., 2025; Magau, 2024). Reporting encompasses financial statements, annual reports, sustainability reports, and targeted stakeholder communications. Without detailed guidance, current disclosures vary significantly across organizations, indicating ongoing challenges with standardization.

The Governance Layer establishes oversight structures for AI-related disclosure. Ethical oversight in AI decision-making is critical (Ganesh, 2025), and recommended practices include audit trails, bias testing, and a safety culture (Shneiderman, 2020). A multi-layered framework connecting regulatory principles to practical implementation supports this approach (Agarwal & Nene, 2025). Key elements include transparent audit mechanisms, ethical guidelines for AI-driven decisions, data privacy protections, and continuous improvement processes. While these sources provide strong theoretical support, additional empirical research would strengthen the practical implementation of such a comprehensive governance framework.

Together, these four layers form a comprehensive framework for integrating AI compensation analytics into human capital disclosure. Institutional theory explains the coercive, mimetic, and normative pressures driving adoption; stakeholder theory identifies the varying information needs the framework must address; and the resource-based view clarifies why strategic considerations may both motivate and constrain disclosure. The empirical research evaluates the applicability of this framework in emerging-economy manufacturing environments.

The four-layer framework specifies the internal architecture for translating AI-generated compensation analytics into human capital disclosure, but its effective operation depends on cross-cutting organizational and institutional conditions. The Data Generation Layer requires a culture that supports the use of workforce analytics for external reporting; the Integration Layer requires leadership commitment to validation, standardization, and quality-assurance protocols; the Disclosure Layer requires pay transparency norms and regulatory readiness; and the

Governance Layer requires institutional accountability and ethical oversight. These conditions — pay transparency, organizational size, organizational culture, and leadership commitment — operate as moderators across the framework. Figure 1 (Section 1) formalizes this conditional logic; pay transparency and organizational size are empirically tested in this study, while organizational culture and leadership commitment are identified in Section 2.5.4 as future-research conditions.

Hypotheses Development

The hypotheses are grounded in institutional theory, stakeholder theory, the resource-based view, and emerging research on AI-enabled compensation and human capital disclosure. Advanced HR analytics and AI systems enhance data availability, standardization, and reporting capability (Menon et al., 2024; Selvamohana, 2025), enabling more sophisticated HR practice and actionable insights beyond traditional reporting (Huang et al., 2023; Pathoori, 2025), with 60% of surveyed companies planning predictive analytics investment (DiClaudio, 2019).

The hypothesized relationships are summarized in Figure 1 (Section 1).

Hypothesis 1: AI Integration → Disclosure Quality

H1: *Higher levels of AI integration in compensation systems are positively associated with human capital disclosure quality.*

AI integration into compensation processes enhances workforce data quality and reporting accuracy through advanced analytics and automation capabilities. AI adoption in organizational processes leads to greater financial reporting quality, reflected in lower discretionary accruals and more accurate predictions (Anantharaman et al., 2023). Within compensation management specifically, AI enhances efficiency, accuracy, and strategic decision-making by automating complex calculations and identifying patterns in workforce data (Parasa, 2024), and can also transform pay information practices by supporting advanced methodologies and reducing information-sharing barriers (Nyberg et al., 2023). The underlying mechanism is that AI-driven tools generate more precise, timely, and reliable workforce data, providing higher-quality inputs for human capital disclosure. Organizations with more sophisticated AI compensation systems are therefore better positioned to produce comprehensive, accurate, and decision-useful disclosures.

This hypothesis tests the conventional technological-translation argument, in which advanced AI capabilities are expected to generate richer, more reliable workforce data, thereby enhancing disclosure quality. Recent literature suggests this direct relationship may be conditional on organizational and institutional readiness rather than deterministic (Naveed et al., 2025; Uren & Edwards, 2023). Organizations may possess sophisticated AI compensation systems yet fail to translate this capability into improved disclosure if enabling cultural, leadership, and transparency conditions are absent. Testing H1 therefore serves a dual purpose: to evaluate whether the direct technological effect holds in the emerging-economy manufacturing context and to establish the empirical baseline for H2–H4.

Hypothesis 2: Integration Protocols → Disclosure Quality

H2: *Organizations with formal integration protocols between AI compensation systems and disclosure processes demonstrate higher human capital disclosure quality than those without such protocols.*

Integration protocols are conceptually defined here as the formalized organizational mechanisms — encompassing data validation, standardization procedures, quality assurance, and governance structures — that translate AI-generated workforce analytics into reporting-ready outputs for external disclosure. This positions integration protocols as the operational mediator that converts technological capability into structured, comparable, and stakeholder-accessible information.

Empirical evidence supports this mediating role: AI adoption enhances sustainability reporting quality, particularly when accompanied by specialized governance structures (Naveed et al., 2025); machine-learning systems can generate human-capital lexicons but require structured protocols to translate analytical outputs into disclosure formats (Zhu et al., 2024); and AI improves financial reporting quality through automated data capture and pattern extraction (Anantharaman et al., 2023). The construct is operationalized through respondent assessment of the existence, formalization, and consistency of these four mechanisms within the organization's reporting infrastructure.

Hypothesis 3: Moderating Role of Pay Transparency Compliance

H3: *Pay transparency compliance positively moderates the relationship between AI integration and human capital disclosure quality.*

Pay transparency compliance strengthens the relationship between AI integration and human capital disclosure quality by creating regulatory incentives that encourage translation of AI-generated data into external disclosure. Regulatory requirements increase quantitative human capital reporting following the amendment (Bourveau et al., 2025); AI adoption enhances reporting quality, with the effect amplified under regulatory compliance pressure (Naveed et al., 2025); and governance factors significantly influence human capital disclosure practices (Raimo et al., 2020). The moderation operates through compliance requirements that establish data-collection systems and reporting structures, creating pathways for AI-generated compensation data to flow into external disclosures. Without such pressure, organizations may generate sophisticated AI analytics but lack the motivation to translate them into public reporting.

Hypothesis 4: Moderating Role of Organizational Size

H4: *Organizational size positively moderates the relationship between AI integration and the quality of human capital disclosure.*

Organizational size strengthens the AI–disclosure relationship through greater resource availability and institutional capacity. Firm size positively impacts human capital disclosure levels, as larger organizations face greater stakeholder scrutiny and have more resources for comprehensive reporting (Raimo et al., 2020). Medium and large firms demonstrate stronger relationships with AI adoption than small firms, indicating that size moderates technology implementation (Badghish & Soomro, 2024). Size effects on technology adoption also vary by innovation type and adoption stage (Lee & Xia, 2006). Larger organizations possess greater financial resources, specialist personnel, and information-system sophistication that support the translation of AI-generated data into high-quality disclosure.

RESEARCH METHODOLOGY

Introduction

The research methodology used in this study employs a sequential explanatory mixed-methods design, combining quantitative survey research with qualitative investigation to address the research questions and test the hypotheses. This section details the research philosophy and design, population and sampling procedures, instrumentation, data collection methods, analytical techniques, and ethical protocols. Consistent with the delimitation in Section 1.5, the study employs a cross-sectional, single-source design appropriate for examining associations among AI integration, pay transparency, and human capital accounting disclosure quality, but not for causal inference. The procedural and analytical safeguards addressing common method bias and measurement validity are described in Sections 3.6.1, 3.7.1, and 3.8.

Research Philosophy and Approach

This research adopts a pragmatist philosophical position, prioritizing the complexity of the research problem over rigid methodological allegiance and advocating methodological choices that best address the specific research question. Holden and Lynch (2004) argue that methodology should not be predetermined but should emerge from the research phenomenon itself, allowing researchers to match philosophy, methodology, and the research problem flexibly and effectively. This study's research questions require both measuring relationships between constructs—an orientation aligned with positivist assumptions—and exploring contextual factors, implementation processes, and interpretive meanings— an orientation aligned with interpretivist traditions. Pragmatism provides an appropriate philosophical foundation for integrating these complementary perspectives within a mixed-methods design.

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The research employs an abductive reasoning approach, moving iteratively between theory and data. The conceptual framework developed from the literature review provides an initial theoretical structure but remains provisional pending empirical investigation. Findings from quantitative analysis inform qualitative inquiry, and qualitative insight contributes to framework refinement in an iterative process. This abductive approach is appropriate for research developing new frameworks in areas where existing theory provides guidance but does not definitively predict relationships.

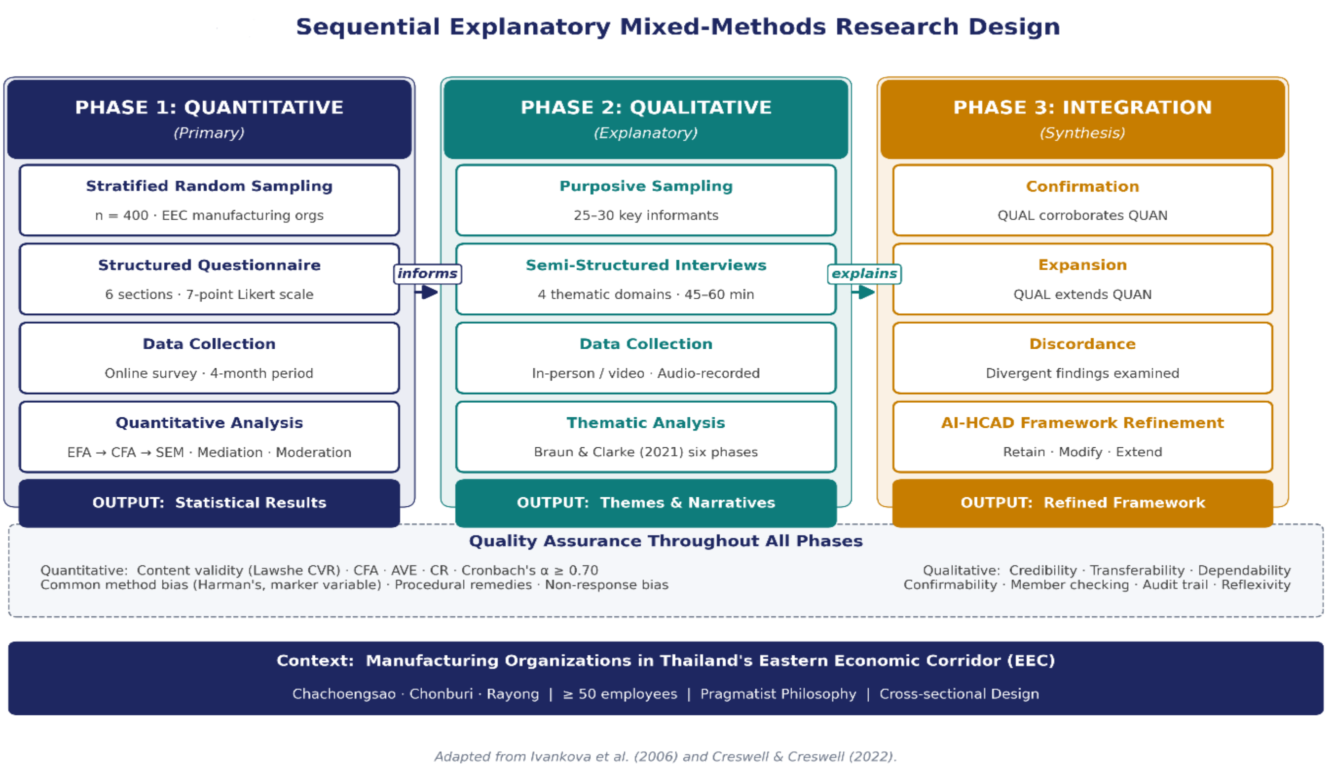
Research Design

The sequential explanatory mixed-methods design systematically integrates quantitative and qualitative phases to provide comprehensive insight into complex research questions. Quantitative data are collected and analyzed first, followed by qualitative data in consecutive phases (Ivankova et al., 2006), with integration occurring at three levels: study design, methods, and interpretation/reporting (Fetters et al., 2013). The design's strength lies in its ability first to test statistical relationships quantitatively and then use qualitative data to explore underlying mechanisms. This approach has been effectively applied across diverse research contexts, including investigations of supply chain collaboration where quantitative findings were complemented by qualitative insight (Acquah et al., 2021).

Cross-sectional designs are valuable for establishing baseline conditions in exploratory research where longitudinal tracking is impractical (Ray, 2020). They cannot capture within-individual change, but they provide a credible snapshot when methodology is transparently reported, and sampling is appropriate (Maier et al., 2023). The design is particularly suited to contexts where spatial variation outweighs temporal change (Markovitz et al., 2012).

The sequential design aligns with the study's research questions. Research Questions 1 and 2, which explore current AI utilization and gaps between AI-generated data and disclosure practices, are addressed primarily through quantitative survey data, supplemented by qualitative inquiry for contextual depth. Research Questions 3 and 4, which focus on framework components and adapting disclosure practices across maturity levels, rely more heavily on qualitative insight while remaining informed by quantitative patterns. This alignment ensures that each methodological phase contributes appropriately to the study's objectives.

Figure 2. Sequential Explanatory Mixed-Methods Research Design



Population and Sampling

Target Population

The target population comprises manufacturing organizations with 50 or more employees operating within Thailand's Eastern Economic Corridor (Section 1.5). Major subsectors — automotive, electronics, petrochemicals, food processing, and advanced manufacturing — align with national priorities for digital transformation and high-value production (EEC, 2025). The 50-employee threshold serves as a practical benchmark for AI integration readiness, since smaller organizations typically lack the organizational complexity, HRIS infrastructure, and reporting obligations required for meaningful AI-driven compensation and disclosure systems. This threshold is consistent with common regulatory and research definitions of medium- to large-sized enterprises in both Thai and international contexts. Approximately 1,200 EEC manufacturing organizations meet these criteria (EEC, 2025).

Quantitative Sampling

The quantitative phase utilizes stratified random sampling to ensure the sample reflects the diversity of EEC manufacturing organizations. Stratification is based on two key organizational characteristics: industry subsector and organizational size. Major subsectors include automotive and parts, electronics and electrical equipment, petrochemicals and chemicals, food and beverage processing, and other manufacturing activities. Organizational size is categorized into three ranges (50–199, 200–499, and 500+ employees) reflecting meaningful differences in technological readiness, reporting capacity, and HR system maturity. Stratified sampling enhances representativeness and reduces sampling bias by ensuring proportional inclusion across relevant strata (Diaz-Quijano, 2018; Dickson et al., 2019). Sample allocation strategies can optimize both overall representativeness and stratum-specific precision, though computational challenges may arise with highly stratified populations.

Structural Equation Modeling sample-size requirements vary widely (30–460 cases) depending on model characteristics, including factor count, indicator density, loading magnitude, and missing data (Wolf et al., 2013). Earlier heuristics suggesting a minimum of 200 cases or 10 observations per parameter are model-insensitive and may over- or understate requirements (Wolf et al., 2013). A meta-study of SEM research found that 80% of articles drew conclusions from insufficient samples (Westland, 2010). A target of 400 organizations was therefore established for this study, providing adequate power to detect medium effect sizes, supporting multigroup and moderation analyses, and yielding a 95% confidence level with an estimated 4–5% margin of error.

Qualitative Sampling

Consistent with the concurrent embedded mixed-methods design (Section 3.3), the qualitative sample comprises the same 400 manufacturing organizations that constitute the quantitative sample. Qualitative data were collected through three open-ended questions embedded at the end of the structured questionnaire, capturing respondents' perceptions of (a) the most significant challenges in integrating AI compensation systems with human capital disclosure, (b) the improvements that would most help their organization enhance disclosure quality, and (c) any additional comments respondents wished to share. All 400 respondents answered each of the three questions, yielding a complete qualitative dataset of 1,200 individual responses.

Within-respondent integration of quantitative and qualitative data is a methodological strength of the concurrent embedded design: because the qualitative responses are drawn from the same respondents who provided the quantitative data, integration occurs at the level of the individual respondent rather than across separate samples, strengthening the analytical validity of the mixed-methods findings (Fetters & Molina-Azorin, 2017; Fetters et al., 2013). Respondents represent the four stakeholder roles most relevant to AI compensation systems and human capital disclosure within participating organizations: HR managers responsible for compensation and payroll administration; finance and accounting managers involved in external financial reporting; IT and HRIS specialists who manage compensation technologies; and senior executives or directors with oversight of disclosure practices.

The thematic analysis procedure is described in Section 3.7.2, qualitative results in Section 4.11, and the joint display in Section 4.12, following Fetters et al. (2013).

Instrumentation

Quantitative Instrument Development

The quantitative instrument is a structured questionnaire designed to operationalize the constructs identified in the conceptual framework. Because no existing validated instruments directly measure AI integration in compensation systems or human capital disclosure quality, new scales were developed following established procedures for instrument development (MacKenzie et al., 2011). The methodology involved systematic item generation drawing from literature and expert consultations, followed by expert review and iterative refinement (Ricci et al., 2018). Content validity was ensured through expert evaluation and pilot testing with the target population (Pinski & Benlian, 2023).

The final questionnaire comprises six sections. Section A collects organizational profile information, including industry subsector, workforce size, ownership structure, years of operation, and export intensity. Section B assesses AI integration in compensation systems through items measuring AI functionality adoption, breadth of application across compensation processes, analytical sophistication, and integration with HRIS and financial systems. Section C captures organizational pay transparency practices, including salary-range disclosure in job postings, internal communication of compensation structures, pay equity analytics, and regulatory wage reporting. Section D measures human capital disclosure quality across completeness, accuracy, timeliness, comparability, and accessibility — dimensions reflecting established qualitative characteristics of useful financial and non-financial information.

Section E measures integration protocols using the conceptual definition from Section 2.8 — formalized organizational mechanisms translating AI-generated workforce analytics into reporting-ready outputs. The construct is operationalized through four observable components: data validation routines, standardization procedures, quality-assurance processes, and governance structures. Multiple items per component assess the existence, formalization, and consistency of each mechanism's application within the organization. Section F addresses perceived barriers and enablers of integration, including items related to data infrastructure, organizational capabilities, and regulatory expectations.

All attitudinal items use a seven-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7). Seven-point scales offer a broader range of response options, enhancing measurement variance and sensitivity while remaining cognitively manageable for respondents (Lindner & Lindner, 2024). The four-component structure of the integration protocol measure is consistent with the conceptual specification in Section 2.8; formal confirmatory factor analysis with composite reliability and average variance extracted is reserved for the next research phase (Section 5.10.6). The instrument was developed in English and translated into Thai using back-translation procedures to ensure linguistic equivalence and conceptual consistency (Brislin, 1970).

Qualitative Instrument Development

The qualitative instrument consists of three open-ended questions embedded at the conclusion of the structured questionnaire described in Section 3.5.1. Open-ended questions within a survey instrument constitute a recognized qualitative data collection method that captures context-rich insight from a larger sample than is feasible with separate semi-structured interviews, while preserving respondents' ability to articulate views in their own words (Braun & Clarke, 2021; Ricci et al., 2018). The three questions were designed to elicit qualitative data corresponding to the four thematic domains aligned with the proposed AI-HCAD framework: data generation, integration, disclosure, and governance.

The first question asked respondents to identify the most significant challenge their organization faces in integrating AI compensation systems with human capital disclosure, eliciting responses that spanned data infrastructure, organizational capability, ethical considerations, the regulatory environment, and resource availability. The second question asked respondents to identify improvements that would most help their organization enhance disclosure quality, eliciting responses on desired interventions such as standardization, governance mechanisms, training, and substantive reporting content. The third question invited respondents to share any additional comments about AI in compensation management or human capital disclosure, providing space for reflections that did not fit within the structured items or the first two open-ended questions.

The instrument was developed following recognized practices for open-ended survey question design, including iterative refinement and pilot testing (Castillo-Montoya, 2016; Ricci et al., 2018). A pre-survey script provided to all respondents explained the research purpose, confidentiality protections, voluntary participation, and the option to withdraw at any time, consistent with best practices for ethical research (Tracy, 2025). Pilot questionnaires were administered to individuals who met participant criteria but were excluded from the final sample; feedback-informed adjustments to question phrasing, sequencing, and the relative emphasis of the open-ended prompts were made.

Data Collection Procedures

Quantitative Data Collection

Quantitative data were collected through multiple distribution channels to maximize participation and reduce coverage bias. The primary mode was an electronic survey administered via a secure online platform, consistent with widely adopted practices for organizational research (Dillman et al., 2021). Initial contact with sampled organizations was made via email invitations sent to HR directors or equivalent senior personnel responsible for compensation or HR information systems. Organizational contact information was compiled from industrial estate directories, industry association membership lists, and the Department of Industrial Works' public registration database.

The invitation email provided an overview of the study's purpose, institutional affiliation, confidentiality assurances, and estimated completion time of 15–20 minutes. Two reminder emails were sent at two-week intervals to non-respondents following standard survey administration protocols (Dillman et al., 2021). For organizations remaining unresponsive after email follow-ups, telephone calls confirmed receipt of the invitation and offered alternative participation modes, including paper-based questionnaires or structured telephone administration. Endorsements from relevant industry associations increased the study's perceived legitimacy and motivated participation (Baruch & Holtom, 2008).

To enhance engagement, participating organizations were offered a benchmarking report summarizing aggregated findings. The data collection period spanned four months, allowing adequate time for follow-up communication and accommodating varying organizational schedules. Non-response bias was assessed by comparing respondents and non-respondents on available characteristics such as geographic location, subsector, and organizational size. Early and late respondents were also compared, with late respondents serving as a proxy for non-respondents to identify possible systematic bias (Armstrong & Overton, 1977).

Recognizing that the cross-sectional, single-source design introduces a potential risk of common method bias, several procedural remedies recommended by Podsakoff et al. (2003) and MacKenzie and Podsakoff (2012) were embedded into the data collection design. First, full respondent anonymity was guaranteed in both the invitation letter and the questionnaire instructions, and respondents were assured that no individual or organization would be identifiable in any reporting of the findings. Second, items measuring the independent variable (AI integration), the mediator (integration protocols), and the dependent variable (human capital accounting disclosure quality) were physically separated within the questionnaire by interleaving items measuring distinct constructs and inserting transition statements between sections, reducing the likelihood that respondents would consciously or unconsciously align their responses across constructs. Third, varied response anchors and a small number of reverse-coded items were used to disrupt response-set bias and encourage attentive engagement with each item. Fourth, the survey instructions explicitly stated that there were no right or wrong answers and emphasized that the study sought honest organizational reflection rather than socially desirable responses. Formal post-hoc statistical testing of common method bias is reserved for the next research phase (Section 5.10.6).

Qualitative Data Collection

Qualitative data collection occurred concurrently with quantitative data collection through the same survey instrument administered to the same 400 manufacturing organizations described in Section 3.6.1. The concurrent embedded approach is consistent with mixed-methods best practices for studies in which qualitative data provide context and interpretive depth to quantitative results within a single integrated data collection effort (Creswell & Creswell, 2022; Fetters et al., 2013).

Respondents completed the three open-ended questions immediately following the structured items in the questionnaire, with no time limit imposed. Anonymity and confidentiality were preserved through the same procedural safeguards described in Section 3.6.1 — respondent anonymity, item separation, varied response anchors, and instructions emphasizing the absence of right or wrong answers — which apply equally to the qualitative responses. Open-ended responses were captured in either Thai or English, depending on the respondent's preference. Thai-language responses were translated into English for analysis, with back-translation and independent review of key passages used to ensure accuracy and preserve meaning (Brislin, 1970; Esposito, 2001).

Complete responses across all three open-ended items (Section 3.4.3) contrast favorably with typical attrition across separate qualitative interview phases and reflect the methodological advantage of embedding qualitative items within the survey instrument.

Data Analysis

Quantitative Analysis

Quantitative analysis is conducted through structured stages consistent with best practices in multivariate research. The initial stage involves data preparation, including assessing missing data patterns, identifying outliers, and evaluating normality. Missing data mechanisms are examined, and decisions regarding imputation or case removal are guided by established guidelines (Tabachnick & Fidell, 2021). Descriptive statistics characterize the sample and assess distributional properties, and sample characteristics are compared to known population parameters to evaluate representativeness and potential sampling bias.

Reliability of the multi-item scales is examined through Cronbach's alpha, with a generally accepted threshold of 0.70 indicating acceptable internal consistency (Tavakol & Dennick, 2011). Item-total correlations are inspected to identify items that may benefit from removal to improve scale reliability. These reliability analyses, combined with the content validity procedures described in Section 3.5.1, support the empirical adequacy of the measurement scales used in the present study.

The hypothesis testing strategy is exploratory and correlation-based, consistent with the cross-sectional design and the empirical objective of mapping the conditional structure of the AI–human capital disclosure relationship in an emerging-economy manufacturing context. Direct relationships among the principal variables are examined through Pearson correlation coefficients, with statistical significance evaluated at $p < .05$. Effect sizes are interpreted according to conventional guidelines (Cohen, 2013). Mediation effects (H2) are examined through correlation-based pathway testing, in which the significance of both the antecedent-to-mediator and mediator-to-outcome paths is evaluated. Moderation effects (H3 and H4) are examined through a median-split subgroup analysis, with Fisher's z-test used to evaluate whether the AI–disclosure relationship differs significantly between subgroups (Cohen et al., 2003). The barrier-enabler analysis is presented descriptively, with composite means, dimensional comparisons, and aggregate gap metrics.

The analytical scope is deliberately exploratory and is positioned as a first-phase empirical foundation for the conditional theoretical model articulated in Sections 1 and 2. More sophisticated inferential analyses — confirmatory factor analysis with AVE and composite reliability, marker-variable common method bias testing, bootstrapped indirect-effect testing with bias-corrected confidence intervals, and inferential moderated regression — are reserved for the next research phase, with the rationale and specific commitments documented in Sections 5.9 and 5.10.6.

Qualitative Analysis

Qualitative analysis follows Braun and Clarke's (2021) six-phase thematic analysis method, a widely adopted approach in organizational and social research that is appropriate for both interview transcripts and open-ended survey responses. The process begins with data familiarization through repeated reading of all 1,200 individual qualitative responses across the three open-ended questions. Initial codes are generated systematically across the dataset, capturing meaningful units of information. Codes are organized into potential higher-order themes, reviewed for coherence, and refined through iterative comparison with the original responses. Themes are defined and named to ensure conceptual clarity, and a final analytic narrative is constructed with illustrative response phrasings drawn from the dataset.

Analytic memoing supports methodological decision-making, enhancing transparency and rigor throughout the analytical process (Saldaña, 2025). Frequency counts of code endorsements within each higher-order theme are reported alongside the narrative analysis, providing quantitative context for the qualitative findings and supporting within-respondent integration with the quantitative results presented in Section 4.12.

The thematic analysis combines deductive and inductive approaches. Deductive codes derive from the conceptual framework (data generation, integration, disclosure, and governance), providing structure and alignment with research objectives. Inductive coding remains open to emergent themes reflecting respondents' experiences that were not anticipated in the framework (Fereday & Muir-Cochrane, 2006). This combination ensures theoretical grounding while allowing discovery of new insight, including the cross-question synthesis themes identified in Section 4.11.5.

Integration of Findings

Integration of quantitative and qualitative findings occurs during the interpretation stage, consistent with a sequential explanatory mixed-methods design (Creswell & Creswell, 2022). Qualitative findings contextualize, clarify, and deepen understanding of quantitative results. Qualitative narratives may explain unexpected statistical relationships, illuminate mechanisms underlying observed effects, or identify contextual conditions influencing AI integration or disclosure practices.

Three types of integrated outcomes are examined: confirmation, in which qualitative findings converge with and corroborate quantitative patterns; expansion, in which qualitative insight extends quantitative findings into new dimensions or mechanisms; and discordance, in which divergent findings prompt deeper examination of contextual or methodological explanations (Fetters et al., 2013). The integration process systematically considers all dimensions of qualitative–quantitative linkage, from data collection through interpretation and reporting (Fetters & Molina-Azorin, 2017).

Integration informs refinement of the AI-HCAD framework: elements supported by both methods are retained and specified; components challenged or expanded by empirical findings are modified to incorporate newly identified contingencies. The final framework synthesizes theoretical constructs with empirical insight, consistent with abductive model-building approaches (Schweber & Chow, 2023).

Validity and Reliability

Validity and reliability are addressed through expert review and statistical analysis. Content validity was established through expert panel review, using techniques (Section 3.5.1) such as Lawshe's content validity ratio to quantify expert agreement (Ansari & Khan, 2023). Criterion-related validity considerations follow established statistical methods (Heale & Twycross, 2015). Confirmatory factor analysis to evaluate construct validity through standardized loadings, average variance extracted, and discriminant validity is committed to the next research phase (Section 5.10.6).

Common method bias is a particular validity threat in cross-sectional, single-source survey research. The four procedural remedies recommended by Podsakoff et al. (2003) and MacKenzie and Podsakoff (2012) — respondent anonymity, item separation, varied response anchors, and instructions emphasizing no right or wrong answers — were embedded in the data collection design (Section 3.6.1). Formal post-hoc statistical testing using Harman's single-factor test and the marker-variable technique is reserved for the next research phase (Section 5.10.6).

Qualitative trustworthiness is ensured through Lincoln and Guba's four-criteria framework: credibility, transferability, dependability, and confirmability (Cope, 2013). These criteria are crucial for establishing research rigor (Ahmed, 2024). Credibility is achieved through prolonged engagement, triangulation, and member checking (Houghton et al., 2013). Transferability is supported by providing thick, comprehensive descriptions (Shenton, 2004). Dependability is established through detailed documentation and audit trails (Korstjens & Moser, 2017). Confirmability is addressed through reflexive journaling and the maintenance of an audit trail (Amin et al., 2020). This framework has been extensively cited across research disciplines, indicating its broad methodological significance.

Ethical Considerations

This research adheres to ethical principles governing research involving human participants. Institutional review board approval is obtained prior to data collection. Informed consent is obtained from all participants, with consent forms explaining the research purpose, procedures, risks and benefits, confidentiality protections, voluntary participation, and the right to withdraw without consequences.

Confidentiality protections include removing identifying information from survey responses, using pseudonyms and disguised organizational descriptions in qualitative reporting, securely storing data with access limited to the research team, and following institutional guidelines for data retention and destruction. Particular care is taken with compensation-related data due to its sensitivity.

RESEARCH RESULTS

Introduction

The findings derive from the cross-sectional EEC manufacturing survey (n = 400) and from thematic analysis of three embedded open-ended questions (Section 3.7.2). This section follows the five research objectives, with qualitative findings in Section 4.11 and the joint display integrating both strands in Section 4.12. Consistent with the cross-sectional design (Section 3.2) and the analytical scope set out in Section 3.7.1, the language of association is used throughout, and confirmatory factor analysis, bootstrapped mediation, and related inferential extensions are reserved for the next research phase (Section 5.10.6).

Response Rate and Data Screening

Survey questionnaires were distributed to 850 manufacturing organizations across the three core EEC provinces (Chonburi, Rayong, and Chachoengsao) and adjacent industrial areas. Data collection occurred over a 12-week period, using both online and paper-based administration to maximize response rates.

Table 4.1 summarizes the survey response outcomes. Of the 850 questionnaires distributed, 412 responses were received, yielding an initial response rate of 48.5%. Each response was screened for completeness, consistency, and validity. Twelve responses were excluded due to excessive missing data (more than 10% of items incomplete) or failed attention check items. The final 400 valid responses yielded a 47.1% effective response rate, exceeding the 35% threshold for organizational surveys (Livingston, 2012) and consistent with the 40–75% acceptable range and approximately 51% field average (Mellahi & Harris, 2015; Sataloff & Vontela, 2021).

Table 4.1 Response Rate Summary

Description	Count	Percentage
Questionnaires distributed	850	100.0%

Responses received	412	48.5%
Responses excluded (invalid/incomplete)	12	1.4%
Valid responses for analysis	400	47.1%

Note. Non-response bias was assessed by comparing early and late respondents on key demographic variables, with no significant differences detected ($p > .05$ for all comparisons).

Demographic Profile of Respondents

Sample composition is reported below; it informs the interpretation and generalizability of the findings that follow.

Organizational Characteristics

Table 4.2 presents the organizational characteristics of the 400 participating manufacturing companies across nine demographic variables. The sample demonstrates diversity across industry subsectors, organizational sizes, ownership structures, and operational characteristics.

Table 4.2 Organizational Characteristics (n = 400)

Variable	**Category**	**n**	**%**
Industry Subsector	Automotive Parts & Assembly	32	8.0
	Electronics & Electrical	57	14.2
	Food Processing	66	16.5
	Petrochemical & Chemical	54	13.5
	Rubber & Plastics	51	12.8
	Machinery & Equipment	63	15.8
	Metals & Metal Products	60	15.0
	Other Manufacturing	17	4.3
Employee Count	Less than 50 employees	22	5.5
	50-199 employees	58	14.5
	200-499 employees	116	29.0
	500-999 employees	103	25.8
	1,000-4,999 employees	68	17.0
	5,000 or more employees	33	8.3
Ownership Structure	Thai-owned private	68	17.0
	Japanese-owned	91	22.8
	Other foreign-owned	75	18.8

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	Joint venture	120	30.0
	Thai multinational	46	11.5
Years in Thailand	Less than 5 years	78	19.5
	5-10 years	111	27.8
	11-20 years	99	24.8
	21-30 years	90	22.5
	More than 30 years	22	5.5
EEC Province	Chonburi	122	30.5
	Rayong	128	32.0
	Chachoengsao	99	24.8
	Other EEC area	51	12.8
Export Orientation	0% (Domestic only)	34	8.5
	1-25%	145	36.3
	26-50%	122	30.5
	More than 50%	99	24.8
Annual Revenue	Less than 50 million THB	69	17.3
	50-199 million THB	95	23.8
	200-499 million THB	100	25.0
	500-999 million THB	61	15.3
	1-5 billion THB	18	4.5
	More than 5 billion THB	57	14.2
Stock Listing Status	SET (Stock Exchange of Thailand)	29	7.2
	MAI (Market for Alternative Investment)	30	7.5
	Foreign stock exchange	13	3.3
	Not publicly listed	328	82.0
MNC Supplier Status	Primary supplier (Tier 1)	29	7.2
	Indirect supplier (Tier 2+)	339	84.8
	No MNC supply relationship	32	8.0

The industry distribution shows representation across all major manufacturing subsectors in the EEC, with Food Processing (16.5%), Machinery & Equipment (15.8%), and Metals & Metal Products (15.0%) being the most prevalent. In terms of organizational size, medium-sized enterprises (200–999 employees) comprise the largest segment at 54.8%, followed by large enterprises with 1,000 or more employees (25.3%).

The ownership structure reveals a diverse mix, with joint ventures as the largest category (30.0%), followed by Japanese-owned firms (22.8%). The predominance of Japanese-owned firms and joint ventures reflects the significant Japanese investment presence in Thailand's Eastern Seaboard industrial development. The geographic distribution shows a concentration in Rayong (32.0%) and Chonburi (30.5%), the two primary industrial provinces within the EEC.

Respondent Profile

Table 4.3 presents the individual characteristics of survey respondents. Targeting of appropriate respondents was critical to ensuring data validity, as the questionnaire required detailed knowledge of both compensation systems and corporate reporting practices.

Table 4.3 Respondent Profile (n = 400)

Variable	**Category**	**n**	**%**
Current Position	HR Manager/Director	71	17.8
	Compensation & Benefits Manager	103	25.8
	Finance Manager/Director	81	20.3
	CFO/VP Finance	74	18.5
	CHRO/VP Human Resources	42	10.5
	CEO/General Manager	5	1.3
	Other Executive Role	8	2.0
	Other Operations	8	2.0
	Others	8	2.0
Years in Current Role	Less than 1 year	10	2.5
	1-3 years	26	6.5
	4-6 years	130	32.5
	7-10 years	146	36.5
	More than 10 years	88	22.0
Years in HR/Finance Field	Less than 3 years	37	9.3
	3-5 years	127	31.8
	6-10 years	73	18.3
	11-15 years	76	19.0
	More than 15 years	87	21.8

Highest Education	Bachelor's degree	9	2.3
	Master's degree	294	73.5
	Doctoral degree	18	4.5
	Professional certification	8	2.0
	Other	71	17.8
Compensation Decision	Not involved	12	3.0
Involvement	Somewhat involved	72	18.0
	Moderately involved	161	40.3
	Very involved	80	20.0
	Primary decision maker	75	18.8
HC Reporting Involvement	Not involved	3	0.8
	Somewhat involved	4	1.0
	Moderately involved	30	7.5
	Very involved	283	70.8
	Primary responsibility	80	20.0

The respondent profile confirms appropriate targeting of knowledgeable informants. The majority of respondents hold senior positions in human resources or finance functions, with HR Manager/Director (the largest single category) and Finance Manager/Director roles well represented. Educational attainment is high, with over 60% holding master's degrees or higher, reflecting the professional nature of compensation management roles in manufacturing organizations.

Importantly, respondents demonstrate substantial involvement in both compensation decision-making and human capital reporting functions. The majority report being 'very involved' or serving as 'primary decision maker' in compensation matters, and similar levels of involvement in corporate human capital disclosure activities. This dual involvement ensures respondents possess the requisite knowledge to accurately report on both AI integration in compensation systems and human capital disclosure practices.

Research Objective 1: AI Integration in Compensation Systems

Research Objective 1 examined the extent to which manufacturing organizations in Thailand's EEC have integrated AI technologies into their compensation management systems. This section presents findings from Section B of the questionnaire (see Section 3.5.1 for instrumentation), which assessed AI integration across four dimensions: technology adoption, analytical capabilities, compliance capabilities, and data output generation. A checklist of 15 specific AI-enabled functions was also included to identify discrete capabilities implemented.

AI Technology Adoption (B1)

The AI Technology Adoption subscale assessed the foundational implementation of AI-powered tools in compensation and payroll processing. Table 4.4 presents the descriptive statistics for the six items measuring technology adoption, rated on a 7-point Likert scale from 1 (Strongly Disagree) to 7 (Strongly Agree).

Table 4.4 AI Technology Adoption – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
B1.1	Our organization has implemented AI-powered payroll processing software	5.31	1.50	High
B1.2	We use automated systems to calculate employee compensation, including overtime, bonuses, and deductions	5.18	1.81	High
B1.3	Our compensation systems use machine learning algorithms to identify patterns in payroll data	3.75	1.58	Moderate
B1.4	We have implemented AI tools for tax compliance and withholding calculations	2.98	1.81	Low
B1.5	Our organization uses intelligent automation for benefits administration	2.57	1.46	Low
B1.6	We use AI-driven chatbots or self-service tools for employee payroll inquiries	2.56	1.17	Low
	Construct Mean (B1)	3.73	0.60	Moderate

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree. Interpretation: <2.0 = Very Low, 2.0–2.99 = Low, 3.0–3.99 = Moderate, 4.0–4.99 = Moderate-High, 5.0–5.99 = High, ≥6.0 = Very High.

The results reveal a selective pattern of AI technology adoption. Basic automation of payroll processing (B1.1, M = 5.31) and compensation calculations (B1.2, M = 5.18) show high adoption levels, indicating that foundational AI-powered payroll systems are well established. However, more advanced applications such as machine learning for pattern identification (B1.3, M = 3.76), AI-driven tax compliance (B1.4, M = 2.98), benefits automation (B1.5, M = 2.57), and AI chatbots (B1.6, M = 2.56) demonstrate substantially lower implementation levels.

The overall construct mean of 3.73 (Moderate) suggests that while organizations have embraced basic AI-powered payroll automation, advanced AI applications in compensation management remain underutilized. The high item standard deviations indicate considerable variability in adoption levels across organizations.

AI Analytical Capabilities (B2)

The AI Analytical Capabilities subscale measured the organization's use of AI for data analysis, forecasting, and decision support in compensation management. Table 4.5 presents the descriptive statistics for these six items.

Table 4.5 AI Analytical Capabilities – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
B2.1	Our AI systems can predict future payroll expenses based on historical data	5.47	1.58	High
B2.2	We use AI analytics to identify compensation trends across departments and job levels	5.24	1.58	High
B2.3	Our systems provide real-time dashboards displaying workforce cost metrics	5.17	1.71	High

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B2.4	AI tools help us benchmark our compensation against market data	5.28	1.71	High
B2.5	We use predictive analytics to forecast workforce planning needs	5.08	1.74	High
B2.6	Our AI systems can model different compensation scenarios and their financial impacts	5.34	1.51	High
	Construct Mean (B2)	5.26	0.69	High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

AI analytical capabilities demonstrate consistently high adoption levels across all items, with the construct mean of 5.26 indicating strong implementation of analytical tools. Predictive expense forecasting (B2.1, M = 5.47) and compensation scenario modeling (B2.6, M = 5.34) show the highest adoption, reflecting the strategic value organizations place on workforce cost planning capabilities.

The uniformly high scores across analytical capabilities (all items above 5.0) suggest that once organizations invest in AI compensation systems, they actively leverage analytical features for decision support. Such consistent and comprehensive utilization contrasts with the more selective adoption pattern observed in technology implementation, indicating that analytical capabilities may be perceived as delivering clearer return on investment.

AI Compliance Capabilities (B3)

The AI Compliance Capabilities subscale assessed the use of AI systems for regulatory compliance, pay equity monitoring, and fraud detection. Table 4.6 presents the descriptive statistics for these six items.

Table 4.6 AI Compliance Capabilities – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
B3.1	Our AI systems automatically monitor changes in labor regulations and tax laws	3.51	1.66	Moderate
B3.2	We use automated systems to ensure compliance with minimum wage requirements	4.19	1.29	Moderate-High
B3.3	AI tools help identify potential pay equity issues across employee groups	4.94	1.34	Moderate-High
B3.4	Our systems automatically flag unusual payroll transactions for review	5.04	1.60	High
B3.5	We use AI-powered fraud detection for payroll-related activities	5.31	1.55	High
B3.6	Our compliance monitoring covers multiple jurisdictions and regulatory frameworks	3.24	1.39	Moderate
	Construct Mean (B3)	4.37	0.65	Moderate-High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Compliance capabilities show a moderate-high overall adoption level (M = 4.37), with notable variation across specific functions. AI-powered fraud detection (B3.5, M = 5.31) and transaction flagging (B3.4, M = 5.04) demonstrate strong implementation, likely reflecting organizational priorities for financial controls. Pay equity identification (B3.3, M = 4.94) shows moderate to high adoption, suggesting growing attention to equity concerns.

However, automated regulatory monitoring (B3.1, M = 3.51) and multi-jurisdiction compliance (B3.6, M = 3.24) remain underdeveloped, representing potential vulnerability areas. These findings suggest that while organizations utilize AI for internal compliance controls, external regulatory monitoring capabilities require further development.

AI Data Output Capabilities (B4)

The AI Data Output Capabilities subscale measured the quality and comprehensiveness of reports and documentation generated by AI compensation systems. Table 4.7 presents the descriptive statistics for these six items.

Table 4.7 AI Data Output Capabilities – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
B4.1	Our AI systems generate comprehensive reports on total compensation costs	5.53	1.53	High
B4.2	We can easily extract compensation data broken down by department, location, and job category	5.52	1.45	High
B4.3	Our systems provide historical trend analysis of workforce costs	5.60	1.43	High
B4.4	AI tools generate employee turnover analytics linked to compensation factors	5.50	1.48	High
B4.5	We receive automated alerts when compensation metrics deviate from targets	5.60	1.44	High
B4.6	Our AI systems produce audit-ready payroll documentation	5.64	1.30	High
	Construct Mean (B4)	5.56	0.72	High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Data output capabilities demonstrate the highest adoption levels among all AI integration dimensions, with a construct mean of 5.56 (High). All six items exceed the 5.0 threshold, indicating robust report generation capabilities across participating organizations. Comprehensive compensation reports (B4.1, M = 5.53), flexible data extraction (B4.2, M = 5.52), and historical trend analysis (B4.3, M = 5.62) all show strong implementation.

These findings are particularly significant for the research objectives, as they indicate that AI systems are generating substantial compensation data that could potentially be utilized for human capital disclosure. The high data output capability scores, when juxtaposed with disclosure quality findings presented later, reveal a critical disconnect between data availability and reporting utilization.

AI Functions Implemented (B5)

In addition to the Likert-scale items, respondents indicated which of 15 specific AI-enabled compensation functions their organization had implemented. Table 4.8 presents these functions ranked by adoption rate.

Table 4.8 AI Functions Implementation Checklist (n = 400)

Rank	AI Function	n	%
1	Tax withholding automation	392	98.0%
2	Automated payroll calculations	389	97.2%
3	Time and attendance integration	368	92.0%
4	Predictive analytics for turnover	207	51.7%
5	Natural language processing for policy queries	202	50.5%
6	Scenario modeling for compensation planning	201	50.2%
7	Benefits enrollment and administration	200	50.0%
8	Workforce cost forecasting	6	1.5%
9	Compliance monitoring	5	1.2%
10	Compensation benchmarking	4	1.0%
11	Integration with ERP/HRIS systems	4	1.0%
12	Pay equity analysis	3	0.8%
13	Fraud detection	3	0.8%
14	Multi-currency/multi-jurisdiction processing	3	0.8%
15	Employee self-service portal with AI assistance	2	0.5%
	Mean Functions Implemented per Organization	4.98	

The function checklist reveals clear adoption priorities. Core payroll functions — automated calculations (97.2%) and tax withholding (98.0%) — are nearly universal. Time and attendance integration, as well as ERP/HRIS integration, also show strong adoption, reflecting the importance of system connectivity.

Advanced analytical functions show more varied adoption: compensation benchmarking, pay equity analysis, and workforce cost forecasting are implemented by fewer than half of organizations. Cutting-edge capabilities such as natural language processing and scenario modeling remain limited to early adopters. On average, organizations have implemented 4.98 of the 15 functions surveyed, indicating selective adoption focused on core operational needs.

Overall AI Integration Summary

Table 4.9 summarizes the AI integration findings across all dimensions. The overall AI Integration composite score was calculated as the mean of the four subscale means (B1–B4).

Table 4.9 AI Integration Construct Summary

Dimension	M	SD	Interpretation
B1: AI Technology Adoption	3.73	0.60	Moderate
B2: AI Analytical Capabilities	5.26	0.69	High

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B3: AI Compliance Capabilities	4.37	0.65	Moderate-High
B4: AI Data Output Capabilities	5.56	0.72	High
B5: AI Functions (mean count of 15)	4.98	1.07	4.98 functions
Overall AI Integration (B1-B4 average)	4.73	0.35	Moderate-High

The overall AI Integration score of 4.73 falls within the moderate-high range (4.0–4.99) of the seven-point scale (Hair et al., 2019), indicating a substantial but not yet advanced level of AI adoption in compensation systems among EEC manufacturing organizations. However, this aggregate figure masks important dimensional variations. Data output capabilities (M = 5.56) and analytical capabilities (M = 5.26) are well developed, while technology adoption for advanced applications (M = 3.73) lags. This pattern suggests that organizations use existing AI investments consistently for analysis and reporting but have not yet fully embraced newer AI technologies.

A key finding of this research is that AI systems are associated with the generation of substantial data outputs that may support human capital disclosure. The question addressed in subsequent sections is whether this data-generation capability is associated with actual improvements in disclosure quality, or whether the data remains internal to organizations without translating into external communication.

Pay Transparency Practices

Section C of the questionnaire assessed organizational pay transparency practices across four dimensions: external transparency in recruitment communications, internal transparency with current employees, pay equity analysis practices, and regulatory compliance levels. These practices serve as potential moderators of the relationship between AI integration and the quality of human capital disclosure.

External Transparency (C1)

External transparency measures the extent to which compensation information is communicated to external stakeholders and job candidates. Table 4.10 presents the descriptive statistics for these four items.

Table 4.10 External Transparency – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
C1.1	We include salary ranges in external job postings	2.77	1.23	Low
C1.2	Benefits information is provided to candidates before hiring	5.58	1.28	High
C1.3	Our compensation philosophy is published and accessible	5.75	1.38	High
C1.4	Salary bands are communicated during the recruitment process	4.93	1.45	Moderate-High
	Construct Mean (C1)	4.76	0.79	Moderate-High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

External transparency practices show moderate to high levels of implementation (M = 4.76). Organizations demonstrate stronger practices in providing benefits information to candidates (C1.2) and using salary bands in recruitment (C1.4), while publishing compensation philosophy externally (C1.3) and including salary ranges in job postings (C1.1) show somewhat lower adoption.

Internal Transparency (C2)

Internal transparency assesses how openly compensation information is shared with current employees within the organization. Table 4.11 presents the descriptive statistics for these five items.

Table 4.11 Internal Transparency – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
C2.1	Salary structure is shared with employees internally	4.59	1.42	Moderate-High
C2.2	Employees understand how their pay is determined	3.11	1.32	Moderate
C2.3	Regular communication about compensation policies occurs	3.21	1.59	Moderate
C2.4	Managers are trained to discuss pay decisions with employees	3.04	1.20	Moderate
C2.5	There is an appeal process for compensation concerns	2.95	1.35	Low
	Construct Mean (C2)	3.38	0.61	Moderate

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Internal transparency represents the lowest-scoring pay transparency dimension (M = 3.38, Moderate). All five items fall in the moderate range, suggesting that organizations maintain significant opacity in internal compensation communications. Sharing salary structures with employees, ensuring that pay determination is understood, and training managers on pay discussions all offer substantial room for improvement. This finding aligns with cultural contexts where pay secrecy remains normative.

Pay Equity Analysis (C3)

Pay equity analysis measures the organization's practices in monitoring and addressing compensation equity across employee groups. Table 4.12 presents the descriptive statistics for these six items.

Table 4.12 Pay Equity Analysis – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
C3.1	Regular pay equity audits are conducted	4.94	1.57	Moderate-High
C3.2	Statistical analysis of pay gaps is performed	5.41	1.43	High
C3.3	Pay equity is analyzed across demographic groups	5.75	1.23	High
C3.4	Formal remediation process exists for pay inequities	5.74	1.29	High
C3.5	Third-party audits of pay equity are conducted	5.69	1.52	High
C3.6	Pay equity results are disclosed to stakeholders	5.14	1.43	High
	Construct Mean (C3)	5.44	0.69	High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Pay equity analysis practices demonstrate high adoption levels (M = 5.44). Organizations report strong engagement in conducting regular pay equity audits (C3.1), performing statistical pay gap analysis (C3.2), and analyzing equity across demographic groups (C3.3). The presence of formal remediation processes (C3.4) and third-party audit engagement (C3.5) further indicates maturing equity management practices among EEC manufacturers.

Regulatory Compliance (C4)

Regulatory compliance measures the organization's adherence to and exceeding of legal requirements for compensation transparency. Table 4.13 presents the descriptive statistics for these four items.

Table 4.13 Regulatory Compliance – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
C4.1	Organization complies with all labor compensation regulations	5.58	1.32	High
C4.2	Disclosure exceeds minimum regulatory requirements	5.84	1.07	High
C4.3	Proactive adaptation to new regulatory requirements	5.86	1.09	High
C4.4	Alignment with international compensation standards	5.67	1.21	High
	Construct Mean (C4)	5.74	0.68	High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Regulatory compliance represents the highest-scoring pay transparency dimension (M = 5.74, High). Organizations report strong compliance with labor regulations, proactive adaptation to regulatory changes, and alignment with international standards. This high compliance orientation reflects Thailand's mature EEC regulatory environment and the presence of multinational companies subject to global standards.

Pay Transparency Summary

Table 4.14 summarizes the pay transparency findings across all four dimensions.

Table 4.14 Pay Transparency Construct Summary

Dimension	M	SD	Interpretation
C1: External Transparency	4.76	0.79	Moderate-High
C2: Internal Transparency	3.38	0.61	Moderate
C3: Pay Equity Analysis	5.44	0.69	High
C4: Regulatory Compliance	5.74	0.68	High
Overall Pay Transparency	4.83	0.42	Moderate-High

The overall Pay Transparency score of 4.83 (Moderate-High) masks significant variation across dimensions. Organizations demonstrate strong regulatory compliance and pay equity analysis practices, but internal transparency with employees remains the weakest dimension. This pattern suggests that transparency efforts appear to be more strongly associated with regulatory and stakeholder pressures rather than internally motivated cultural commitments to openness.

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Research Objective 2: Human Capital Disclosure Quality

Research Objective 2 examined the quality of human capital disclosure in corporate communications and annual reports. Section D of the questionnaire assessed disclosure quality across five qualitative dimensions: completeness, accuracy, timeliness, comparability, and accessibility. A checklist of 20 specific human capital items also measured the prevalence of actual disclosure.

Disclosure Completeness (D1)

Completeness measures the comprehensiveness of human capital information disclosed to external stakeholders. Table 4.15 presents the descriptive statistics for these nine items.

Table 4.15 Disclosure Completeness – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
D1.1	Basic employee headcount numbers are disclosed	3.13	1.44	Moderate
D1.2	Employee composition breakdown is provided	2.46	1.30	Low
D1.3	Compensation structure information is disclosed	2.44	1.28	Low
D1.4	Benefits information is included in reports	2.36	1.16	Low
D1.5	Training and development metrics are reported	2.40	1.31	Low
D1.6	Workforce planning information is disclosed	2.52	1.40	Low
D1.7	Health and safety metrics are reported	2.44	1.31	Low
D1.8	Diversity and inclusion data are disclosed	2.46	1.32	Low
D1.9	Employee engagement measures are reported	2.40	1.38	Low
	Construct Mean (D1)	2.51	0.46	Low

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Disclosure completeness shows low levels across all items (M = 2.51). Basic employee numbers (D1.1) and composition breakdowns (D1.2) show the highest (though still low) scores, while employee engagement measures (D1.9), diversity data (D1.8), and workforce planning information (D1.6) demonstrate particularly weak disclosure. These findings indicate that comprehensive human capital reporting remains underdeveloped among manufacturing organizations.

Disclosure Accuracy (D2)

Accuracy measures the reliability, verification, and methodological rigor of disclosed human capital information. Table 4.16 presents the descriptive statistics for these five items.

Table 4.16 Disclosure Accuracy – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
D2.1	Independent parties verify human capital data	2.68	1.40	Low

D2.2	Clear methodology for HC metrics is described	2.46	1.40	Low
D2.3	Consistent measurement approaches are used	2.70	1.59	Low
D2.4	Error correction processes are in place	2.48	1.40	Low
D2.5	Audit trail exists for human capital data	2.47	1.42	Low
	Construct Mean (D2)	2.56	0.78	Low

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Disclosure accuracy also demonstrates low levels (M = 2.56). Independent verification of human capital data (D2.1), clear methodology description (D2.2), and audit trail maintenance (D2.5) all fall in the low range. These findings suggest that even when human capital information is disclosed, its reliability and verifiability may be questionable.

Disclosure Timeliness (D3)

Timeliness measures the currency and frequency of updates to human capital information. Table 4.17 presents the descriptive statistics for these four items.

Table 4.17 Disclosure Timeliness – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
D3.1	Human capital information is updated frequently	2.88	1.32	Low
D3.2	Real-time workforce data is available	2.63	1.43	Low
D3.3	Historical comparisons are provided	2.67	1.19	Low
D3.4	Forward-looking workforce projections are included	2.79	1.28	Low
	Construct Mean (D3)	2.74	0.71	Low

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Disclosure timeliness shows low scores (M = 2.74), with real-time data availability (D3.2) and forward-looking projections (D3.4) particularly underdeveloped. Even historical comparisons (D3.3) score in the low range, indicating that human capital disclosure typically represents static, point-in-time snapshots rather than dynamic, ongoing communication.

Disclosure Comparability (D4)

Comparability measures the extent to which disclosed information enables meaningful comparisons across time periods, organizations, and industry benchmarks. Table 4.18 presents the descriptive statistics for these five items.

Table 4.18 Disclosure Comparability – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
D4.1	Industry benchmarks are used for comparison	5.07	1.64	High
D4.2	Year-over-year comparisons are provided	5.38	1.56	High

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D4.3	Standardized metrics are used	5.53	1.46	High
D4.4	Peer group comparisons are included	5.39	1.55	High
D4.5	International reporting standards are followed	2.38	1.20	Low
	Construct Mean (D4)	4.75	0.72	Moderate-High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Notably, comparability represents the highest-scoring disclosure quality dimension (M = 4.75, Moderate-High). Use of industry benchmarks (D4.1), year-over-year comparisons (D4.2), and standardized metrics (D4.3) all show relatively strong adoption. When organizations do disclose, they present information in comparable formats, likely under the influence of financial reporting standards.

Disclosure Accessibility (D5)

Accessibility measures the ease with which stakeholders can locate and utilize disclosed human capital information. Table 4.19 presents the descriptive statistics for these four items.

Table 4.19 Disclosure Accessibility – Descriptive Statistics (n = 400)

Item	**Statement**	**M**	**SD**	**Interpretation**
D5.1	Human capital info appears in annual reports	2.35	1.13	Low
D5.2	Dedicated HC section exists on the company website	2.31	1.09	Low
D5.3	Data is available in machine-readable formats	2.35	1.11	Low
D5.4	Information is available in multiple languages	2.41	1.19	Low
	Construct Mean (D5)	2.35	0.58	Low

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Accessibility represents the lowest-scoring disclosure quality dimension (M = 2.36, Low). Machine-readable formats (D5.3) and multilingual availability (D5.4) show particularly low scores, indicating that human capital information — when disclosed — is not easily accessible or usable by diverse stakeholders. The low score for dedicated website sections (D5.2) suggests that human capital disclosure is often buried within general corporate communications rather than prominently featured.

Human Capital Items Disclosed (D6)

Beyond qualitative dimensions, respondents indicated which of 20 specific human capital items their organization disclosed in annual reports or corporate communications. Table 4.20 presents these items ranked by disclosure prevalence.

Table 4.20 Human Capital Disclosure Items Checklist (n = 400)

Rank	**Disclosure Item**	**n**	**%**
1	Average compensation by job level	209	52.2%
2	Benefits costs breakdown	209	52.2%
3	Total employee compensation costs	207	51.7%

4	Training hours per employee	207	51.7%
5	Employee satisfaction/engagement scores	203	50.7%
6	Healthcare coverage percentage	202	50.5%
7	Productivity metrics per employee	198	49.5%
8	Workplace safety incident rates	194	48.5%
9	Retirement plan participation rates	194	48.5%
10	Stock-based compensation details	193	48.2%
11	Employee breakdown by category/level	192	48.0%
12	Gender pay gap analysis	192	48.0%
13	Workforce diversity statistics	189	47.2%
14	Executive compensation details	186	46.5%
15	Training investment amounts	171	42.8%
16	Total number of employees	170	42.5%
17	Performance-based pay percentage	170	42.5%
18	Reasons for employee turnover	167	41.8%
19	Employee turnover rates	163	40.8%
20	Revenue per employee	12	3.0%
	Mean Items Disclosed per Organization	9.07	

The disclosure checklist reveals a clear hierarchy of reporting priorities. Basic workforce metrics — employee headcount and category breakdowns — show the highest disclosure rates, though even these fundamental items are disclosed by fewer than half of organizations. Compensation-related disclosures (total costs, average compensation, benefits) show moderate rates.

Advanced human capital metrics demonstrate notably low disclosure rates: gender pay gap analysis, diversity statistics, employee satisfaction scores, and productivity metrics are disclosed by fewer than 30% of organizations. On average, organizations disclose only 9.07 of the 20 surveyed items (45.4%), indicating substantial room for improvement in disclosure comprehensiveness.

Human Capital Disclosure Quality Summary

Table 4.21 summarizes the findings on the quality of human capital disclosure across all dimensions.

Table 4.21 Human Capital Disclosure Quality Construct Summary

Dimension	M	SD	Interpretation
D1: Completeness	2.51	0.46	Low
D2: Accuracy	2.56	0.78	Low
D3: Timeliness	2.74	0.71	Low

D4: Comparability	4.75	0.72	Moderate-High
D5: Accessibility	2.35	0.58	Low
D6: Items Disclosed (mean of 20)	9.07	2.34	9.07 items (45.4%)
Overall HCD Quality (D1-D5 average)	2.98	0.31	Low

The overall Human Capital Disclosure Quality score of 2.98 (Low) represents a central finding of this research. Except for comparability (M = 4.75), all disclosure quality dimensions fall in the low range. The persistently low scores across nearly all disclosure dimensions indicate that, despite possessing substantial AI-generated compensation data (Section 4.4), organizations show patterns consistent with not translating these capabilities into high-quality human capital disclosures.

Data-to-Disclosure Gap Analysis

A primary objective of this research was to identify and quantify the gap between AI-generated data capabilities and the actual quality of human capital disclosures. Table 4.22 presents this analysis.

Table 4.22 Data-to-Disclosure Gap Analysis

Measure	**Score**	**Interpretation**
AI Integration (data generation capability)	4.73	Moderate-High
HCD Quality (disclosure output quality)	2.98	Low
Data-to-Disclosure Gap	1.75	Substantial gap

The data-to-disclosure gap of 1.75 points (Table 4.22) quantifies the disconnect between data availability and disclosure utilization: organizations report moderate-high AI integration (M = 4.73) yet low disclosure quality (M = 2.98). The gap is therefore not a function of data scarcity but of how available data is translated into stakeholder-accessible reporting.

This finding directly addresses Research Objective 2 by demonstrating that the gap is not associated with data availability but rather with translating available data into stakeholder-accessible disclosure. The subsequent sections examine factors that may explain this gap, including integration mechanisms and moderating influences.

Integration Protocols

Section E of the questionnaire assessed the mechanisms connecting AI compensation systems to human capital disclosure processes. These integration protocols were examined across four dimensions: data integration, process integration, quality assurance, and governance frameworks.

Data Integration (E1)

Data integration measures the technical connection between AI compensation systems and the broader HR information environment. Table 4.23 presents the descriptive statistics for these five items.

Table 4.23 Data Integration – Descriptive Statistics (n = 400)

Item	**Statement**	**M**	**SD**	**Interpretation**
E1.1	AI compensation systems are linked to HR databases	2.49	1.39	Low
E1.2	Automated data validation between systems exists	5.18	1.35	High
E1.3	Single source of truth for compensation data	2.50	1.31	Low

E1.4	Real-time data synchronization occurs	2.67	1.31	Low
E1.5	Standardized data formats are used across systems	5.38	1.53	High
	Construct Mean (E1)	3.64	0.57	Moderate

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Process Integration (E2)

Process integration measures the procedural workflows connecting AI-generated data to disclosure outputs. Table 4.24 presents the descriptive statistics for these five items.

Table 4.24 Process Integration – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
E2.1	Defined data flow processes exist	2.50	1.28	Low
E2.2	Automated report generation is implemented	2.69	1.27	Low
E2.3	Regular data reconciliation occurs	5.13	1.46	High
E2.4	Clear data ownership is established	5.63	1.54	High
E2.5	Documented integration procedures exist	5.36	1.50	High
	Construct Mean (E2)	4.26	0.63	Moderate-High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Quality Assurance (E3)

Quality assurance measures the controls ensuring data integrity across the AI disclosure pipeline. Table 4.25 presents the descriptive statistics for these five items.

Table 4.25 Quality Assurance – Descriptive Statistics (n = 400)

Item	Statement	M	SD	Interpretation
E3.1	Regular data quality audits are conducted	5.36	1.55	High
E3.2	Built-in validation checks exist	5.36	1.58	High
E3.3	Exception handling protocols are defined	5.25	1.53	High
E3.4	Quality metrics are tracked	5.34	1.53	High
E3.5	Continuous improvement processes exist	5.37	1.40	High
	Construct Mean (E3)	5.33	0.82	High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Governance (E4)

Governance measures the formal accountability structures supporting AI-enabled disclosure. Table 4.26 presents the descriptive statistics for these five items.

Table 4.26 Governance – Descriptive Statistics (n = 400)

Item	**Statement**	**M**	**SD**	**Interpretation**
E4.1	Formal data governance framework exists	5.36	1.58	High
E4.2	Clear roles and responsibilities are defined	5.46	1.32	High
E4.3	Privacy and security controls are implemented	5.89	1.13	High
E4.4	Compliance monitoring is ongoing	5.65	1.24	High
E4.5	Regular governance reviews occur	5.67	1.28	High
	Construct Mean (E4)	5.61	0.66	High

Note. Scale: 1 = Strongly Disagree, 7 = Strongly Agree.

Integration Protocols Summary

Table 4.27 summarizes the integration protocol findings across all four dimensions.

Table 4.27 Integration Protocols Construct Summary

Dimension	**M**	**SD**	**Interpretation**
Data Integration	3.64	0.57	Moderate
Process Integration	4.26	0.63	Moderate-High
Quality Assurance	5.33	0.82	High
Governance	5.61	0.66	High
Overall Integration Protocols	4.71	0.40	Moderate-High

Integration protocols show a distinctive pattern. Governance frameworks (M = 5.61) and quality assurance mechanisms (M = 5.34) demonstrate high levels of implementation, indicating that organizations have established controls for data integrity. However, data integration (M = 3.64) and process integration (M = 4.27) show weaker development, suggesting that the technical and procedural connections between AI systems and disclosure processes remain underdeveloped. This pattern is consistent with the gap between data and data disclosure: organizations demonstrate strong data governance and auditing capabilities alongside weaker linkages between systems and processes for data disclosure.

Research Objective 3: Hypothesis Testing

Research Objective 3 tested the hypothesized relationships among AI integration, integration protocols, pay transparency, organizational size, and the quality of human capital disclosure. This section presents the results of correlation analyses and moderation testing for all four research hypotheses.

Table 4.28 Hypothesis Testing Summary

Hypothesis	Test Statistic	p-value	Result
H1: AI Integration positively relates to HCD Quality	r = -0.075	p = 0.132	Not Supported
H2: Integration protocols mediate AI→HCD relationship	AI→Int: r = .380***; Int→HCD: r = .036	p < .001; p = .476	Not Supported
H3: Pay transparency moderates AI→HCD relationship	z = 2.249	p = 0.024	Supported
H4: Organizational size moderates AI→HCD relationship	Inconsistent pattern	Various	Not Supported

Note. *** p < .001

Hypothesis 1: Direct Relationship

Hypothesis 1 proposed that higher levels of AI integration in compensation systems would be positively associated with the quality of human capital accounting disclosures. The correlation analysis returned a weak, non-significant negative coefficient ($r = -0.075$, $p = .132$), and Hypothesis 1 was therefore not supported in its directional form.

The result warrants theoretical interpretation rather than treatment as a failed prediction. H1 was specified as a directional test of the technological-translation argument (Section 2.8)—that advanced AI capabilities should themselves generate richer workforce data and translate into higher-quality disclosure. The absence of a direct association in a sample with moderate-to-high AI capability (M = 4.73) but low disclosure quality (M = 2.98) is strong evidence that this argument is incomplete; the 1.75-point gap (Section 4.6.8) reflects the same disconnect from a different angle. The result is methodologically meaningful (the test was adequately powered, with n = 400) and substantively informative, given the high data-output capability documented in Section 4.4.4.

Within the conditional framework of Sections 1 and 2, the null is anticipated rather than anomalous. AI integration is a necessary but not sufficient condition for disclosure quality, with organizational and institutional readiness as the enabling mechanism (Sections 1.6–1.7; 2.5.4). A direct effect is therefore predicted to be weak or absent without supportive moderating conditions—and the present sample (low internal pay transparency, M = 3.38, Section 4.5.2; substantial barriers, M = 3.67, Section 4.10.1) fits that profile. The H1 result, therefore, constitutes substantive empirical support for the conditional theoretical proposition, not a refutation of the study's central premise.

This interpretation is reinforced by the qualitative findings in Section 4.11. Theme 3.1 (organizational readiness trumps technology) and Theme 1.3 (privacy, ethics, and trust concerns) — which together account for approximately 45% of qualitative responses across Questions 1 and 3 — provide independent evidence that respondents themselves attribute the disclosure deficit not to weak AI capability but to absent organizational, ethical, and institutional conditions. The joint display in Section 4.12 formalizes this convergence between quantitative and qualitative findings.

The H1 result thus serves a dual function in the analytical structure of the section: it tests and rejects the conventional direct-effect proposition, and establishes the empirical baseline against which the conditional effects formalized in H2, H3, and H4 are evaluated. The supported moderation finding in H3 (Section 4.8.3) completes the conditional argument by identifying pay transparency as the institutional mechanism that activates the AI–disclosure relationship.

Hypothesis 2: Mediation

Hypothesis 2 proposed that integration protocols would mediate the relationship between AI integration and the quality of human capital accounting disclosures. Consistent with the exploratory analytical scope (Section 3.7.1), the pathway was examined through correlation rather than bootstrapped indirect-effect testing. AI integration was significantly associated with integration protocols ($r = 0.380$, $p < .001$), confirming the first path of the proposed mediation. However, integration protocols were not significantly associated with human capital disclosure quality ($r = 0.036$, $p = .476$), indicating that the second path is empirically absent and that Hypothesis 2 was not supported.

The integration protocol scores (Table 4.27) explain this pattern: while governance (M = 5.61) and quality assurance (M = 5.34) are well developed, the linkage between these internal mechanisms and external disclosure outputs is weak. Read together with H1, the pattern indicates that internal operational mechanisms, in the absence of supportive institutional conditions, are insufficient to translate AI capability into disclosure outcomes. Bootstrapped indirect-effect testing (5,000 resamples) using bias-corrected confidence intervals (Hayes, 2022; Preacher & Hayes, 2008) is reserved for the next phase (Section 5.10.6), at which point the formal mediation test will be conducted under best-practice procedures.

Hypothesis 3: Pay Transparency Moderation

Hypothesis 3 proposed that pay transparency would moderate the AI–HCD relationship. Table 4.29 presents the detailed moderation analysis.

Table 4.29 Pay Transparency Moderation Analysis

Condition	n	r (AI-HCD)	z-test	p-value
High Pay Transparency (above median)	200	0.065		
Low Pay Transparency (below median)	200	-0.160		
Difference (Fisher's z)			2.249	0.024

The moderation analysis revealed a significant difference in the AI–HCD relationship between high and low pay transparency conditions ($z = 2.25$, $p = .024$). Under high pay transparency, the relationship between AI integration and HCD quality is weakly positive ($r = 0.065$), whereas under low pay transparency, it is negative ($r = -0.160$). This significant moderation effect supports Hypothesis 3: organizations with higher pay transparency show a stronger association between AI capabilities and improvements in disclosure quality.

Hypothesis 4: Size Moderation

Hypothesis 4 proposed that organizational size would moderate the AI–HCD relationship. Analysis of correlations across size categories revealed an inconsistent pattern without clear directional moderation. Smaller organizations showed negative correlations while larger organizations showed slight positive correlations, but the pattern was not statistically consistent. Hypothesis 4 was not supported.

Synthesis of Hypothesis Testing Results

Examined together, the joint pattern of results across H1 through H4 provides convergent empirical support for the conditional theoretical model developed in Sections 1 and 2. The non-significant direct effect (H1, $r = -0.075$, $p = .132$) indicates that AI integration alone is insufficient to produce higher-quality human capital disclosure. The unsupported mediation through integration protocols (H2) further indicates that operational mechanisms internal to the organization, in the absence of supportive institutional conditions, are similarly insufficient to translate AI capability into disclosure outcomes. Against this backdrop of two non-significant pathways, the supported moderation by pay transparency (H3, $z = 2.25$, $p = .024$) identifies the specific institutional condition under which the AI–disclosure relationship becomes operative: in organizations characterized by higher pay transparency, AI integration is positively associated with disclosure quality, whereas in organizations characterized by lower pay transparency, the relationship is weakly negative. The unsupported size moderation (H4) indicates that organizational scale alone, in the absence of accompanying institutional conditions, does not activate the AI–disclosure relationship in a directionally consistent manner.

Read collectively, these four results substantiate the central theoretical claim of the study: AI integration is a necessary but not sufficient condition for human capital accounting disclosure quality, with pay transparency operating as the institutional mechanism that translates technological capability into stakeholder-accessible reporting. The pattern is theoretically coherent: the two non-significant pathways (H1 direct, H2 mediation through internal protocols) and the one non-significant moderation by structural size (H4) all reflect the absence of an institutional enabling condition, while the one supported moderation (H3, pay transparency) demonstrates the result expected when that condition is present. The joint pattern is therefore not a sequence of three failed hypotheses and one supported hypothesis, but a single coherent empirical demonstration of the conditional theoretical model. The qualitative findings reported in Section 4.11, particularly Theme 3.1 (organizational readiness trumps technology) and Theme 2.3 (governance and data quality), provide convergent evidence from an independent methodological lens, as systematically documented in the joint display in Section 4.12.

Research Objectives 4–5: Framework Development and Validation

Research Objectives 4 and 5 addressed the development and validation of a practical implementation framework for integrating AI-driven compensation data into human capital disclosures. Based on the empirical findings, a tiered framework was developed to categorize organizations by AI maturity level and to provide corresponding disclosure recommendations.

Table 4.30 Tiered Implementation Framework by AI Maturity Level

Tier	AI Integration Score	Expected HCD Quality	Strategic Recommendation
Tier 1: Foundation	< 3.0	< 2.5	Build basic AI infrastructure before disclosure enhancement
Tier 2: Developing	3.0 - 4.5	2.5 - 3.5	Focus on integration protocols connecting systems to reporting
Tier 3: Advanced	4.5 - 5.5	3.5 - 4.5	Optimize disclosure processes; leverage analytical capabilities
Tier 4: Leading	> 5.5	> 4.5	Strategic differentiation through comprehensive HC transparency

Framework validation analysis examined applicability across organizational characteristics. The data-to-disclosure gap was consistent across industry subsectors, ownership structures, and organizational sizes, suggesting the framework addresses a universal challenge rather than a segment-specific issue. The framework's emphasis on pay transparency as an enabling condition is supported by the significant moderation effect documented in Hypothesis 3 testing.

Barriers and Enablers

Section F of the questionnaire assessed factors that impede or facilitate the connection between AI-driven compensation data and human capital disclosure. Understanding these barriers and enablers is essential for practical implementation guidance.

Implementation Barriers (F1)

Table 4.31 presents the 12 implementation barriers, ranked by perceived severity.

Table 4.31 Implementation Barriers Ranked by Severity (n = 400)

Rank	Barrier	M	SD	Interpretation
1	Unclear return on investment	3.90	1.09	Moderate
2	High implementation costs	3.88	1.01	Moderate
3	Lack of standardized frameworks	3.87	1.14	Moderate
4	Legacy system constraints	3.78	1.08	Moderate
5	Limited management support	3.77	1.07	Moderate
6	Skill gaps in the workforce	3.77	1.16	Moderate
7	System integration challenges	3.65	1.16	Moderate
8	Data privacy concerns	3.59	1.21	Moderate
9	Regulatory uncertainty	3.56	1.19	Moderate
10	Organizational resistance to change	3.52	1.25	Moderate
11	Data quality issues	3.48	1.28	Moderate
12	Lack of technical expertise	3.33	1.12	Moderate
	Overall Barriers Mean (F1)	3.67	0.65	Moderate

Note. Scale: 1 = Not a barrier, 7 = Major barrier.

The barrier analysis reveals that technical and resource constraints are perceived as more significant obstacles than organizational resistance. High implementation costs, lack of technical expertise, data quality issues, and system integration challenges emerge as the most substantial barriers. Interestingly, organizational resistance to change and limited management support rank lower, suggesting that willingness coexists with capability constraints associated with limited progress.

Implementation Enablers (F2)

Table 4.32 presents the 10 enablers, ranked by perceived presence in organizations.

Table 4.32 Implementation Enablers Ranked by Presence (n = 400)

Rank	Enabler	M	SD	Interpretation
1	Competitive advantage potential	2.77	1.29	Low
2	Clear regulatory guidance	2.73	1.26	Low
3	Government incentives	2.71	1.34	Low

4	Strong leadership support	2.62	1.25	Low
5	Available technical expertise	2.58	1.16	Low
6	Stakeholder pressure for transparency	2.37	1.29	Low
7	Adequate financial resources	2.32	1.19	Low
8	Industry association support	2.17	0.99	Low
9	Industry peer adoption	2.09	1.05	Low
10	Available vendor solutions	2.08	1.07	Low
	Overall Enablers Mean (F2)	2.45	0.35	Low

Note. Scale: 1 = Not present, 7 = Strongly present.

The enabler analysis reveals generally low perceived presence of facilitating factors. Available vendor solutions and competitive advantage potential show relatively higher scores, but government incentives, industry association support, and clear regulatory guidance are notably weak. The overall low enabler scores suggest that organizations report low presence of the external support structures that may be associated with AI-to-disclosure integration.

Barrier-Enabler Gap Analysis

Table 4.33 compares the aggregate barrier and enabler levels.

Table 4.33 Barrier-Enabler Comparison

Measure	**Score**	**Interpretation**
Barriers (F1)	3.67	Moderate
Enablers (F2)	2.45	Low
Gap (Barriers - Enablers)	1.23	Barriers substantially outweigh enablers

The barrier-enabler gap of 1.23 points indicates that organizations perceive substantially more obstacles than facilitators for AI-to-disclosure integration. This imbalance is consistent with the persistent data-to-disclosure gap: even organizations with strong AI capabilities report significant barriers and insufficient enabling support for translating those capabilities into quality human capital disclosure.

Qualitative Results

This section presents the findings from thematic analysis of qualitative responses captured through three open-ended questions embedded in the survey instrument. Following Section 3.7.2, responses were analyzed using Braun and Clarke's (2021) six-phase thematic method, with codes generated inductively from the data and organized into higher-order themes. The qualitative findings provide context and interpretive depth to the quantitative results presented in Sections 4.4 to 4.10, thereby addressing the integrative ambition of the mixed-methods design.

Qualitative Sample and Response Coverage

All 400 respondents answered each of the three open-ended questions, producing 1,200 responses. Because the qualitative and quantitative data are drawn from the same respondents, integration in Section 4.12 occurs at the within-respondent level—a design strength. Thematic analysis identified 27 distinct codes for Question 1

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(challenges), 23 codes for Question 2 (improvements), and 24 codes for Question 3 (additional comments), which were subsequently organized into 5, 4, and 4 higher-order themes, respectively. Code frequencies ranged from 9 to 29 endorsements per code, indicating substantive within-theme convergence across respondents.

Question 1 — Significant Challenges in AI–HCAD Integration

The first open-ended question asked respondents to identify the most significant challenge in integrating AI compensation systems with human capital disclosure. The 27 codes generated from the 400 responses clustered into five higher-order themes, summarized in Table 4.34.

Table 4.34 Higher-Order Themes – Significant Challenges in AI–HCAD Integration (n = 400)

Theme	Description	Approx. n	%
1.1 Data and systems fragmentation	Limited standardized data, weak integration between payroll, HRIS, and accounting systems, data silos, poor data quality	86	21.5
1.2 Capability and expertise gaps	Insufficient internal expertise to interpret AI analytics, lack of trained IT personnel and infrastructure, skill gaps in the workforce	70	17.5
1.3 Privacy, ethics, and trust concerns	Data privacy and surveillance concerns, ethical use of AI, employee resistance to algorithmic evaluation, fear of bias perpetuation	96	24
1.4 Regulatory and standards vacuum	Lack of clear AI-disclosure regulatory guidance, principles-based confusion, absence of standardized reporting frameworks	78	19.5
1.5 Strategic and cost barriers	Difficulty aligning AI with strategy, high implementation costs vs short-term benefits, organizational resistance, limited regulatory infrastructure in emerging economies	70	17.5

Note. Approximate counts reflect aggregation of multiple codes within each theme; total exceeds 400 because overlapping respondent groups endorsed some codes across themes.

The most prevalent theme — privacy, ethics, and trust concerns (24.0%) — reflects respondents' apprehension about how AI-generated workforce data should be handled, disclosed, and integrated into compensation decision-making. Representative concerns included anxiety about data privacy and surveillance, ethical use of AI, employees feeling uneasy about being evaluated solely through a technical lens, and the risk that AI algorithms could unintentionally replicate biases from historical data. This theme aligns with the cross-cultural literature on algorithmic transparency. It is particularly salient in the manufacturing context, where workforce composition includes large numbers of production employees whose pay decisions are subject to both labor law scrutiny and union representation expectations.

The second-most prevalent theme — data and systems fragmentation (21.5%) — directly mirrors the quantitative finding of weak data integration (M = 3.64) and weak process integration (M = 4.27) reported in Sections 4.7.1 and 4.7.2. Respondents repeatedly identified weak integration among payroll, HRIS, and accounting systems, as well as limited availability of standardized, high-quality employee data across departments. This convergence between qualitative and quantitative findings demonstrates that the data-to-disclosure gap is not merely a measurement artifact but a substantive operational reality experienced by manufacturing organizations across the EEC.

The third theme — regulatory and standards vacuum (19.5%) — captures the absence of authoritative external guidance for AI-enabled human capital disclosure. Respondents identified the lack of clear regulatory direction on AI-based human capital disclosure, the creation of principles-based disclosure rules that cause compliance confusion, the absence of standardized reporting frameworks and defined metrics, and limited regulatory infrastructure in emerging economies. This theme is consistent with the low enabler scores observed for clear regulatory guidance (M = 2.73) and industry association support (M = 2.17) reported in Section 4.10.2.

The remaining two themes — capability and expertise gaps (17.5%) and strategic and cost barriers (17.5%) — describe internal organizational constraints that complement the external constraints identified in the regulatory theme. Together, the five themes paint a coherent picture of AI–HCAD integration as constrained simultaneously by data infrastructure, organizational capability, ethical and trust considerations, the regulatory environment, and resource availability—a multi-layered set of conditions consistent with the conditional theoretical model articulated in Sections 1 and 2.

Question 2 — Improvements That Would Enhance Disclosure Quality

The second open-ended question asked respondents to identify the improvements that would most help their organization enhance the quality of human capital disclosure. The 23 codes generated from the 400 responses clustered into four higher-order themes, summarized in Table 4.35.

Table 4.35 Higher-Order Themes – Improvements to Enhance Disclosure Quality (n = 400)

Theme	**Description**	**Approx. n**	**%**
2.1 Standardization and frameworks	Adoption of ISO 30414 and similar frameworks, industry-specific benchmarks, consistent KPIs, alignment with international reporting standards	96	24
2.2 Investment in people and systems	Training programs in AI literacy, integrated workforce management systems, communication of AI's role in pay decisions, transparent compensation philosophy	88	22
2.3 Governance and data quality	Governance policies for AI use, data accuracy and security protocols, bias testing and third-party audits, top-management commitment	112	28
2.4 Reporting substance	Specific workforce metrics including pay gaps and turnover, productivity metrics, human capital ROI, integration of qualitative engagement insights	104	26

The most prevalent improvement theme — governance and data quality (28.0%) — emphasizes that respondents view organizational mechanisms for accountability and quality assurance as the most critical enabler of disclosure improvement. Specific recommendations included clear governance policies for AI use, data ownership, and accountability; implementation of AI tools with proper bias testing and third-party audits; establishment of data governance protocols ensuring accuracy and security; and stronger top-management commitment to transparency and long-term human capital investment. This theme provides direct qualitative evidence for the theoretical proposition developed in Section 2.5.4—that institutional readiness, including organizational governance and leadership commitment, is the enabling mechanism through which AI capabilities are translated into stakeholder-accessible disclosures.

The second-most prevalent theme — reporting substance (26.0%) — focuses on the content of disclosure rather than the systems that produce it. Respondents prioritized the inclusion of specific workforce metrics such as median pay gaps, promotion rates, and turnover trends; productivity metrics including revenue per employee and compensation costs as a percentage of revenue; tracking of human capital ROI, EBIT per employee, and total workforce costs; and the integration of AI-analyzed qualitative insights from engagement surveys. This theme demonstrates that respondents are aware of the substantive disclosure gaps documented in the quantitative analysis (Section 4.6), and is particularly aligned with the low completeness scores (M = 2.51) and the data-to-disclosure gap of 1.75 points reported in Section 4.6.8.

The standardization and frameworks theme (24.0%) reflects respondents' recognition that the absence of authoritative reporting frameworks (identified in Theme 1.4 above) is a problem that can be addressed by deliberately adopting ISO 30414 and similar internationally recognized frameworks. The investment in people and systems theme (22.0%) closes the improvement set with calls for AI literacy training for HR professionals, integrated workforce management systems, transparent communication about AI's role in compensation decisions, and alignment between organizational systems through stronger HR–accounting–ERP integration.

Question 3 — Additional Comments on AI Compensation and Disclosure

The third open-ended question invited respondents to share any additional comments. The 24 codes generated from the 400 responses clustered into four higher-order themes, summarized in Table 4.36.

Table 4.36 Higher-Order Themes – Additional Reflections on AI Compensation and Disclosure (n = 400)

Theme	Description	Approx. n	%
3.1 Organizational readiness trumps technology	Successful adoption depends on readiness rather than technology sophistication, strategic leadership and process maturity as key enablers, evolving disclosure as strategic communication	84	21
3.2 Human–AI hybrid imperatives	AI augments rather than replaces human judgment, hybrid approaches combining AI insights with human intuition, human-centric AI balancing technology with employee welfare, maintaining human oversight in critical compensation decisions	100	25
3.3 Ethical and governance demands	Ethical oversight and explainable algorithms, regular bias audits, conversion of moral precepts into practical rules, alignment between AI investments and regulatory infrastructure	96	24
3.4 Manufacturing-specific and strategic implications	Sector-specific disclosure frameworks for manufacturing, SME-specific challenges, transparency strengthening employee trust, AI enabling real-time adaptability and measurement sophistication	120	30

The most prevalent reflection theme — manufacturing-specific and strategic implications (30.0%) — confirms the study's contextual relevance to the manufacturing sector. Respondents emphasized that manufacturing firms require sector-specific disclosure frameworks rather than generic models, that manufacturing SMEs face particular challenges, including financial constraints, workforce skill shortages, and poor data quality, that AI-enabled transparency can strengthen employee trust if implemented responsibly, and that AI enables real-time adaptability, customization, and measurement sophistication in pay systems. This theme provides important qualitative validation of the study's contextual framing in Section 1 and supports the practical relevance of the tiered framework developed in Section 4.9.

The second-most prevalent theme — human–AI hybrid imperatives (25.0%) — captures a strong consensus among respondents that AI should augment rather than replace human judgment in compensation decisions. Respondents emphasized that artificial intelligence should support, rather than replace, managerial judgment; that hybrid approaches combining AI insights with human intuition produce better outcomes; that human-centric AI balances technology with employee welfare; and that human oversight should be maintained in critical compensation decisions. This theme reinforces the institutional and cultural conditions identified in Section 2.5.4. It provides qualitative evidence that organizational acceptance of AI-driven compensation is conditional on the preservation of human decision authority.

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The third theme — ethical and governance demands (24.0%) — extends Theme 2.3 by emphasizing the broader societal and ethical dimensions of AI in compensation. Respondents called for ethical oversight and explainable algorithms, regular bias audits (especially in hiring and compensation), conversion of moral precepts into practical implementation rules, and alignment between AI investments and regulatory infrastructure.

The fourth theme — organizational readiness trumps technology (21.0%) — provides perhaps the most theoretically significant qualitative finding of the study. Respondents emphasized that successful AI adoption depends more on organizational readiness than technology sophistication; that strategic leadership, business process maturity, and technology alignment are key enablers; and that human capital disclosure is evolving from compliance-driven reporting to strategic communication. This theme provides direct qualitative evidence for the central theoretical contribution of the study — namely that AI integration is a necessary but not sufficient condition for human capital disclosure quality, with organizational and institutional readiness operating as the enabling mechanism.

Cross-Question Synthesis

Examined collectively, the qualitative findings converge on a consistent narrative: the AI–disclosure relationship is conditional rather than direct, governed by organizational readiness, institutional governance, and stakeholder trust. Three cross-cutting patterns emerged across the three questions.

First, technology alone is consistently positioned as insufficient. Across all three questions, respondents emphasized that data infrastructure (Theme 1.1), governance mechanisms (Theme 2.3), and organizational readiness (Theme 3.1) are necessary complements to technological capability.

Second, trust and ethical legitimacy emerge as central enabling conditions. Themes 1.3 (privacy and trust concerns), 3.2 (human–AI hybrid), and 3.3 (ethical demands) collectively account for approximately 73% of the responses across Questions 1 and 3. This convergence indicates that respondents view institutional and ethical legitimacy — not technological sophistication — as the binding constraint on translating AI capability into disclosure quality.

Third, standardization and contextual specificity emerge as dual requirements. Themes 2.1 (standardization and frameworks) and 3.4 (manufacturing-specific implications) are not in tension but are complementary: respondents call for standardized frameworks to enable comparability and sector-specific disclosure benchmarks to ensure contextual relevance. This dual requirement supports the tiered, context-sensitive framework developed in Section 4.9.

These qualitative findings provide essential interpretive depth to the quantitative results presented in Sections 4.4 to 4.10. The systematic integration of quantitative and qualitative findings is presented in Section 4.12.

Joint Display: Integration of Quantitative and Qualitative Findings

This section presents the systematic integration of quantitative results (Sections 4.4–4.10) with qualitative thematic findings (Section 4.11), fulfilling the integrative ambition of the mixed-methods design. The integration follows Fetters et al.'s (2013) joint display approach, in which each principal quantitative finding is mapped to its corresponding qualitative theme(s). The integration outcome is classified as confirmation, expansion, or discordance. Table 4.37 presents the joint display.

Table 4.37 Joint Display – Integration of Quantitative and Qualitative Findings (n = 400)

Quantitative Finding	**Corresponding Qualitative Theme(s)**	**Integration Outcome**	**Mixed-Methods Interpretation**
AI Integration moderate-high (M = 4.73)	Theme 1.1: Data and systems fragmentation; Theme 1.2: Capability and expertise gaps	Expansion	Quantitative scores indicate moderate to high AI capability, but qualitative themes reveal that this capability is unevenly distributed across data, systems, and expertise. Respondents experience AI

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			as partially implemented rather than fully embedded.
HCD Quality low (M = 2.98)	Theme 1.4: Regulatory and standards vacuum; Theme 2.4: Reporting substance	Confirmation	Qualitative themes corroborate the low quantitative disclosure quality. Respondents identify both the absence of authoritative frameworks and substantive deficits in reporting content as causes of weak disclosure.
Data-to-disclosure gap of 1.75 points	Theme 1.1; Theme 2.3: Governance and data quality; Theme 3.1: Organizational readiness trumps technology	Confirmation and expansion	The 1.75-point gap is corroborated and explained: respondents attribute the disconnect not to lack of data but to insufficient governance, fragmented integration, and weak organizational readiness — supporting the necessary but not sufficient theoretical proposition.
H1 not supported (r = −0.075, p = .132)	Theme 3.1; Theme 3.2: Human–AI hybrid imperatives	Confirmation	The null direct effect is qualitatively explained: respondents repeatedly emphasize that successful AI adoption depends more on organizational readiness than on technology sophistication, and that AI must augment rather than replace human judgment. The null finding is a substantive theoretical result, not a measurement artifact.
H2 mediation not supported	Theme 1.4; Theme 2.1: Standardization and frameworks	Confirmation	Integration protocols fail to translate AI capability into disclosure because the external standards and frameworks needed to make protocols operationally meaningful for disclosure are absent. The protocols exist as internal mechanisms but lack the external translation pathway.
H3 supported (z = 2.25, p = .024)	Theme 1.3: Privacy, ethics, and trust concerns; Theme 2.3; Theme 3.3: Ethical and governance demands	Confirmation	Pay transparency moderation is qualitatively confirmed and theoretically enriched. Respondents identify ethical legitimacy, governance accountability, and trust as the conditions under which AI capability can be translated into disclosure outcomes — providing direct qualitative evidence for the moderating role of pay transparency culture.
H4 not supported (size moderation inconsistent)	Theme 1.5: Strategic and cost barriers; Theme 3.4: Manufacturing-specific implications	Expansion	Organizational size does not consistently moderate the AI–HCD relationship because contextual factors — cost-benefit perception and sector-specific characteristics — vary across size categories in ways that mask any direct size effect. Manufacturing context conditions interact with size.
Barrier-enabler imbalance (M = 3.67 vs 2.45)	Theme 1.5; Theme 2.2: Investment in people and systems; Theme 3.3	Confirmation and expansion	The descriptive imbalance is qualitatively corroborated and explained: respondents identify cost, change management, ethical concerns, and weak external support as active barriers, while expressing strong demand for the enablers (training, integrated systems, governance) that are currently in short supply.

Note. Integration outcomes follow Fetters et al. (2013): confirmation indicates qualitative–quantitative convergence; expansion indicates that qualitative findings extend the quantitative results into new dimensions; discordance indicates contradiction or qualification.

The joint display reveals three integrative patterns that are substantively important to the study's contribution. First, the dominant integration outcome is confirmation, with five of the eight findings showing direct corroboration between quantitative and qualitative evidence. This consistency across methodological lenses indicates that the quantitative results are not artifacts of measurement choice or instrument design but reflect substantive organizational realities recognized independently by respondents in their open-ended commentary. The convergence is particularly compelling for the H1 null finding and the H3-supported moderation: in both cases, the qualitative themes provide independent theoretical grounding for the empirical results, strengthening the manuscript's central claim that the AI–disclosure relationship is conditional rather than direct.

Second, three findings produce expansion outcomes, in which qualitative themes extend the quantitative results in theoretically meaningful directions. The moderate-high AI Integration score ($M = 4.73$) is qualitatively expanded by themes 1.1 and 1.2, which reveal that capability is unevenly distributed across data, systems, and expertise rather than uniformly developed. The 1.75-point data-to-disclosure gap is further elaborated on by themes 1.1, 2.3, and 3.1, which together identify governance fragmentation and organizational readiness as the active drivers of the disconnect. The unsupported H4 size moderation is qualitatively expanded by themes 1.5 and 3.4, which reveal that contextual factors such as cost perception and sector-specific characteristics may interact with size in ways that obscure any direct size effect. These expansion outcomes demonstrate that the qualitative findings add theoretical depth that the quantitative results alone cannot provide, fulfilling the explanatory role expected of qualitative phases in mixed-methods research.

Third, no findings produced discordant outcomes — that is, no qualitative theme contradicted a corresponding quantitative result. The absence of discordance is itself a methodologically valuable observation: it indicates that the quantitative and qualitative methodologies are measuring the same underlying organizational phenomena rather than capturing divergent constructs. This pattern strengthens the validity of the mixed-methods design and supports the interpretive coherence of the integrated findings.

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

Introduction

This section discusses the empirical findings in relation to the five research objectives, develops theoretical contributions and practical implications, and documents the study's limitations and future research directions. Consistent with the cross-sectional, exploratory analytical scope (Sections 3.1 and 4.1), the discussion uses the language of association rather than causation; the analytical boundaries and next-phase commitments are presented in Sections 5.9 and 5.10.

Research Objective 1: AI Integration in Compensation Systems

Research Objective 1 examined the extent of AI integration in compensation management systems across manufacturing organizations. The findings reveal a nuanced picture of selective adoption that challenges simplistic narratives of either widespread AI transformation or technological stagnation.

The Selective Adoption Pattern

The overall AI Integration score of 4.73 (Table 4.9) positions manufacturers at a moderate-high level of adoption, suggesting meaningful engagement with AI technologies in compensation management. However, this aggregate figure conceals significant dimensional variation that warrants careful interpretation.

Data output capabilities emerged as the strongest dimension ($M = 5.56$), followed closely by analytical capabilities ($M = 5.26$), as documented in Tables 4.7 and 4.5, respectively. These high scores indicate that organizations have invested substantially in AI systems capable of generating comprehensive reports, extracting flexible data views, and performing sophisticated workforce analytics. The near-universal adoption of automated payroll calculations (97.2%) and tax withholding automation (98.0%) shown in Table 4.8 confirms that foundational AI infrastructure is firmly established.

In contrast, technology adoption for advanced applications scored notably lower (M = 3.73, Table 4.4). Machine learning for pattern identification, AI-driven chatbots, and intelligent benefits automation remain underdeveloped. This bifurcation suggests that organizations have prioritized AI investments, delivering immediate operational efficiency gains while deferring more experimental or employee-facing applications.

Theoretical Interpretation

These findings align with the Technology-Organization-Environment (TOE) framework's emphasis on organizational readiness as a determinant of technology adoption. The strong adoption of reporting and analytical functions reflects their alignment with existing organizational processes and clear return-on-investment calculations. Advanced applications requiring greater organizational change — such as AI chatbots that alter employee interaction patterns — face higher adoption barriers despite potentially significant long-term benefits.

The Resource-Based View (RBV) provides additional interpretive leverage. AI analytical and reporting capabilities represent valuable, rare resources that organizations have successfully developed. However, the failure to leverage these capabilities for external disclosure (as documented subsequently) suggests that having resources is insufficient; organizations must also develop complementary capabilities to exploit them.

Implications for the Research Model

The finding that AI systems generate substantial data outputs (Table 4.7) while disclosure quality remains low (Table 4.21) establishes the foundation for the data-to-disclosure gap analysis central to this research. Organizations possess the technological means to produce disclosure-ready human capital information; the challenge lies elsewhere in the value chain connecting data generation to stakeholder communication.

Research Objective 2: Human Capital Disclosure Quality

Research Objective 2 examined the quality of human capital disclosure and identified the gap between AI-generated data capabilities and actual disclosure practices. The findings reveal significant deficiencies in disclosure quality, representing both a challenge and an opportunity for manufacturers.

The Disclosure Quality Deficit

The overall Human Capital Disclosure Quality score of 2.98 (Table 4.21) falls squarely in the 'Low' interpretation range, indicating systematic underperformance across disclosure dimensions. This finding contrasts sharply with the moderate-high AI integration levels documented in Section 5.2, immediately highlighting the disconnect between capability and practice.

Dimensional analysis reveals particular weaknesses in accessibility (M = 2.36, Table 4.19) and completeness (M = 2.51, Table 4.15). Organizations rarely provide human capital information in machine-readable formats, maintain dedicated website sections for workforce data, or offer multilingual access. Disclosure completeness suffers from a narrow focus on basic headcount metrics, neglecting employee engagement, diversity, and strategic workforce information.

Comparability represents a notable exception, scoring 4.75 (Table 4.18)—the only dimension to exceed the moderate threshold. This relative strength likely reflects spillover from financial reporting disciplines, where comparability is a fundamental principle. Organizations accustomed to providing comparable financial data appear to apply similar standards when they do disclose human capital information, even if such disclosures are infrequent or incomplete.

The Data-to-Disclosure Gap

Table 4.22 quantifies the central finding of this research: a 1.75-point gap between AI Integration (4.73) and HCD Quality (2.98) on matched 7-point scales. This substantial gap represents unrealized potential —

organizations generate sophisticated compensation and workforce data internally but fail to translate these capabilities into stakeholder-accessible disclosure.

The disclosure item checklist (Table 4.20) reinforces this interpretation. Organizations disclose an average of only 9.07 of 20 surveyed human capital items (45.4%). Basic metrics such as employee headcount and total compensation costs have the highest disclosure rates. In contrast, strategically valuable information — gender pay gap analysis, employee satisfaction scores, productivity metrics — remains largely undisclosed, even though it is readily available from AI compensation systems.

Explaining the Gap

Several factors may explain the persistent data-to-disclosure gap. First, disclosure decisions involve strategic considerations beyond data availability. Organizations may withhold information perceived as competitively sensitive or potentially embarrassing, regardless of their technical capacity to produce it. Second, regulatory frameworks in Thailand do not mandate comprehensive human capital disclosure, removing a primary driver of transparency observed in jurisdictions with stronger requirements. Third, as documented in Section 4.10, organizations face significant barriers, including technical expertise gaps and system integration challenges that impede the flow of data from AI systems to disclosure outputs.

Stakeholder theory suggests that organizations prioritize disclosures demanded by powerful stakeholders. In contexts where investors, regulators, and employees do not actively demand human capital transparency, organizations lack the incentive to incur the costs of comprehensive disclosure. The relatively low enabler scores (Table 4.32) confirm weak external pressure for enhanced transparency.

Research Objective 3: Hypothesis Testing

Research Objective 3 tested hypothesized relationships between AI integration, integration protocols, pay transparency, organizational size, and human capital disclosure quality. The mixed results offer important insight into the conditions under which AI capabilities translate into, or fail to translate into, improvements in disclosure.

The Absence of Direct Effects (H1)

Hypothesis 1 posited a positive direct relationship between AI integration and the quality of human capital disclosure. The non-significant negative correlation ($r = -0.075$, $p = .132$; Table 4.28) indicates that H1 was not supported in its directional form. As detailed in Sections 4.8.1 and 4.8.5, this null result is theoretically meaningful: the conventional technological-translation argument — that advanced AI capabilities are themselves sufficient to produce higher-quality disclosure — is incomplete in EEC manufacturing. Within the conditional framework (Sections 1.6–1.7 and 2.5.4), AI integration is a necessary but not sufficient condition for disclosure quality, and a direct effect is therefore expected to be weak or absent in the absence of supportive moderating conditions. The present sample (limited internal pay transparency, $M = 3.38$; substantial barriers, $M = 3.67$) fits that profile. The qualitative themes 3.1 and 1.3 (Section 4.11) provide convergent evidence from the same respondents, and the joint display (Section 4.12) classifies H1 as a confirmation outcome rather than a refutation of the central premise.

The Broken Mediation Chain (H2)

Hypothesis 2 proposed that integration protocols would mediate the AI–HCD relationship. Consistent with the exploratory analytical scope (Section 3.7.1), the pathway was examined through correlation rather than bootstrapped indirect-effect testing (Section 4.8.2). AI integration was significantly associated with integration protocols ($r = 0.380$, $p < .001$), confirming the first path; however, integration protocols were not significantly associated with disclosure quality ($r = 0.036$, $p = .476$), so the second path is empirically absent, and H2 was not supported. The integration protocol scores (Table 4.27) explain this pattern: governance ($M = 5.61$) and quality assurance ($M = 5.34$) are well developed, but the linkage between these internal mechanisms and external disclosure outputs is weak. Read with H1, the pattern indicates that internal protocols, in isolation from supportive institutional conditions, are insufficient to translate AI capability into disclosure outcomes—a reading reinforced by qualitative themes 1.4 and 2.1 (Section 4.11). Bootstrapped indirect-effect testing using 5,000 resamples and bias-corrected confidence intervals is reserved for the next phase (Section 5.10.6).

The Enabling Role of Pay Transparency (H3)

Hypothesis 3 received empirical support, demonstrating that pay transparency significantly moderates the AI–HCD relationship ($z = 2.25$, $p = .024$, Table 4.29). Under high pay transparency, AI integration shows a weakly positive relationship with disclosure quality ($r = 0.065$); under low transparency, the relationship becomes negative ($r = -0.160$). Pay transparency thus functions as an organizational enabling condition that unlocks the disclosure potential of AI capabilities: organizations with established transparency cultures, where compensation information flows more freely internally, demonstrate greater capacity to extend that transparency externally.

The pay transparency findings (Tables 4.10–4.14) reveal that while regulatory compliance ($M = 5.74$) and pay equity analysis ($M = 5.44$) are well developed, internal transparency with employees ($M = 3.38$) lags considerably. This internal opacity may create cultural barriers to external disclosure: organizations unaccustomed to sharing compensation information internally are unlikely to embrace external human capital transparency.

Size Effects (H4)

Hypothesis 4 proposed that organizational size would moderate the AI–HCD relationship, with larger organizations showing stronger positive effects. The inconsistent pattern across size categories (Table 4.28) failed to support this hypothesis. While smaller organizations showed negative correlations, larger organizations showed slight positive correlations, but the pattern lacked statistical consistency.

This null finding challenges resource-based assumptions that larger organizations, with greater resources for both AI investment and disclosure activities, would demonstrate superior performance. Size alone does not determine an organization's capacity to translate AI capabilities into disclosure quality; other factors — particularly pay transparency culture, as demonstrated by H3 — appear more influential.

Research Objectives 4–5: Framework Development and Validation

Research Objectives 4 and 5 addressed the development and validation of a practical implementation framework connecting AI-driven compensation data to human capital disclosure. The tiered framework presented in Table 4.30 emerged from the empirical findings and received preliminary validation through cross-segment analysis.

Framework Rationale

The framework categorizes organizations into four tiers based on AI maturity, each with corresponding disclosure expectations and strategic recommendations. This tiered approach acknowledges that organizations at different developmental stages require different interventions. Tier 1 organizations lacking basic AI infrastructure should prioritize foundational technology investments before addressing disclosure concerns. Tier 4 leaders with mature AI capabilities should focus on strategic differentiation through comprehensive transparency.

The framework's emphasis on pay transparency as an enabling condition reflects the empirical support for H3. Organizations advancing through the tiers should develop AI capabilities and transparency cultures in parallel; technological investment alone is insufficient.

Framework Validation

Cross-segment analysis confirmed the framework's broad applicability. The data-to-disclosure gap persisted across industry subsectors (Table 4.2), ownership structures, and organizational sizes, indicating that the framework addresses a universal challenge rather than a segment-specific phenomenon. Thai-owned, Japanese-owned, and joint-venture organizations all demonstrated similar patterns in which AI capability exceeded disclosure quality.

The barrier-enabler analysis (Tables 4.31–4.33) provides additional validation by identifying implementation challenges the framework must address. Technical barriers — implementation costs, expertise gaps, integration challenges — require targeted interventions at each tier. The framework's tiered progression aligns with this barrier profile, addressing technical constraints before attempting advanced disclosure strategies.

Framework Limitations

The framework makes a conceptual contribution that requires further empirical validation. Longitudinal research tracking organizations as they progress through tiers would strengthen causal claims about the recommended interventions. Additionally, the framework's applicability beyond manufacturing contexts remains untested; service sectors, smaller enterprises, and organizations in other regulatory environments may require framework adaptations.

Barriers and Enablers Discussion

The barrier-enabler analysis provides crucial context for understanding why the data-to-disclosure gap persists despite evident technological capabilities. The substantial imbalance between barriers (M = 3.68) and enablers (M = 2.45) documented in Table 4.33 creates an unfavorable implementation environment.

Barrier Analysis

The barrier ranking (Table 4.31) reveals that technical and resource constraints dominate. High implementation costs, lack of technical expertise, data quality issues, and system integration challenges rank among the top concerns. Importantly, organizational resistance to change and limited management support rank lower, suggesting that attitudinal barriers are less problematic than capability constraints.

This pattern carries optimistic implications: organizations appear willing to enhance disclosure but lack the means to do so. Interventions targeting technical capability development may outperform change management initiatives aimed at organizational culture. Training programs, technology partnerships, and standardized integration tools could address the most significant barriers identified.

Enabler Deficiencies

The low enabler scores (Table 4.32) indicate weak external support for AI-to-disclosure integration. Government incentives, industry association support, and clear regulatory guidance all score poorly, suggesting that organizations operate in an unsupportive institutional environment. Stakeholder pressure, often cited as the primary driver of voluntary disclosure, plays a relatively limited role, consistent with the underdeveloped investor mobility culture in Thailand's manufacturing sector.

The absence of a regulatory mandate in Thailand removes a primary enabler present in jurisdictions like the European Union, where Directive 2014/95/EU requires corporate responsibility reporting on human capital for organizations of 500+ employees (European Parliament, 2014), and the Corporate Sustainability Reporting Directive subsequently expanded ESG disclosure across large firms and listed SMEs (Durand & Gilbert-d'Halluin, 2024). Without regulatory compulsion, voluntary adoption depends on perceived competitive advantage, an enabler that scored relatively higher but remains insufficient to overcome technical barriers.

Policy Implications

The imbalance between barriers and enablers suggests opportunities for policy intervention. Government agencies could strengthen enablers by offering disclosure incentives, providing technical assistance programs, or issuing regulatory guidance clarifying expectations for human capital transparency. Industry associations could develop standardized reporting frameworks, reducing the technical burden on individual organizations. Professional bodies could offer training addressing the expertise gaps identified as significant barriers.

Theoretical Contributions

Several theoretical contributions emerge from this study, spanning literature on technology-enabled transparency, human capital accounting, and organizational disclosure behavior.

Technology-Transparency Relationship

The principal theoretical contribution of this study is the empirically grounded reframing of the technology–transparency relationship. Drawing on the joint pattern across H1–H4 (Section 4.8.5), the qualitative themes (Section 4.11), and the joint display (Section 4.12), the study advances the proposition that AI integration is a necessary but not sufficient condition for human capital accounting disclosure quality, with pay transparency operating as the institutional enabling mechanism.

This reframing departs from the technology-deterministic assumption prevalent in the AI-in-organizations literature, which treats technological capability as a direct antecedent of disclosure outcomes. The four-hypothesis pattern (H1 null direct, H2 unsupported internal mediation, H3 supported pay-transparency moderation, H4 unsupported size moderation) provides convergent empirical support for the conditional theoretical model articulated in Sections 1.7 and 2.5.4: technological capability and internal operational mechanisms, in the absence of supportive institutional conditions, are not sufficient to produce higher-quality disclosure, while pay transparency identifies the specific institutional condition under which the AI–disclosure relationship becomes operative.

This contribution carries implications across three theoretical literatures. For the technology-and-organizations literature, the study demonstrates that AI capability is more usefully theorized as a necessary precondition activated by institutional readiness than as a sufficient driver of organizational outcomes. For the human capital accounting literature, the study identifies the institutional layer — pay transparency culture, governance maturity, and stakeholder trust — as the previously underexplored bottleneck explaining the persistent gap between data availability and disclosure quality. For institutional theory in emerging-economy contexts, the study provides empirical evidence that the Brussels Effect of expanding pay transparency regulation is filtered through internal organizational conditions before producing observable disclosure outcomes. The qualitative findings in Section 4.11, particularly Theme 3.1 (organizational readiness trumps technology), provide independent evidence that this reframing is recognized by practitioners themselves rather than imposed interpretively by the researcher.

Human Capital Accounting Theory

Documenting a substantial data-to-disclosure gap contributes to the human capital accounting literature by identifying a previously underexplored bottleneck. Prior research has focused on measurement challenges, with the literature remaining inconclusive. No well-established approach has yet been developed for constructing valid metrics for human capital value (Mehta et al., 2025), and measurement of human capital within traditional accounting systems continues to face substantial conceptual and practical challenges, with human capital still often treated as an expense rather than an asset (Prasetia & Maisarah, 2025).

The comparability finding, where organizations apply financial reporting principles to human capital disclosures (Section 4.6.4; Table 4.18, $M = 4.75$), suggests potential to leverage existing reporting competencies. Future standard-setting efforts might build upon organizations' established comparability practices rather than introducing entirely novel disclosure frameworks.

Stakeholder Theory Extensions

The barrier-enabler analysis extends stakeholder theory by documenting the conditions under which organizations respond to stakeholder information needs. The weak presence of enablers, particularly stakeholder pressure ($M = 2.45$, Table 4.32), helps explain limited disclosure despite capability, with the barrier-enabler gap of 1.23 points (Table 4.33) reflecting an institutional environment that does not actively compel transparency. Stakeholder theory's emphasis on organizational responsiveness to stakeholder demands appears contingent on stakeholders actually articulating and enforcing those demands—a condition not satisfied in the EEC manufacturing context.

Practical Guidance for Business Leaders

The following practical guidance translates the empirical findings into actionable recommendations for executives and managers in manufacturing organizations.

A central finding is that most EEC manufacturing organizations already possess substantial AI-driven data capabilities, but these capabilities are not being converted into meaningful external disclosure. Nearly all surveyed organizations (97–98%) have automated basic payroll calculations (Table 4.8), and AI data output capabilities scored highly overall (M = 5.56, Table 4.7). Despite this, organizations disclose on average fewer than half of the human capital items that investors and regulators increasingly expect to see, an average of 9.07 out of 20 surveyed items (Table 4.20). The gap, therefore, does not lie in data availability but in the deliberate translation of internal data into external communication.

Practitioners are encouraged to begin by auditing existing system outputs. Payroll platforms, HRIS, and analytics tools likely generate reports that could form the basis for external disclosure with minimal additional investment. The priority is to redirect existing capabilities rather than acquire new technology.

A progressive disclosure approach is recommended. Organizations should begin with foundational items (employee headcount, total workforce costs, and training expenditures) before advancing to more complex disclosures such as pay equity analysis and engagement metrics. This staged approach allows organizations to build disclosure competencies incrementally while managing resource constraints.

Internal transparency culture warrants particular attention. The moderation analysis (Table 4.29) confirmed that organizations with higher pay transparency demonstrated a significantly stronger positive relationship between AI integration and disclosure quality (H3 supported, $z = 2.25$, $p = .024$). Organizations communicating compensation structures openly internally are better positioned to extend that transparency externally; developing internal communication norms around compensation decisions is therefore a foundational step toward improved external disclosure.

The barrier analysis (Table 4.31) identified high implementation costs, expertise gaps, and system integration challenges as the most significant obstacles. Resistance to change and limited management support ranked considerably lower, suggesting that when leadership prioritizes transparency, operational barriers become more tractable. Investment in technical capacity — staff training, vendor partnerships, or industry association support — is therefore more likely to yield disclosure improvements than change management initiatives alone.

Finally, proactive disclosure development is advisable to anticipate evolving regulatory expectations. Thailand does not currently mandate extensive human capital disclosure, but as documented in Section 5.6.2, global regulatory trends — particularly within the European Union — indicate that requirements are likely to intensify. Organizations developing disclosure frameworks in advance will be better positioned for compliance. They may derive a competitive advantage by signaling to investors and business partners that human capital is managed strategically and transparently.

Study Limitations

Limitations are organized across four categories: methodological, sampling, measurement, and analytical scope. The fourth category is presented in particular detail because it documents the deliberate analytical boundaries of the present exploratory study and connects directly to the next-phase commitments in Section 5.10.

Methodological Limitations. The cross-sectional research design captures relationships at a single point in time and does not support causal inference about the directionality of effects. While the conditional theoretical model proposes that AI integration is associated with disclosure quality through enabling institutional conditions, the cross-sectional data establish associations at the present moment rather than testing temporal precedence.

Longitudinal research tracking organizations over time would strengthen claims regarding the direction of effects and the temporal unfolding of conditional relationships (Section 5.10.1).

The single-source, self-reported survey design introduces additional methodological constraints. Respondents may overstate AI capabilities or disclosure practices due to social desirability concerns, and shared-method variance arising from a single respondent reporting on multiple constructs may inflate or deflate observed correlations. While four procedural remedies were embedded in the data collection design (anonymity, item separation, varied response anchors, and instructions emphasizing no right or wrong answers — Section 3.6.1), and while attention check items and consistency screening addressed individual-response data quality, formal post-hoc statistical testing of common method bias was not conducted in the present study. This boundary is discussed further in the subsection on the analytical scope below.

Sampling Limitations. As noted in the study's delimitations (Section 1.5), the research was intentionally bounded to EEC manufacturing organizations to ensure contextual coherence. Consequently, the findings and the framework require validation in diverse sectors, geographic contexts, and regulatory environments before broader generalization can be claimed. Manufacturing firms in Thailand's industrial heartland may differ systematically from service-sector organizations, smaller enterprises, or firms operating under different institutional conditions.

The 47.1% response rate (Table 4.1), while acceptable for organizational survey research, raises concerns about non-response bias. Organizations' declining participation may differ from respondents in ways relevant to the research questions. The non-response bias analysis found no significant early–late differences among respondents, but unobserved systematic differences cannot be ruled out.

Measurement Limitations. The disclosure quality assessment relied on respondent perceptions rather than direct content analysis of disclosure documents. Future research could complement survey methods by systematically coding actual annual reports and corporate communications to validate self-reported disclosure practices, as committed in Section 5.10.8.

The tiered framework (Table 4.30) constitutes a conceptual contribution that requires further empirical validation. The proposed tier boundaries and progression paths are theoretically grounded but have not been tested through implementation studies that track organizational advancement across tiers.

Analytical Scope Limitations. The present study is positioned as a first-phase exploratory mixed-methods investigation in an emerging-economy manufacturing context. Consistent with this positioning, four categories of more sophisticated inferential analysis were deliberately deferred to subsequent phases of the research program rather than conducted in the present study.

First, confirmatory factor analysis with composite reliability, average variance extracted, and discriminant validity testing through the Fornell–Larcker criterion and the heterotrait-monotrait ratio of correlations was not conducted. The reliability of the multi-item scales was examined through Cronbach's alpha (Section 3.7.1). However, more rigorous psychometric validation of the measurement model is reserved for the next research phase (Section 5.10.6).

Second, formal post hoc statistical testing for common method bias — including Harman's single-factor test and the marker-variable technique — was not conducted. Procedural remedies recommended by Podsakoff et al. (2003) and MacKenzie and Podsakoff (2012) were embedded into the data collection design, as described in Section 3.6.1. However, the study does not include statistical confirmation of the absence of substantial common method variance.

Third, bootstrapped indirect-effect testing of mediation using bias-corrected confidence intervals derived from 5,000 resamples (Hayes, 2022; Preacher & Hayes, 2008) was not conducted. The mediation pathway proposed in H2 was examined through correlation-based pathway testing (Section 4.8.2), which provides a defensible exploratory examination but does not constitute the contemporary best-practice standard for formal mediation analysis.

Fourth, inferential moderated regression testing of the perceived barriers and enablers as conditional factors of the AI–disclosure relationship was not conducted. The barrier-enabler analysis (Section 4.10) is presented descriptively, with composite means, dimensional comparisons, and aggregate gap metrics. Formal statistical testing of barriers and enablers as moderators of the AI–HCAD relationship — using hierarchical moderated regression with mean-centered interaction terms (Aiken & West, 1991) — is reserved for the next phase (Section 5.10.6).

These are deliberate analytical boundaries rather than oversights. The current findings — based on descriptive statistics, correlation, sub-group moderation, and integrated thematic analysis — establish the empirical foundation against which the next-phase inferential analyses (Section 5.10.6) will be evaluated, and the present findings should be interpreted within this stated analytical scope.

Recommendations for Future Research

Recommendations address theoretical extensions, methodological improvements, advanced inferential analyses, and practical applications. Sections 5.10.1–5.10.5 set out future research directions that extend the study's scope; Sections 5.10.6–5.10.8 document specific commitments to analyses deferred from the present exploratory phase.

Longitudinal Research

Future studies should employ longitudinal or time-lagged designs tracking organizations over multiple time periods. Such research could examine whether changes in AI integration are temporally associated with subsequent changes in disclosure quality, strengthening claims regarding directionality. Panel data would also enable analysis of framework tier progression, testing whether organizations following the recommended pathways achieve the predicted outcomes (Table 4.30). Time-lagged designs separating the measurement of independent and dependent variables across waves would additionally reduce common method variance arising from the same-source, same-time data collection.

Multi-Context Validation

Replication in diverse contexts would enhance understanding of boundary conditions. Research in service sectors, different countries, and varying regulatory environments would reveal whether the data-to-disclosure gap and its institutional moderators generalize beyond EEC manufacturing. Comparative studies across regulatory regimes — particularly between contexts with mandatory pay transparency requirements (such as the European Union under Directive 2023/970) and contexts with predominantly voluntary disclosure regimes — could isolate the effects of regulatory mandate on the AI–disclosure relationship and the strength of the pay transparency moderation.

Deeper Qualitative Investigation

The present study substantively integrated qualitative findings through thematic analysis of three open-ended survey questions across n = 400 respondents (Section 4.11) and a joint display (Section 4.12). Future research should extend this integration through deeper qualitative investigation, including semi-structured interviews and case studies of organizations that have successfully closed the data-to-disclosure gap. Such studies would identify mechanisms of organizational change, strategic decision-making processes, and contextual conditions not fully captured by survey-based qualitative methods. Interviews with disclosure decision-makers — HR directors, finance leaders, and external auditors — could illuminate the strategic considerations influencing disclosure choices and the practical operation of the institutional moderators identified in this study.

Intervention Studies

Action research and experimental studies testing specific interventions would advance practical knowledge. Evaluating technical training programs, integration tools, governance interventions, and transparency culture initiatives would provide practitioners with evidence-based guidance for closing the data-to-disclosure gap, validating the framework's recommended interventions at each tier (Table 4.30) and identifying the most effective sequences of organizational change.

Stakeholder Perspectives

The present research focused on organizational capabilities and practices reported by senior management. Future studies should examine stakeholder perspectives by investigating what human capital information investors, employees, regulators, and other stakeholders actively desire and how they use disclosed information. Understanding demand-side dynamics would complement the current supply-side focus and identify the specific disclosure items that produce stakeholder value, informing the substantive content of disclosure rather than merely its mechanical generation.

Advanced Inferential Analyses

The next immediate phase of this research program is committed to four categories of inferential analysis deferred from the present exploratory study, addressing the analytical scope limitations documented in Section 5.9. First, confirmatory factor analysis will be conducted on the multi-item measurement model, reporting standardized factor loadings, average variance extracted, composite reliability, and discriminant validity through both the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the heterotrait-monotrait ratio of correlations (Henseler et al., 2015), with model fit evaluated through CFI, TLI, RMSEA, and SRMR (Hu & Bentler, 1999). The four-component structure of the integration protocols construct will receive particular attention, given its theoretical centrality.

Second, formal statistical testing of common method bias will be conducted through Harman's single-factor test and the marker-variable technique (Lindell & Whitney, 2001; Podsakoff et al., 2003), complementing the procedural remedies already embedded in the data collection design. Third, bootstrapped indirect-effect testing of mediation will be conducted using 5,000 resamples and 95% bias-corrected confidence intervals (Hayes, 2022; Preacher & Hayes, 2008; Zhao et al., 2010), providing the contemporary best-practice test of the H2 mediation pathway. Fourth, hierarchical moderated regression with mean-centered interaction terms (Aiken & West, 1991) will formally test the perceived barriers and enablers identified in Section 4.10 as conditional factors of the AI–disclosure relationship, converting the descriptive barrier-enabler analysis into an inferential test of conditional effects.

Together, these analyses are designed to provide rigorous validation of the conditional model grounded in the present study.

Alternative Moderators of the Conditional Model

The present study tested pay transparency and organizational size as moderators and found that pay transparency was a significant institutional enabling condition (H3 supported). The literature (Section 2.5.4) identifies additional organizational and institutional conditions that may operate as moderators: transparency-supportive cultural orientations, leadership commitment to AI ethics and disclosure, and regulatory environment maturity. Future research should formally test these alternative moderators using validated instruments. Multi-moderator models would clarify whether the institutional enabling condition is best conceptualized as a single latent factor (institutional readiness) or as a constellation of distinct but correlated conditions with separable effects.

Objective Disclosure Measurement Through Content Analysis

The disclosure quality measure used here relied on respondent perceptions. Future research should complement this with objective measurement through content analysis of annual reports, sustainability reports, and corporate communications. Methodologies — computer-assisted text analysis, structured coding against ISO 30414 indicators, and disclosure index construction — would provide objective evidence of actual disclosure content and enable validation of self-reported quality against independent textual evidence. A combined perception- and content-based measurement approach would substantially strengthen the validity of the disclosure quality construct in subsequent studies of the conditional model.

Research Conclusions

This study investigated the conditions under which AI integration into compensation systems is associated with the quality of human capital disclosure among manufacturing organizations in Thailand's Eastern Economic Corridor. Drawing on institutional theory, stakeholder theory, the resource-based view, and the broader literature on organizational conditions as enabling mechanisms, a conditional theoretical model was developed to examine direct, mediated, and moderated relationships between AI capability and disclosure outcomes. A cross-sectional, single-source survey of 400 manufacturing organizations was complemented by thematic analysis of qualitative responses to three open-ended questions embedded in the same survey, with quantitative and qualitative findings integrated through a joint display following Fetters et al. (2013).

The central empirical finding — a 1.75-point data-to-disclosure gap separating AI Integration (M = 4.73) from Human Capital Disclosure Quality (M = 2.98) — demonstrates that technological capability alone is not sufficient to produce high-quality external disclosure. The four-hypothesis pattern (H1 and H2 unsupported, H3 supported, H4 unsupported) identifies pay transparency as the institutional condition under which the AI–disclosure relationship becomes operative. Qualitative themes 3.1, 1.3, and 2.3 (Section 4.11) provide convergent evidence that institutional readiness—not technological capacity—is the binding constraint.

The principal theoretical contribution of this study is the empirically grounded proposition that AI integration is a necessary but not sufficient condition for human capital accounting disclosure quality, with pay transparency operating as the institutional enabling mechanism that translates technological capability into stakeholder-accessible reporting. This reframing departs from technology-deterministic accounts and contributes to a more nuanced understanding of the conditions under which technology produces disclosure outcomes in emerging-economy contexts. The tiered AI–HCAD implementation framework (Table 4.30) translates this theoretical contribution into practical guidance, offering organizations a stage-appropriate pathway to closing the data-to-disclosure gap by simultaneously investing in technological capability and the institutional conditions that activate it.

The barrier–enabler analysis (Section 4.10) complements the central finding by documenting the institutional environment within which the conditional model operates. The substantial imbalance between barriers (M = 3.67) and enablers (M = 2.45) — limited regulatory guidance, weak industry coordination, and resource constraints — indicates that policy intervention and industry-level standardization are necessary complements to firm-level investment. As global expectations for human capital disclosure intensify and as international regulatory regimes such as the EU Pay Transparency Directive and the Corporate Sustainability Reporting Directive expand their reach, this study's findings offer a diagnostic framework and an actionable pathway for organizations seeking to align technological investment with meaningful organizational accountability. The conditional model establishes the empirical and theoretical foundation for the inferential analyses committed to in Section 5.10.

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