

Accountability Mechanisms in AI Projects: An Empirical Analysis of Governance, Performance Control, Delivery, and Misconduct Management

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Abstract—Artificial intelligence (AI) projects create significant opportunities but also raise complex accountability challenges due to system autonomy, opacity, and multi-stakeholder involvement. While accountability is widely recognized in AI governance, limited research has examined how it is operationalized within project environments. This study addresses this gap by identifying and empirically examining accountability mechanisms in AI projects. Drawing on project governance and AI governance literature, accountability is conceptualized as a system of interrelated mechanisms embedded within project organizations. Survey data from AI project practitioners are used to examine how accountability mechanisms cluster and how their use is influenced by system autonomy, project experience, and organizational role distribution. The results identify 18 accountability mechanisms, operationalized through 23 measurement items, and structured into four accountability dimensions: *directing the project*, *controlling performance*, *managing delivery*, and *treating misconduct*. A key contribution is the identification of *treating misconduct* as a distinct accountability dimension that is not represented in major project governance standards and extends accountability beyond project execution to the investigation, remediation, and management of harmful outcomes. The findings further show that system autonomy selectively increases the use of delivery and misconduct-related mechanisms, while foundational governance mechanisms remain stable. Experience is positively associated with all accountability dimensions, indicating that accountability mechanisms become more prevalent as organizations accumulate AI project experience. The study contributes an empirically grounded framework of accountability mechanisms in AI projects and demonstrates that effective accountability requires mechanisms not only for governance and control but also for addressing the downstream consequences of AI system behavior.

Index Terms—Artificial Intelligence, AI Projects, Accountability Mechanisms, AI Governance, Project Governance, Reviewability, Transparency, Explainability, Risk Management, Stakeholder Engagement

I. INTRODUCTION

ARTIFICIAL INTELLIGENCE (AI) is increasingly recognized as a general-purpose technology comparable to transformative innovations such as the internet, personal computers, the steam engine, and electricity [1]. Recent advances, particularly in generative AI applications such as ChatGPT, have demonstrated the ability to enhance performance in tasks that were previously unaffected by digital technologies. Estimates suggest that AI could contribute between 0.4–0.9 percentage points to labor productivity growth [1, p. 10], while the global AI market is projected to grow from approximately

\$235 billion to more than \$631 billion by 2028 [2]. As AI systems become increasingly embedded in organizational processes and decision-making, the scale of their economic and societal impact amplifies the importance of governance and accountability.

Despite these benefits, AI systems introduce significant risks. They can cause harm ranging from minor to severe or even lethal, whether intentional or unintentional [3]. Decisions made during AI development are therefore high stakes, as they shape system behavior and potential societal impact. Even systems designed to be unbiased and technically robust may be deployed in harmful ways [4]. These concerns elevate the importance of governance and accountability in AI projects.

Among ethical design principles, accountability is consistently identified as one of the most important by the public, surpassing fairness, privacy, security, and accuracy [5]. Accountability mechanisms—defined as the arrangements that govern actors’ behavior within stakeholder relationships [6]—are therefore critical in ensuring responsible AI development and deployment. However, while accountability is widely discussed at a conceptual and normative level, there is limited integrated understanding of how it is operationalized in practice within AI projects and how it is shaped by system characteristics and organizational context.

Existing research approaches accountability from several perspectives. AI governance literature emphasizes principles such as transparency, explainability, and responsibility, often framing accountability as a process involving justification, evaluation, and consequences [7, 8, 4]. More recent work conceptualizes accountability as a lifecycle-spanning property enabled through practices such as documentation, logging, auditing, and investigation, highlighting the importance of “reviewability” in complex socio-technical systems [9]. In parallel, project management literature conceptualizes accountability as embedded in governance structures, coordination mechanisms, and stakeholder relationships, emphasizing distributed and relational accountability across actors and organizations [10, 11, 12].

While these streams provide important insights, they remain largely disconnected. AI governance research tends to operate at a normative or institutional level, offering high-level principles but limited guidance for implementation within project environments. Conversely, project management research pro-

vides detailed insights into governance and coordination mechanisms but has only recently begun to address the specific challenges associated with AI systems. As a result, there is limited understanding of how accountability mechanisms are implemented and coordinated within AI projects.

This study addresses these gaps by moving beyond normative AI ethics and conceptual discussions to empirically examine how accountability is operationalized in AI projects. Specifically, it identifies a comprehensive set of accountability mechanisms, analyzes how these mechanisms cluster into functional dimensions, and investigates how their use is influenced by system autonomy, project experience, and organizational role distribution. The study is guided by the following research question:

Research Question: What accountability mechanisms are used in AI projects, and how are they influenced by system autonomy, project experience, and organizational role distribution?

To address this question, the study adopts a quantitative research design grounded in accountability theory. Accountability mechanisms identified through a structured literature review are operationalized into a survey instrument and analyzed using data collected from AI project practitioners.

Building on this approach, the study develops a meso-level perspective on accountability in AI projects. It conceptualizes accountability as a structured and lifecycle-spanning system of interrelated mechanisms embedded within project organizations. These mechanisms operate across interrelated dimensions of governance, performance control, delivery, and remediation. In this way, the study bridges the gap between high-level AI governance principles and project-level implementation by demonstrating how accountability is enacted in practice.

This study contributes to project governance and AI governance literature by identifying accountability mechanisms used in AI projects, revealing a four-dimensional accountability structure, introducing treating misconduct as a distinct accountability dimension, and examining how accountability varies according to system autonomy, project experience, and role distribution.

The remainder of the paper is structured as follows. The next section reviews the literature on AI projects and accountability to develop the theoretical framework and hypotheses. This is followed by a description of the methodology, including data collection and analysis procedures. The subsequent sections present the findings and discuss their implications. The paper concludes with contributions, limitations, and directions for future research.

II. LITERATURE REVIEW

A. Artificial Intelligence Projects

AI projects integrate technologies and methods from multiple disciplines to develop data-driven and algorithmic decision-making systems [13]. Unlike traditional IT projects, AI projects operate in environments characterized by data dependence, model uncertainty, evolving system behavior, and increasing regulatory oversight [14, 15, 16, 17]. Their

outcomes may affect individuals, organizations, and society, creating heightened demands for governance, transparency, and accountability [18, 19, 4]. These characteristics make accountability a particularly important consideration in AI project environments.

B. Accountability in AI Projects

AI systems function as artificial agents that can influence or guide human decision-making [20]. As decision authority is partially delegated to automated systems, questions arise regarding responsibility for outcomes. Prior research highlights persistent ambiguity in assigning accountability between developers, users, and organizations [3, 4]. This ambiguity may create a “moral buffer,” in which responsibility is diffused across actors and insufficiently assumed by any single party [21].

Despite these advances, the literature remains fragmented across levels of analysis. Ethical frameworks define what accountability should entail, governance studies outline structures for oversight, and project research explains how responsibilities are distributed in practice. However, there is limited understanding of how accountability is operationalized within AI projects as a set of concrete, interrelated mechanisms, and how these mechanisms vary across different project conditions.

C. Research Gap

While prior literature establishes the importance of accountability and identifies relevant principles and practices, it does not provide a systematic, empirically grounded understanding of accountability mechanisms within AI projects. As illustrated in Figure 1, existing research remains fragmented across ethical, governance, and project-oriented perspectives, with limited integration at the project level. In particular, there is insufficient insight into how accountability mechanisms are operationalized within AI projects and how their use varies across key project conditions, such as system autonomy, project experience, and the distribution of roles. This study addresses this gap by identifying accountability mechanisms used in AI projects, examining how they cluster into broader accountability dimensions, and analyzing how their use varies according to system autonomy, project experience, and role distribution.

III. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

A. Accountability Theory

This study adopts accountability theory to examine how accountability is operationalized in AI projects. Accountability is defined as a relationship between an actor and a forum in which the actor must explain and justify actions, and the forum can evaluate and impose consequences [27]. Accountability is task-specific and shaped by stakeholder expectations, contractual obligations, and governance structures [28, 10].

Accountability can be conceptualized either as a virtue or as a mechanism [6]. This study focuses on accountability as a mechanism, emphasizing the arrangements that structure

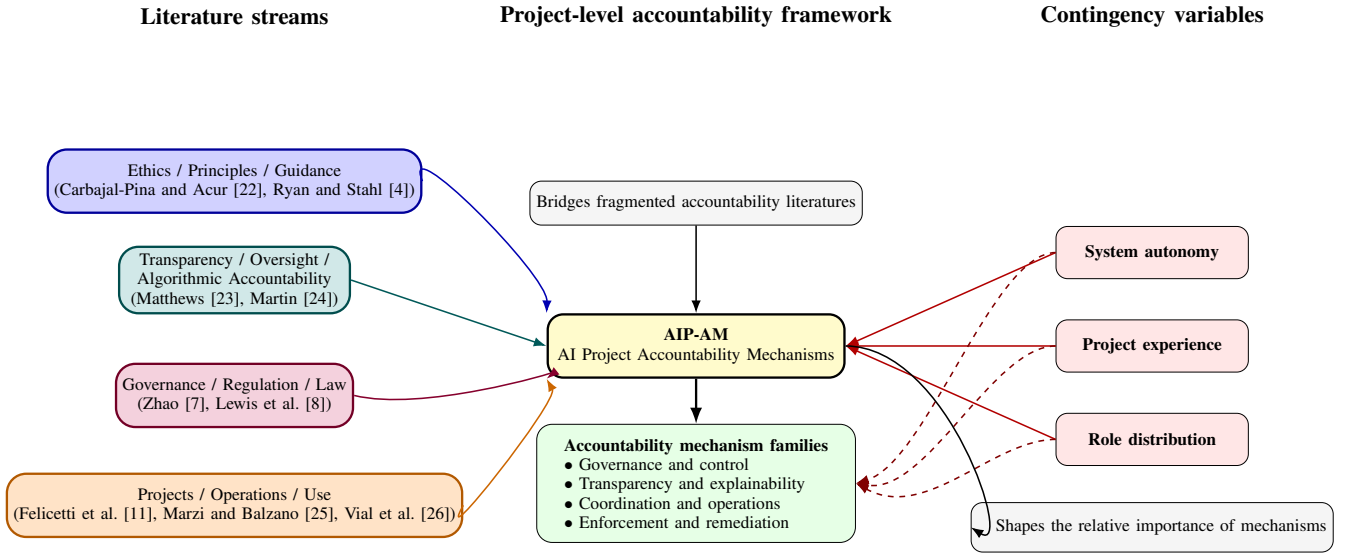


Figure 1. Integrated conceptual framework of the AI accountability literature and the positioning of AIP-AM (AI Project Accountability Mechanisms). The accountability mechanism families shown are literature-derived categories used to develop the survey instrument and inform the theoretical framework.

behavior within accountability relationships. These arrangements include information sharing, discussion, monitoring, and evaluation processes that connect actors and stakeholders.

Building on this perspective, accountability in AI projects is understood as an emergent property of a structured system of mechanisms rather than as a single practice or attribute.

The relevance and configuration of accountability mechanisms vary across project contexts. In particular, system autonomy influences the need for transparency and oversight, project experience affects the capability to implement accountability mechanisms, and organizational role distribution shapes how accountability is enacted across project stakeholders.

B. Accountability Mechanisms

Accountability in AI projects is not realised through isolated practices but through a system of interrelated mechanisms that structure how actors justify decisions, are evaluated, and are held responsible. Prior literature provides important insights into these mechanisms, particularly in ethics, governance, and project management research. However, these streams are rarely integrated into a unified, project-level framework.

This study adopts a structured view in which accountability mechanisms serve distinct but complementary functions within accountability relationships. These functions include (1) establishing expectations, (2) monitoring and explaining actions, (3) enabling coordination and decision-making, and (4) enforcing consequences and remediation.

Recent AI governance literature further extends this view by conceptualizing accountability as a lifecycle-wide property of socio-technical systems rather than a set of isolated mechanisms. The concept of “reviewability” emphasizes systematic record-keeping, logging, and documentation across all stages of the AI system lifecycle, enabling oversight, audit, and intervention [9]. This perspective highlights that accountability

depends not only on individual mechanisms, but on their integration across processes and organizational roles.

Based on the literature, a comprehensive set of accountability mechanisms relevant to AI projects was identified and is summarized in Table I. To provide analytical clarity, the mechanisms are grouped into four functional categories.

Governance and control mechanisms form the foundation of accountability systems. These include controlling, oversight, compliance, risk management, reporting, and formal structures, which ensure that project activities adhere to defined rules, standards, and objectives. These mechanisms are consistently emphasized across governance literature but are rarely examined within the context of AI project execution.

Transparency and explanation mechanisms enable actors to understand and justify decisions. Disclosure, auditing, and transparency provide visibility into processes and outcomes. While widely discussed in AI ethics and governance literature, their implementation within project environments remains underexplored.

Coordination and operational mechanisms support the day-to-day enactment of accountability. Alignment, delegation, capability building, artifact existence, and flexible operations enable coordination and responsibility distribution. These mechanisms are well established in project management literature but are rarely linked explicitly to AI accountability.

Enforcement and remediation mechanisms address failures and misconduct. Investigations and redress mechanisms ensure that harms are identified and addressed. These mechanisms are central in AI governance literature but less developed in project management contexts.

The mechanisms summarized in Table I provide the basis for examining how accountability is operationalized within AI projects. The extent to which these mechanisms are employed may vary according to project characteristics, including system autonomy, organizational experience, and the distribution of

project roles.

Table I
ACCOUNTABILITY MECHANISMS IN AI PROJECTS

<i>Governance and Control Mechanisms (Core Layer)</i>
Controlling [12, 29, 30, 6]: Formal monitoring to ensure adherence to operational norms
Overseeing (rules) [6, 12, 7]: Monitoring and enforcement through rules and governance practices
Overseeing (automated) : Using automated monitoring and validation to continuously assess system behavior [4, 8, 9]; an emerging AI-Specific mechanism
Compliance [6, 30, 31, 9]: Adhering to standards, policies, and procedures
Risk management [30, 12, 7, 9]: Establishing and executing risk management procedures
Reporting [6, 29, 30, 9]: Reporting performance against goals and other measures
Formal structure [12, 29, 30, 9]: Structuring roles, contracts, and stakeholder engagement
<i>Transparency and Explainability Mechanisms</i>
Disclosure (explain) [7, 9]: Providing information to understand and explain decisions
Disclosure (decision) [30, 7, 9]: Providing information to support decision-making
Transparency [23, 30, 7, 9]: Ensuring records and system capabilities are open to review
Auditing [6, 7, 12, 9]: Independent evaluation of compliance and system behavior
<i>Coordination and Operational Mechanisms</i>
Alignment [12, 32]: Aligning stakeholders for effective collaboration
Effective delegation (accountability) [29, 11, 9]: Ensuring actors are accountable for decisions and performance
Effective delegation (authority) [29, 30, 9]: Delegating authority appropriately across roles
Goal setting [12, 29]: Establishing shared performance objectives
Capability building [12, 11, 32]: Ensuring actors possess required skills and competencies
Artifact existence [30, 9]: Ensuring the existence of robust, traceable, and reviewable project artifacts
Approval [33, 12]: Approval and acceptance of work products or decisions
Flexible operations [32]: Enabling adaptive coordination and resource allocation
<i>Enforcement and Remediation Mechanisms (Ethical Layer)</i>
Investigations [6, 9]: Examining misconduct or uncovering hidden issues
Redress (report) [4, 23, 9]: Reporting misconduct or harmful outcomes
Redress (compensate) [4, 23]: Providing compensation or restitution for harm
Redress (fix causes) [4, 23, 9]: Addressing root causes to prevent recurrence

C. AI Project Scope and Roles

For this study, an algorithm is defined as a repeatable process based on data and assumptions, an AI system as a system that learns from data and supports or automates decision-making, and an AI project as a temporary organization that develops such systems. Autonomous AI systems are characterized by their ability to operate or learn with limited human intervention and by the potential opacity of their internal processes, consistent with regulatory definitions such as those in the EU AI Act [16].

In analysing accountability, it is essential to distinguish between *stakeholders*, *actors*, and *roles*, as these represent different levels at which accountability relationships are formed and enacted. Stakeholders comprise entities that influence or are affected by AI projects, while actors are those that actively participate in accountability relationships. Roles refer to the specific functional positions that actors assume within the project, such as project sponsor, project manager, and team member.

This distinction is critical because accountability mechanisms are enacted through roles that distribute authority, responsibility, and control. In AI projects, this distribution is

particularly important due to the interaction between human and algorithmic decision-making, which can blur traditional lines of accountability.

AI project stakeholders can be grouped into development, usage, and external stakeholders. Accountability mechanisms operate across these groups, linking roles through processes of reporting, oversight, explanation, and remediation [34]. As a result, accountability in AI projects is inherently distributed and multi-level, spanning organizational boundaries and extending beyond the project itself.

This distribution of roles is particularly relevant for understanding how accountability mechanisms are implemented in AI projects, as it shapes where and how responsibility is enacted.

D. Hypothesis Development

Building on the identified research gap, this study examines how accountability mechanisms vary across key dimensions of AI projects. Specifically, it considers the influence of system autonomy, project experience, and the distribution of roles on the deployment of accountability mechanisms. Based on the literature, the following hypotheses are proposed.

AI projects, particularly those involving autonomous systems, introduce higher levels of uncertainty and risk. Autonomous AI systems introduce higher levels of uncertainty and risk, which increase the need for governance and accountability arrangements. Therefore, it is expected that projects developing autonomous systems will employ more accountability mechanisms than those involving non-autonomous systems.

Hypothesis 1: AI projects that develop autonomous systems will exhibit greater use of accountability mechanisms than projects involving non-autonomous systems.

Experience in AI projects is likely to influence how accountability is enacted. Prior research suggests that project management capabilities, including coordination and problem-solving, develop with experience [32]. More experienced actors are therefore expected to deploy a broader set of accountability mechanisms.

Hypothesis 2: AI projects with higher levels of experience will exhibit greater use of accountability mechanisms.

Finally, accountability in projects is increasingly viewed as distributed across multiple actors rather than centralized in a single role. AI projects involve diverse stakeholders with different responsibilities and expertise. Given this distribution of tasks and knowledge, accountability mechanisms are expected to be implemented across multiple project roles rather than concentrated solely within management functions.

Hypothesis 3: Accountability mechanisms in AI projects will be distributed across multiple project roles rather than being exclusively associated with management roles.

IV. RESEARCH METHODOLOGY

A. Research Design

This study adopts a quantitative research design using survey data to examine how accountability mechanisms identified in the literature are applied in practice. The methodology aligns the theoretical framework with empirical evidence by

analyzing responses from individuals involved in AI projects. This section describes the data collection process, measurement instrument, and analytical methods.

B. Data Collection

Data were collected in November 2023 and November 2024 using two channels: a SurveyMonkey audience panel targeting respondents in the United States and a direct outreach to members of the Project Management Institute (PMI). SurveyMonkey provides access to a proprietary panel of respondents. For the PMI sample, a direct email invitation was sent to 3,000 randomly selected members, followed by a reminder after one week.

Participation was voluntary. Respondents provided informed consent, no personally identifiable information was collected, and no compensation was offered. Screening questions ensured that only individuals with roles in AI projects were included. A control question identified whether respondents had participated in both survey waves.

A total of 529 responses were initiated. Following screening, 158 respondents were excluded for reporting no AI project role, 71 for reporting no AI project experience, and 30 for failing validity checks. The final sample consisted of 270 usable responses. Demographic information is presented in Table A.3 in the Appendix.

C. Measurement Instrument

The measurement instrument was developed based on a structured literature review and thematic analysis. An initial set of 67 articles was reviewed, of which 31 were used to identify accountability mechanisms. These mechanisms informed the design of the survey instrument.

A three-stage validation process was applied. First, a content review ensured alignment with the theoretical framework. Second, a clarity and formatting review addressed typographical and structural issues. Third, an expert review was conducted with practitioners who had participated in at least three AI projects in the past ten years. This process resulted in refinements to improve clarity and relevance.

The survey instrument included definitions of algorithms, AI systems, and AI projects to ensure consistency in interpretation. Respondents self-identified their project role from predefined options based on [34]. For analysis, roles were aggregated into three actor groups: project sponsor, project manager, and project team.

Experience was measured as the number of projects completed during the previous ten years. This continuous variable was transformed into five groups using quartile-based binning (Table A.1).

Project scope was operationalized using respondent-selected characteristics of a reference AI project. A composite variable was constructed based on features such as autonomous decision-making, hidden system functionality, and limited human intervention.

Accountability mechanisms were measured using a set of survey items on a seven-point Likert scale ranging from 1

(*never*) to 7 (*always*), with an additional *not applicable* option. The survey operationalized 18 conceptual accountability mechanisms using 23 measurement items. Four mechanisms (*redress*, *overseeing*, *effective delegation*, and *disclosure*) were represented by multiple items to capture distinct operational forms and reflect their conceptual complexity. Respondents indicated the extent to which each accountability practice was used to demonstrate accountability to stakeholders. All measurement items were included in the factor analysis and reliability assessments to evaluate internal consistency and construct validity.

A count variable, *number mechanisms*, was constructed to represent the total number of accountability mechanism items reported as used by each respondent, with a maximum value of 23. This measure provides an indicator of the breadth of accountability practices employed within a project.

Control variables differed between the two data sources. The SurveyMonkey sample included demographic variables such as gender, age, and household income, while the PMI sample included certification information. Both samples included geographic data. Descriptive statistics for all variables are provided in the Appendix.

D. Analysis Methods

Statistical analyses were conducted using SAS Studio Release 3.8 (Basic Edition). Mean values of survey items were used to construct variables and composite measures. Descriptive statistics and mean rankings were used to summarize respondent characteristics and accountability mechanism usage.

Differences between groups were assessed using the Wilcoxon rank-sum test, with statistical significance evaluated at the 0.05 level. Correlation analysis was used to examine the strength and direction of relationships between variables. Multivariate analysis of variance (MANOVA) was employed to compare groups across multiple dependent variables and to evaluate the effects of AI system autonomy, project experience, and organizational role distribution on accountability dimensions.

To test Hypothesis 2, additional analyses were conducted to examine the relationship between project experience and accountability mechanisms. Spearman rank correlations were calculated between experience level and accountability factor scores to assess monotonic relationships. Polynomial trend analyses and linear contrasts within analysis of variance (ANOVA) were used to evaluate whether accountability mechanisms increased systematically across ordered experience groups.

Exploratory factor analysis was conducted to identify latent constructs and reduce dimensionality for both the accountability mechanism items and AI system autonomy measures. Principal component analysis (PCA) was selected in line with the exploratory objective of identifying underlying structures within the data. Following recommended practices for sample sizes slightly exceeding 200 observations, factor loadings of 0.40 or higher were retained [35].

Factors were retained using a combination of statistical and theoretical criteria, including eigenvalues greater than

1.0, scree plot inspection, cumulative explained variance, interpretability, and consistency with the study's conceptual framework. Because the objective was exploratory, factor retention was not based solely on the eigenvalue-greater-than-one criterion. Composite scores were computed by averaging the items loading on each retained factor.

To facilitate interpretation, orthogonal (varimax) rotation was initially applied to the accountability mechanism items to identify distinct dimensions with minimal overlap. Alternative factor solutions were evaluated by examining explained variance, factor loadings, cross-loadings, and conceptual coherence. The final factor structure was selected based on its statistical adequacy and theoretical interpretability.

The reliability and validity of the retained factors were evaluated using Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), inter-factor correlations, and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. As the study seeks to identify accountability mechanisms rather than validate a predefined measurement model, the resulting factor structure should be interpreted as exploratory and descriptive. Future research may further assess the stability of the factor structure using confirmatory factor analysis.

E. Reliability and Validity

A structured five-step procedure was followed to assess reliability and validity, including checking assumptions, deriving factors, evaluating model fit, interpreting factors, and constructing summated scales [35].

The study sample was constructed using demographic and professional information collected via SurveyMonkey and the Project Management Institute (PMI), leveraging established respondent verification and data quality procedures. Prior evaluations indicate that SurveyMonkey audience panels exhibit error rates statistically indistinguishable from those of established commercial research panels [36], supporting the reliability and validity of this sampling approach.

Data quality checks assessed response completeness, consistency, missing values, and response patterns indicative of low-quality data, including straight-lining (i.e., selecting the same response across Likert-scale items). Responses containing missing, invalid, or inconsistent entries in the open-text experience field were excluded (e.g., "none", "12300", "OK"). Additional screening was conducted for outliers and potential response bias across survey waves and data collection channels. A total of 30 responses failed one or more validity checks and were removed from the analysis.

Internal consistency and construct validity were assessed using Cronbach's alpha, average variance extracted (AVE), and construct reliability (CR). The results indicate acceptable to strong reliability, with Cronbach's alpha values ranging from 0.65 to 0.96, meeting or exceeding the recommended threshold of 0.60 for exploratory research. Convergent validity is supported, with AVE values ranging from 0.47 to 0.64, approaching or exceeding the commonly recommended threshold of 0.50, and construct reliability values exceeding 0.78. Taken together, these results indicate that the retained factor structure demonstrates adequate internal consistency and convergent validity for exploratory analysis.

Discriminant validity was assessed by comparing the AVE values with squared inter-construct correlations, confirming that the constructs are empirically distinct. The overall Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.96, indicating excellent suitability for factor analysis.

Common method variance was assessed using Harman's single-factor test. The first factor accounted for 35% of the variance, below the 50% threshold, indicating that common method bias is unlikely to be a concern. Although Harman's single-factor test has known limitations, the results do not indicate substantial common method variance.

Detailed reliability and validity statistics, including factor-level measures of Cronbach's alpha, AVE, CR, and descriptive statistics, are reported in Table A.2 in the Appendix.

V. DATA ANALYSIS AND RESULTS

This section presents the empirical results structured around the three hypotheses. First, factor analysis is used to identify the underlying dimensions of accountability mechanisms. Second, the hypotheses are tested by examining differences across project scope, experience, and project roles.

Mechanisms represent observable practices, while dimensions represent higher-order groupings identified through factor analysis.

A. Factor Structure of Accountability Mechanisms

Factor analysis of the accountability mechanism items resulted in a four-factor solution. This solution explains 77% of the total variance and provides a substantially clearer and more interpretable structure than the initial three-factor solution, with reduced cross-loadings and improved conceptual distinctiveness among factors. Although the three-factor solution satisfied the eigenvalue-greater-than-one criterion, the pattern of item loadings indicated that conceptually distinct accountability mechanisms were being combined into broader constructs, limiting interpretability. Consistent with recommendations that factor retention should consider both statistical and theoretical criteria, the four-factor solution was selected based on its explanatory power, interpretability, and alignment with the study's conceptual framework [35].

The naming of the resulting dimensions was informed by established project management standards, including *ISO 21502:2020 Project, Programme and Portfolio Management – Guidance on Project Management* [37], the Project Management Institute PMBOK® Guide [38], the Association for Project Management (APM) Body of Knowledge [39], and *Managing Successful Projects with PRINCE2®* [40]. The four dimensions are: *directing the project*, *controlling performance*, *treating misconduct*, and *managing delivery*. Figure 2 provides an integrated view of the accountability structure, illustrating the hierarchical relationships between factors and mechanisms.

The resulting factor structure is broadly consistent with the theoretical framework while also revealing important empirical refinements. Sixteen of the twenty-three measurement items load onto factors consistent with their literature-derived classifications, while seven load onto different factors. These differences suggest that accountability mechanisms are enacted

differently at the project level than implied by existing conceptual models and likely reflect the integration of accountability concepts originating from ethics, governance, and project management literatures into a common project context. Rather than operating as distinct theoretical constructs, some mechanisms appear to function as complementary practices within broader accountability dimensions when implemented in AI projects.

Three of the four dimensions align broadly with concepts found in the reviewed project management standards. In contrast, *treating misconduct* does not have a direct counterpart. While the standards include mechanisms for monitoring performance, reporting issues, conducting assurance activities, and implementing corrective actions, the items loading on this factor cluster around investigations, reporting harmful outcomes, remediation, compensation, and preventative measures. Therefore, the emergence of this factor represents a distinct empirical grouping that is not reflected as a standalone accountability construct in established project management frameworks.

Several mechanisms associated with oversight provide further evidence of the multidimensional nature of accountability. Oversight-related items were included in the survey without predefined categorization, yet the factor analysis shows that they load onto different dimensions rather than forming a single factor. This suggests that oversight is not a homogeneous accountability mechanism but is enacted through different practices depending on context, including governance, performance monitoring, delivery management, and misconduct remediation.

Overall, the empirically derived factor structure partially reconfigures the literature-based grouping while preserving its core conceptual foundations. For example, transparency loads within *controlling performance* rather than emerging as a separate factor, indicating that practitioners view transparency primarily as a mechanism for monitoring, reporting, and evaluating project activities.

Detailed validity and reliability statistics are reported in Table A.2 and Figure 2 reports the standardized factor loadings (λ) for the survey items.

B. Project Scope and Accountability Mechanisms

Hypothesis 1 proposes that AI projects developing autonomous systems will exhibit greater use of accountability mechanisms than projects involving non-autonomous systems.

Based on the project scope classification, 72.96% of respondents reported involvement in projects with autonomous features, including systems that act without human intervention (38.89%), learn from data without manual intervention (44.44%), or exhibit hidden internal functionality (32.59%). The remaining 27.04% reported non-autonomous projects.

H1 is supported. Projects involving autonomous AI systems report a statistically significant increase in the use of accountability mechanisms compared with projects involving non-autonomous systems ($H = 8.90$, $p < 0.001$). However, the effect is not uniform across accountability dimensions. While the overall increase in the number of mechanisms is relatively modest, significant differences emerge within spe-

cific dimensions, particularly *managing delivery* and *treating misconduct*.

The effect of autonomy, however, is selective rather than uniform. While the overall number of accountability mechanisms increases with autonomy, significant differences are concentrated within the *managing delivery* and *treating misconduct* dimensions. Autonomous AI projects place greater emphasis on capability building, artifact robustness, investigation, and redress mechanisms, reflecting the increased uncertainty and potential consequences associated with autonomous system behavior.

In contrast, no significant differences are observed for *directing the project* and *controlling performance*. Mechanisms such as goal setting, formal structures, compliance, and reporting appear to function as baseline governance practices that are applied consistently across AI projects regardless of autonomy level.

Overall, the results suggest that increasing autonomy does not fundamentally alter governance structures but instead increases reliance on accountability mechanisms that support operational adaptation, oversight of emergent behavior, and remediation of potential harms. Appendix Table A.5 presents the detailed comparisons by project scope; for consistency across analyses, group differences were assessed using rank-based tests, reported as Kruskal-Wallis statistics.

C. Experience and Accountability Mechanisms

Hypothesis 2 proposes that AI projects with higher levels of experience will exhibit greater use of accountability mechanisms.

To examine this relationship, respondents were grouped into five experience categories based on the number of AI projects completed. Differences in accountability mechanism use were analyzed using analysis of variance, followed by Spearman rank correlations and polynomial trend analyses.

The ANOVA results indicate significant differences across experience groups for all four accountability dimensions (Appendix Table A.8). These findings suggest that organizations with different levels of AI project experience employ accountability practices to different extents.

To assess whether accountability mechanisms increase systematically with experience, Spearman rank correlations and polynomial trend analyses were conducted. As shown in Tables A.7 and A.9, experience is positively associated with all four accountability dimensions. The trend analyses further indicate that this relationship is predominantly linear across dimensions, although *managing delivery* also exhibits evidence of a higher-order trend.

Collectively, these findings demonstrate that the use of accountability mechanisms increases as organizations accumulate AI project experience. The strongest relationship is observed for *managing delivery*, suggesting that experience particularly contributes to the development of operational capabilities, coordination practices, and delivery controls. Overall, the results indicate that organizational learning through repeated AI project execution supports the progressive adoption and institutionalization of accountability mechanisms. Accordingly, **H2 is supported.**

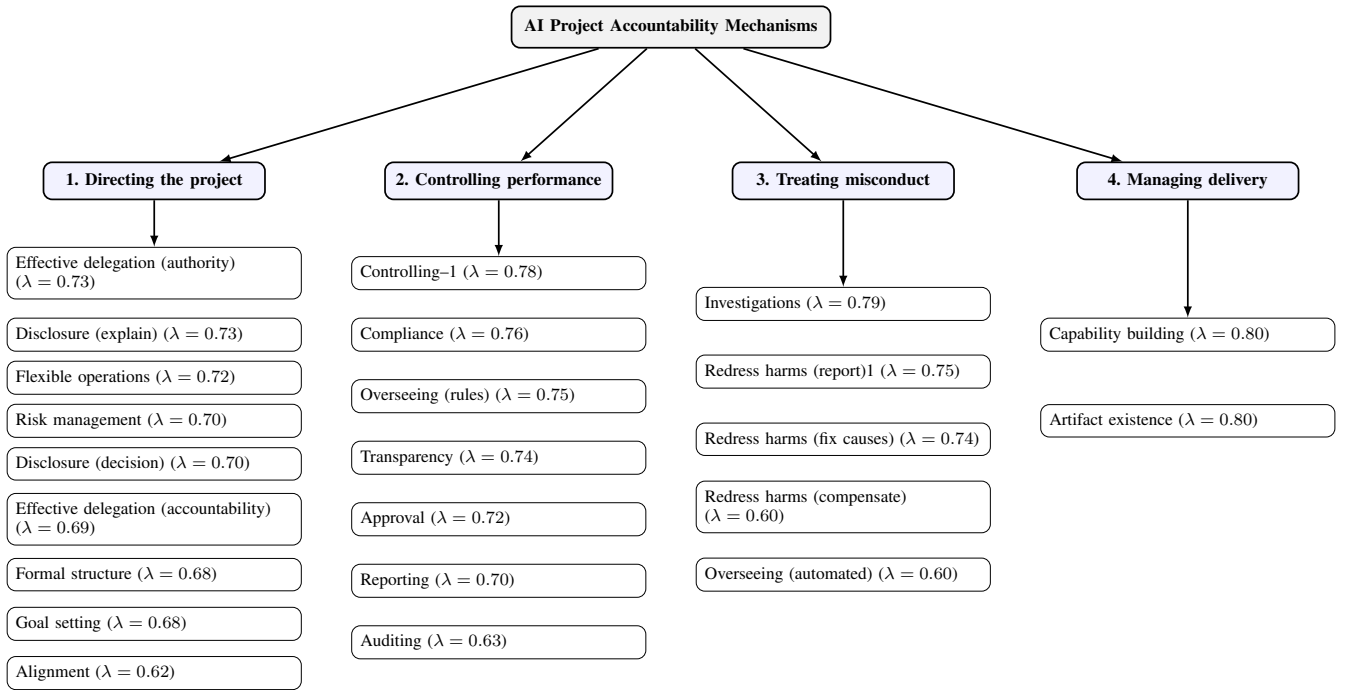


Figure 2. Hierarchical structure of accountability mechanisms. Solid lines indicate the hierarchy from accountability dimensions to retained mechanisms. Item nodes report standardized factor loadings (λ).

D. Project Roles and Accountability Mechanisms

Hypothesis 3 proposes that accountability mechanisms in AI projects are distributed across multiple project roles rather than being exclusively associated with management roles.

The sample includes 95 sponsors (35.19%), 102 project managers (37.78%), and 73 team members (27.04%). Analysis by project role reveals statistically significant differences across all accountability dimensions.

These differences reflect role-specific responsibilities. Sponsors and project managers place greater emphasis on *managing delivery*, while team members more strongly emphasize *controlling performance*. At the same time, all roles engage across multiple dimensions, indicating that accountability is broadly distributed rather than role-bound.

Across all roles, *treating misconduct* is the least emphasized dimension, suggesting that reactive mechanisms are less prominent than operational and governance practices.

The findings **support H3** by demonstrating that accountability mechanisms are distributed across roles and embedded within the project structure. Table A.6 provides detailed comparisons by project role.

E. Summary of Hypothesis Testing

The results support all three hypotheses. Autonomous AI projects employ more accountability mechanisms, with increases concentrated in specific dimensions. Accountability is distributed across project roles, reflecting differentiated responsibilities. Experience is positively associated with all accountability dimensions, indicating that accountability mechanisms become more prevalent as organizations accumulate AI project experience.

VI. DISCUSSION

This study addresses the research question: *What accountability mechanisms are used in AI projects, and how are they influenced by system autonomy, project experience, and organizational role distribution?*

AI projects develop artificial agents that influence human decision-making and may introduce risks to health, safety, fundamental rights, democratic processes, and the environment. At the same time, AI is associated with productivity gains and strong market growth. Public expectations and regulatory developments indicate that accountability is a central requirement for the responsible development and deployment of AI systems. As adoption increases, accountability must be operationalized within project structures and practices.

Positioned against the existing literature, the findings contribute to bridging the fragmentation between ethical principles, governance frameworks, and project-level practices. While prior research defines accountability in normative or institutional terms, this study demonstrates how accountability is implemented in practice within AI projects.

The findings show that accountability in AI projects is implemented through a structured but diverse set of mechanisms. A total of 18 mechanisms operationalized through 23 measurement items were identified and empirically examined, grouped into four dimensions: *directing the project*, *controlling performance*, *treating misconduct*, and *managing delivery*. These mechanisms collectively govern relationships between project actors and stakeholders and translate abstract accountability principles into a project-level system of practices.

The emergence of *treating misconduct* as a separate accountability dimension represents a notable departure from tra-

ditional project management governance frameworks. Across the PMBOK®, APM Body of Knowledge, ISO 21502, and PRINCE2, accountability is primarily operationalized through mechanisms that direct projects, monitor performance, manage delivery, and implement corrective actions. Although these standards provide processes for assurance, issue escalation, audits, and lessons learned, they generally focus on controlling project execution rather than addressing harms arising from project outcomes. In contrast, the *treating misconduct* dimension encompasses mechanisms for investigating adverse events, reporting harmful outcomes, providing remediation or compensation, addressing root causes, and maintaining ongoing oversight. This distinction is particularly relevant for AI projects because AI systems can generate unintended consequences that extend beyond traditional project boundaries and continue after deployment. Therefore, the findings suggest that accountability in AI projects requires mechanisms not only for governing project performance but also for managing and remedying the consequences of AI system behavior throughout the system lifecycle.

With respect to system autonomy, the results indicate that autonomy increases the use of accountability mechanisms, but in a selective rather than uniform manner. The strongest effects are observed for *managing delivery* and *treating misconduct*, suggesting that higher autonomy primarily amplifies mechanisms related to operational robustness, capability development, and the handling of potential harm. In contrast, mechanisms such as *directing the project* and *controlling performance* appear to function as stable baseline practices applied across projects. This indicates that autonomy does not uniformly intensify accountability but shifts emphasis toward mechanisms that address uncertainty, opacity, and downstream consequences.

Regarding project experience, the findings support Hypothesis 2 and indicate that accountability mechanisms become more prevalent as organizations accumulate AI project experience. Positive associations were observed across all four dimensions, with the strongest relationship occurring for *managing delivery*. This suggests that organizational learning through repeated AI project execution contributes to the development of operational capabilities, coordination practices, and delivery controls. The results further indicate that experience supports the progressive institutionalization of accountability practices within AI projects.

In terms of organizational role distribution, the results provide strong evidence that accountability mechanisms are distributed across project roles rather than centralized. Sponsors and project managers emphasize *managing delivery*, while team members place greater emphasis on *controlling performance*. At the same time, all roles contribute across multiple dimensions, indicating that accountability is embedded within the broader project structure rather than confined to formal authority positions. This demonstrates that accountability in AI projects is enacted through coordinated role interactions rather than hierarchical control alone.

The role of the sponsoring organization is particularly important as it connects project execution with organizational governance and external stakeholders. Mechanisms within

controlling performance capture monitoring and reporting relationships that link project activities to broader governance structures. At the same time, the dimensions *managing delivery* and *directing the project* reflect the internal coordination required to manage technical complexity and uncertainty.

External stakeholders influence accountability despite often lacking formal roles in project execution. Mechanisms such as transparency and disclosure enable external observation and evaluation, while engagement practices support interaction across the project lifecycle. The inclusion of redress-related mechanisms further demonstrates that accountability in AI projects extends beyond internal governance structures to encompass the management of impacts on affected stakeholders.

In summary, accountability in AI projects is implemented through a multidimensional system of mechanisms shaped by system autonomy, practitioner experience, and role distribution. Autonomy, experience, and role distribution shape the relative emphasis placed on accountability dimensions, while accountability itself remains a distributed and multidimensional project capability. Together, these findings show that effective accountability in AI projects depends on integrating governance structures, operational practices, stakeholder-oriented mechanisms, and mechanisms for investigating and remedying harmful outcomes within a coherent project-level framework.

VII. CONCLUSIONS

Accountability is widely identified by both the public and regulators as a central ethical principle in AI, often ranked above fairness, security, privacy, and accuracy. This study identified 18 mechanisms operationalized through 23 measurement items, grouped into four dimensions that support the establishment of accountability in AI projects, particularly in the context of emerging regulatory requirements. The findings contribute to both theory and practice in project management and AI governance by demonstrating how accountability is operationalized at the project level.

A. Theoretical Contributions

This study makes five contributions to the literature on project governance and accountability in AI contexts.

First, the study introduces the *treating misconduct* dimension, which is not explicitly represented with a direct counterpart in existing project management literature. This dimension captures mechanisms related to investigation, reporting, and remediation of harm, extending accountability beyond internal project control toward external and affected stakeholders. It reflects a shift from delivery-focused accountability toward socio-technical accountability, where project outcomes are evaluated not only in terms of performance but also in terms of their broader societal impact.

Second, the study develops a structured, empirically grounded view of accountability mechanisms in AI projects by organizing 18 mechanisms operationalized through 23 measurement items into four dimensions: *directing the project*, *controlling performance*, *managing delivery*, and *treating misconduct*. This structure integrates established project governance practices with AI-specific accountability requirements,

showing that while foundational governance mechanisms remain stable, additional mechanisms emerge to address system autonomy, opacity, and potential harm.

Third, the study extends existing conceptualisations of accountability by incorporating a lifecycle perspective into the analysis of project-level mechanisms. Accountability is understood not only as a set of mechanisms but as a property that emerges across the lifecycle of AI systems through processes such as documentation, monitoring, auditing, and investigation. The findings demonstrate how these lifecycle-spanning processes are operationalized within AI projects, highlighting that accountability is dynamic and embedded across stages of development, deployment, and post-deployment evaluation.

Fourth, the study contributes to stakeholder theory in projects by demonstrating how accountability is operationalized through distributed roles and interactions rather than confined to formal authority structures. The findings show that accountability mechanisms are enacted across sponsors, project managers, and teams, while also extending to external stakeholders through mechanisms such as transparency, reporting, and redress. This reinforces the view of accountability as socially embedded and relational, particularly in AI projects where impacts extend beyond organizational boundaries.

Finally, by focusing on AI projects, the study advances project management literature into a domain characterised by high uncertainty, autonomy, and regulatory scrutiny. It provides empirical evidence on how accountability mechanisms are configured in practice and integrates insights from project governance and AI governance into a coherent project-level framework.

B. Practical Implications

The findings have important implications for practitioners involved in the design and governance of AI projects.

First, the study provides a structured framework for operationalising accountability in AI projects. Rather than relying on abstract ethical principles, organizations may operationalize accountability through a set of mechanisms grouped into four dimensions: *directing the project*, *controlling performance*, *managing delivery*, and *treating misconduct*. This structure enables project managers and sponsors to embed accountability directly into project governance, processes, and deliverables from the outset.

Second, the results highlight the need to adopt a lifecycle perspective on accountability. Accountability should be designed across all project stages, including development, deployment, and post-deployment monitoring. In practice, this requires implementing mechanisms such as documentation, logging, auditing, and investigation to ensure traceability and enable review of system behavior, particularly in projects involving autonomous systems.

Third, the study emphasises the importance of aligning accountability mechanisms with role distribution. Sponsors, project managers, and delivery teams should be assigned clear and complementary responsibilities across the four dimensions. In particular, organisations should ensure that accountability is not concentrated in management roles but supported

through distributed mechanisms such as reporting, monitoring, and transparency practices.

Fourth, the findings provide practical guidance for compliance with emerging AI regulations. Regulatory frameworks require organisations to demonstrate accountability, transparency, and risk management. The identified mechanisms offer a concrete basis for translating these requirements into project-level practices, enabling organisations to operationalise compliance within existing project structures.

Finally, the study highlights the importance of mechanisms for handling misconduct and unintended consequences. Organizations should establish processes for investigation, reporting, remediation, and root-cause analysis to ensure that harmful outcomes can be identified and addressed throughout the AI system lifecycle.

C. Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the survey design captures individual perspectives rather than observations within a single project context. As a result, the study cannot directly examine how accountability mechanisms are distributed and enacted across multiple actors within the same project. Future research could address this limitation through case studies, ethnographic approaches, or longitudinal designs that examine accountability practices within specific project environments.

Second, several methodological limitations may affect the generalizability of the findings. The sampling strategy combined respondents from a SurveyMonkey audience panel and members of the Project Management Institute (PMI), which may introduce selection bias and limit sample representativeness. The use of self-reported measures captures respondents' perceptions of accountability mechanisms rather than directly observed practices and may therefore be subject to social desirability bias or the over-reporting of governance activities. In addition, the cross-sectional design limits the ability to infer causal relationships between variables. While associations between system autonomy, experience, and accountability mechanisms were identified, causal direction cannot be established. Finally, the transformation of the continuous experience variable into categorical groups reduces statistical precision and may obscure more nuanced relationships. Future research could address these limitations through more controlled sampling strategies, longitudinal or experimental designs, and observational or mixed-method approaches.

Third, the literature review and mechanism identification process were conducted by a single researcher. Although a structured review process was applied, the resulting set of mechanisms may not be exhaustive. Future studies could employ systematic review methods, Delphi panels, or collaborative coding approaches to validate and extend the accountability mechanism framework.

Fourth, the study focuses on the presence and use of accountability mechanisms rather than their effectiveness. Future research should investigate how specific mechanisms influence project outcomes, organizational performance, risk management, stakeholder trust, and regulatory compliance. Such work

would provide greater insight into which accountability practices create the greatest value in AI projects.

Finally, the analysis primarily reflects the perspectives of organizations developing AI systems. Future research should examine accountability from the perspectives of deploying organizations, affected stakeholders, regulators, and end users, while further investigating risk management and quality management as distinct components of accountability systems. Overall, this study provides an initial empirical foundation for understanding how accountability is operationalized in AI projects and offers a basis for future research into the design, implementation, and effectiveness of accountability mechanisms in increasingly autonomous and socially consequential AI systems.

DECLARATION OF GENERATIVE AI USE

Generative AI (ChatGPT) was utilized to enhance clarity and structure. All outputs were critically reviewed and integrated by the author. The author retains full responsibility for content and conclusions.

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APPENDIX

Table A.1
EXPERIENCE GROUP DEMOGRAPHICS BY NUMBER PROJECTS

Bin	Range	Frequency	Proportion
1	1 – 2 Projects	78	0.29
2	3 Projects	35	0.13
3	4 Projects	73	0.27
4	5 – 10 Projects	39	0.14
5	> 10 Projects	45	0.17

Table A.2
FACTOR RELIABILITY AND VALIDITY STATISTICS

Factor Group	Alpha	AVE	CR	Mean	Std
Directing the project	0.96	0.47	0.90	5.04	1.85
Controlling performance	0.95	0.53	0.89	5.24	1.75
Treating misconduct	0.93	0.49	0.83	4.75	2.04
Managing delivery	0.65	0.64	0.78	5.28	1.62

Abbreviations: Std—standard deviations, AVE—average variance extracted, CR—Construct reliability

Table A.3
SURVEY DEMOGRAPHICS

Group	Label	N	%
Spr	Chief Executive Officer, Business Leader	33	12.2
	Chief Information Officer, IT Mgr	62	23.0
PrjMgr	Project Leader, Project Mgr, Product Owner	102	37.8
Team	Data Sci, Computer Vision, other AI	15	5.56
	Data Engineer, Data Custodian, Curator	10	3.70
	Architect, Developer, Computer Sci, IT Specialist	19	7.04
	Business User, Business Analyst, Subject Matter Expert	29	10.7
Scope:	...created algorithms that decided/acted without human intervention	105	38.9
autonomous	...created algorithms that learned from new data (without manual intervention)	120	44.4
	...created algorithms with their internal functioning hidden from the end user	88	32.6
Scope:	...created proprietary algorithms or business models	125	46.3
non—	...integrated algorithms into distinctive business processes	143	53.0
	autonomous	59	21.9
Source	SurveyMonkey 2023	99	36.7
	Prj Management Institute 2023	54	20.0
	SurveyMonkey 2024	117	43.3
Year	2023	153	56.7
	2024	117	43.3

Abbreviations: *Sci*—Scientist, *Spr*—sponsor, *Prj*—project, *Mgr*—manager

Table A.4
INTER-FACTOR CORRELATIONS AND DISCRIMINANT VALIDITY ASSESSMENT

Factor Group	Kendall Tau b Correlation Coefficients			
	1	2	3	4
1. Directing the project	0.684			
2. Controlling performance	0.652	0.727		
3. Treating misconduct	0.654	0.560	0.700	
4. Managing delivery	0.511	0.478	0.455	0.799

Note: Diagonal values represent the square root of the average variance extracted (SQRT AVE).

Table A.5
ACCOUNTABILITY MECHANISMS BY PROJECT SCOPE

Mechanism	Non-autonomous (N=73)		Autonomous (N=197)	
	Mean	Std	Mean	Std
No. mechanisms (count)	19.44	4.26	20.13	5.52
Managing delivery	4.91	1.76	5.42	1.55
Controlling performance	5.32	1.46	5.21	1.85
Directing the project	5.00	1.47	5.05	1.97
Treating misconduct	4.47	1.80	4.86	2.12

Kruskal–Wallis test results:

No. mechanisms ($H=8.90$, $p<0.001$); Managing delivery ($H=4.79$, $p=0.03$); Treating misconduct ($H=6.22$, $p=0.01$); other differences not significant.

Table A.6
ACCOUNTABILITY MECHANISMS BY PROJECT ROLE: GROUP DIFFERENCES AND RANK ORDER

Mechanism	Sponsor PM rank		Team rank	H	p
Managing delivery	1	2	2	13.88	0.00
Controlling performance	2	1	1	11.85	0.00
Directing the project	3	3	3	20.96	0.00
Treating misconduct	4	4	4	14.99	0.00

Note: H = Kruskal–Wallis statistic. Lower rank values indicate higher relative use within each role.

Table A.7
RELATIONSHIP BETWEEN EXPERIENCE AND ACCOUNTABILITY DIMENSIONS

Dimension	Spearman Correlation		Linear Trend	
	ρ	p	F	p
Directing the project	0.291	<0.001	12.70	<0.001
Controlling performance	0.257	<0.001	8.77	0.003
Treating misconduct	0.266	<0.001	9.17	0.003
Managing delivery	0.311	<0.001	19.17	<0.001

Table A.8
ANOVA RESULTS FOR EXPERIENCE AND ACCOUNTABILITY DIMENSIONS

Accountability Dimension	df	Type III SS	F	p-value
Directing the project	4	48.21	3.67	0.006
Controlling performance	4	31.04	2.60	0.037
Treating misconduct	4	47.68	2.93	0.021
Managing delivery	4	109.43	12.07	<0.001

Note: Type III SS = Type III sum of squares. Experience was measured using five ordered experience groups based on the number of AI projects completed.

Table A.9
POLYNOMIAL TREND COMPONENTS ACROSS EXPERIENCE GROUPS

Dimension	Trend	F	p-value
Directing the project	Linear	12.70	<0.001
	Quadratic	0.31	0.577
	Cubic	0.43	0.515
	Quartic	0.39	0.534
Controlling performance	Linear	8.77	0.003
	Quadratic	0.13	0.715
	Cubic	0.88	0.349
	Quartic	0.60	0.438
Treating misconduct	Linear	9.17	0.003
	Quadratic	0.94	0.334
	Cubic	0.52	0.471
	Quartic	0.27	0.605
Managing delivery	Linear	19.17	<0.001
	Quadratic	17.63	<0.001
	Cubic	0.28	0.594
	Quartic	1.21	0.273