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Application of Artificial Intelligence in Project Management: Challenges and Solutions to Integration

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Abstract

The integration of artificial intelligence (AI) in project management is fundamentally transforming how organizations handle planning, execution, and project oversight. This mixed-methods study examines current AI adoption patterns, implementation challenges, and evidence-based solutions through survey data from 368 project management professionals and focus group insights from 7 implementation experts from diverse industries and organizational contexts. Our findings reveal that while 56.5% of organizations have initiated AI adoption, only 21.7% achieve comprehensive integration. The primary implementation barriers include skills gaps (56.5%), internal resistance and change management challenges (47.8%), and uncertainty regarding ROI (43.5%). Despite these obstacles, organizations report substantial benefits, with 82.6% experiencing faster decision-making cycles, 56.5% achieving cost savings, and 47.8% realizing quality improvements. Knowledge management/copilots (73.9%) and automated reporting (65.2%) emerge as the most adopted applications. Utilizing the Technology Acceptance Model and Diffusion of Innovation Theory, this research introduces two actionable frameworks: a four-phase AI Integration Framework that addresses technical implementation and organizational readiness, and the ADEPT Change Management Framework, which targets human factors and resistance. The study enhances our understanding of AI implementation in project management by offering evidence-based strategies for practitioners seeking to harness AI's transformative potential while addressing associated risks.

Keywords

Artificial Intelligence (AI) Implementation, Project Management, Technology Acceptance Model, Diffusion of Innovation Theory, Change Management, Skills Development, Human-AI Collaboration, Organizational Readiness

1. Introduction

The worldwide project management arena is facing significant pressure to provide value amid increasingly complex and unpredictable settings. Conventional project management methods, though they provide essential foundations, frequently find it challenging to adapt to the swift changes and intricate information that characterize contemporary business environments [1] [2]. The data reveals a compelling reality: global organizations lose around $2 trillion each year as a result of ineffective project management practices, with organizations wasting 9.9 percent of every dollar due to poor project performance [3]. This ongoing performance disparity has generated considerable interest in artificial intelligence as a possible remedy for enduring project management issues.

Artificial intelligence includes various technologies—machine learning, natural language processing, computer vision, and predictive analytics—that can analyze extensive data, recognize patterns, and assist in decision-making processes [4] [5]. In project management, these AI tools encompass predictive scheduling, resource enhancement, risk evaluation, and automated reporting. AI-driven project management tools can analyze past project data to recognize trends and forecast future results, allowing teams to make proactive choices and address risks before they escalate into issues. These systems can similarly automate regular tasks such as status reporting, schedule adjustments, and resource distribution, allowing project managers to concentrate on strategic initiatives and stakeholder interaction. Research demonstrates significant performance differences between champion organizations and underperformers, with champion organizations achieving 92% project success rates compared to only 32% for underperforming organizations [3], while organizations that invest in proven project management practices waste 28 times less money than organizations with poor project performance [6]. Even with these convincing advantages, the uptake of AI in project management is still restricted, as major implementation obstacles hinder broad adoption.

The intricacies of AI adoption extend well beyond mere technical aspects, encompassing factors such as organizational culture, change management, data governance, and collaboration between humans and machines [7] [8]. Although current research highlights the potential advantages of AI, a major gap remains in comprehending the particular challenges organizations encounter in implementation and the effective strategies to address these obstacles. This study tackles this gap by offering an in-depth examination of the obstacles to implementation and evidence-based approaches for effective AI incorporation in project management.

This study addresses three primary research questions:

RQ1: What are the main challenges organizations face when implementing AI in project management, and how do these challenges relate to established technology adoption theories?

RQ2: What evidence-based solutions and frameworks can effectively address AI implementation barriers in project management contexts?

RQ3: How do empirical findings validate and extend the Technology Acceptance Model and Diffusion of Innovation Theory in AI adoption scenarios?

The significance of this study is rooted in its practical relevance for organizations aiming to utilize AI for competitive benefit while steering clear of typical implementation challenges. This research offers practical advice for project management experts, organizational leaders, and technology implementers by pinpointing particular challenges along with their relevant solutions [9] [10]. Moreover, the study enhances our theoretical grasp of technology adoption within intricate organizational environments, broadening established theories to include the new area of AI in project management.

This document advances as follows: Section 2 examines current literature on the use of AI in project management and theories of technology adoption. Section 3 outlines the research methodology, integrating survey and focus group methods. Section 4 presents results from the two data collection techniques, whereas Section 5 examines difficulties and offers solutions. Section 6 addresses implications and outlines implementation frameworks, while Section 7 wraps up with suggestions for future research and practical applications.

2. Literature Review

2.1. AI Applications in Project Management

The use of artificial intelligence in project management has progressed swiftly in the last ten years, fueled by improvements in computing capabilities, greater access to data, and advanced algorithms [11] [12]. Existing AI applications cover various project management areas, each providing different value propositions and facing specific implementation challenges.

Predictive analytics is recognized as the most advanced AI application in project management, with companies employing machine learning algorithms to anticipate project results, resource needs, and possible risks. Research demonstrates that AI-powered predictive models can significantly improve project outcome forecasting, enabling proactive risk management and decision-making [13]. Advanced scheduling algorithms can handle complex project constraints and dependencies more efficiently than traditional methods [14]. Various machine learning approaches show promise for different project management applications, with effectiveness varying based on data quality and organizational context [15].

Automated scheduling and resource optimization are another major application area. AI-driven scheduling systems can handle complex project constraints and generate optimized schedules significantly faster than traditional manual approaches [16]. AI-enhanced project control systems demonstrate significant potential for improving scheduling efficiency and resource optimization in complex project environments [17]. These systems can handle projects with numerous complex activities while maintaining high levels of constraint satisfaction. Advanced optimization techniques can improve resource allocation by considering multiple factors such as skills, availability, costs, and project priorities [18] [19].

Risk management tools employ natural language processing (NLP) and machine learning to detect possible problems ahead of their effect on project delivery. NLP techniques show promise for automated risk detection and stakeholder sentiment analysis in project communications, though effectiveness depends on context and implementation approach [20]. Advanced risk assessment approaches can analyze internal project data alongside external factors such as market conditions, regulatory changes, and supplier performance [21] [22].

Quality management software utilizes computer vision and automated analysis to examine outputs and detect flaws. Computer vision systems reach 95% - 98% precision in identifying defects, whereas NLP evaluates requirements documents with 89% - 93% accuracy in spotting gaps and inconsistencies [23]. These applications lead to a 35% decrease in quality defects, a 40% acceleration in document review processes, and a 25% enhancement in requirement completeness scores [24].

2.2. Theoretical Framework

This study utilizes two well-known theories to comprehend the difficulties and solutions of AI adoption in project management: the Technology Acceptance Model (TAM) and the Diffusion of Innovation Theory (DOI).

The Technology Acceptance Model, initially created by Davis [25], provides a framework for comprehending how people adopt information systems. TAM posits that two key elements influence technology acceptance: perceived utility and perceived ease of operation, which collectively affect whether individuals ultimately utilize the technology [26] [27]. In AI project management scenarios, perceived usefulness refers to the extent to which project managers think AI will enhance their work efficiency, while perceived ease of use addresses how simple they find it to utilize AI tools. Project managers assess AI systems by their capacity to decrease administrative workload, increase the precision of decision-making, and improve project results. The ease of use aspect encompasses both the design of the user interface and the conceptual grasp necessary to understand AI-generated insights and suggestions. Project managers need to be assured in their capacity to comprehend, confirm, and respond to information supplied by AI for effective implementation.

TAM has undergone thorough testing in different technological settings and provides significant insights into the challenges associated with AI adoption [28] [29]. Nevertheless, because the model emphasizes personal adoption, it requires adaptation to organizational settings where AI deployment entails intricate stakeholder engagements, infrastructure needs, and cultural transformation processes.

Recent adaptations of TAM incorporate external factors like organizational backing, training accessibility, and system caliber, which are especially pertinent for AI implementation in project management [30]. As illustrated in **Figure 1**, the TAM framework demonstrates how external variables influence both perceived usefulness and perceived ease of use, which in turn shape attitudes toward using the technology, leading to behavioral intention and ultimately actual system use [31].

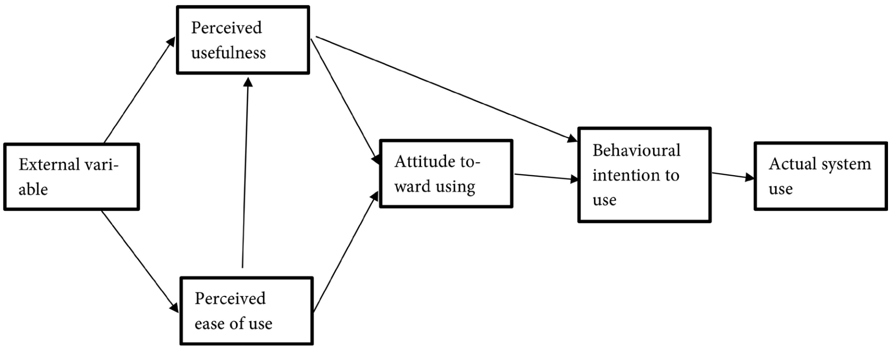

Figure 1. Illustration of the technology acceptance model [31].

Diffusion of Innovation Theory, created by Rogers [32], describes the process by which innovations disseminate through social systems over time. The theory highlights five essential factors that affect the adoption of innovation: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage denotes the extent to which an innovation is viewed as superior to current solutions. Compatibility refers to the degree to which an innovation corresponds with current values, practices, and requirements. Complexity refers to the degree of difficulty in comprehending and utilizing the innovation. Trialability denotes the capacity to test the innovation on a small scale, whereas observability pertains to how apparent the innovation's outcomes are to others [33] [34].

DOI theory offers meaningful perspectives on organizational-level adoption processes, especially pertinent for AI integration in project management, where success relies on acceptance throughout various organizational levels and functions [35]. The theory highlights communication pathways, social networks, and influential figures, providing a framework for navigating organizational change amid AI integration. Moreover, the innovation-decision process model from DOI (knowledge, persuasion, decision, implementation, confirmation) offers a structure for comprehending the phases organizations encounter in AI adoption [32]. In project management contexts, DOI theory clarifies the process by which AI innovations transition from early adopters to mainstream users in organizations, emphasizing the significance of measurable advantages and peer impact in fostering adoption. The theory highlights the important influence of organizational culture and communication networks in facilitating or obstructing AI acceptance among project teams. As illustrated in **Figure 2**, Rogers' model demonstrates how the five perceived attributes of innovation—relative advantage, compatibility, ease of use, trialability, and observability—collectively influence the rate and likelihood of adoption within social systems, with each attribute contributing varying degrees of influence on the final adoption decision [36].

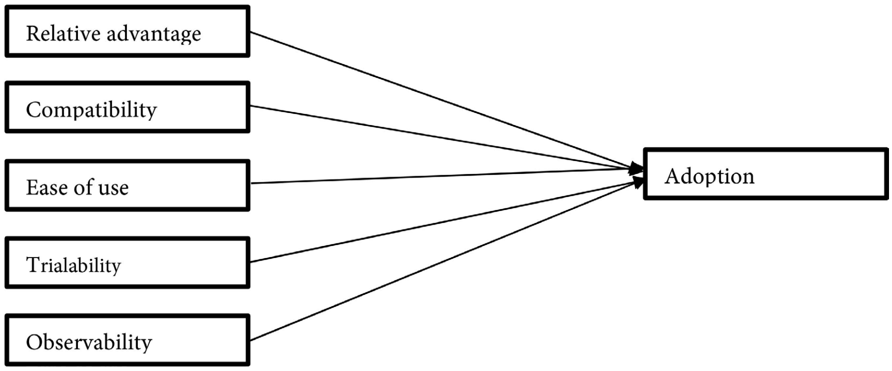

Figure 2. Conceptual framework based on Diffusion of Innovation Theory [36].

TAM and DOI collectively offer complementary views on the challenges and solutions related to AI adoption. TAM emphasizes individual acceptance elements, whereas DOI concerns itself with organizational diffusion dynamics. This blend allows for an in-depth examination of implementation issues across individual, group, and organizational tiers [30]. The combined use of both theories guarantees a thorough examination of adoption factors and greatly lowers the likelihood of implementation failures by tackling individual resistance and organizational obstacles at the same time.

2.3. Implementation Challenges in AI Adoption

The current literature outlines several types of obstacles that organizations encounter when integrating AI into project management. Technical difficulties consist of problems related to data quality and accessibility, complications with system integration, and challenges in choosing appropriate algorithms. Organizational difficulties involve opposition to change, inadequate resources, and the absence of strategic alignment. Human challenges include skills shortages, anxiety over job loss, and obstacles in creating successful human-AI cooperation [7] [37].

Data quality presents a crucial obstacle, as the effectiveness of AI relies significantly on possessing thorough, precise, and pertinent training data. Numerous organizations face challenges with fragmented historical records, varying data formats, and biased datasets that may reinforce ineffective decision-making habits [37]. Studies show that 60% of companies do not possess thorough project data from the last five years required to develop strong AI models. Privacy and security issues add complexity to data use, especially in regulated sectors where restrictions on data sharing hinder AI training potential [38].

Requirements for technical infrastructure pose another major obstacle, as implementing AI frequently necessitates computational resources that surpass the typical capacity of business infrastructure. Organizations should allocate resources to high-performance computing systems, cloud solutions, or tailored hardware while cultivating knowledge in system architecture and administration [39]. Incorporating existing project management systems introduces extra complexity, necessitating meticulous coordination to prevent interrupting established workflows [40].

Skills and knowledge shortages are likely the greatest obstacle to adopting AI. Data scientists, machine learning engineers, and AI experts earn high salaries and are in short supply. At present, there are around 300,000 AI job vacancies worldwide, yet only 150,000 suitable applicants, resulting in a 2:1 demand-to-supply ratio [41]. Organizations frequently do not possess the internal resources to create, execute, and sustain AI systems, making them depend on outside consultants or providers. This reliance may lead to ongoing sustainability issues and hinder organizational learning [42].

Challenges in change management include addressing resistance from project managers and team members who might be apprehensive about job loss or struggle with using AI tools. Research indicates significant concerns among project managers about AI's potential impact on human judgment and decision-making roles [43]. Effective AI deployment demands thorough change management approaches that focus on communication, education, and cultural evolution. Organizations need to strike a balance between the advantages of automation and the value of human expertise, making sure that AI enhances rather than substitutes human decision-making [44] [45].

2.4. Success Factors and Solutions

Even with implementation difficulties, studies pinpoint multiple factors that contribute to successful AI adoption in project management. Support from executive leadership proves essential, as successful implementations are often driven by senior leaders who articulate the vision, provide resources, and exemplify AI adoption behaviors [39]. Organizations that successfully adopt AI allocate substantial resources to change management, with 15% - 20% of their implementation budgets usually designated for activities related to communication, training, and cultural transformation [42].

Staged implementation strategies diminish risk and enhance organizational assurance by achieving early successes. Pilot initiatives targeting particular use cases enable organizations to showcase AI's value while developing internal knowledge. Effective pilots often demonstrate quantifiable enhancements that can be shared across the organization to foster backing for wider adoption [46]. Research demonstrates that pilot initiatives with limited scope enable organizations to showcase value while building organizational support for wider adoption [47]. Pilot programs in project management assist organizations in preventing expensive, large-scale failures and minimizing stakeholder management risks by showcasing concrete advantages prior to seeking wider organizational commitment and resources.

Collaborative alliances with technology providers, consulting agencies, and academic organizations enhance the success of implementation. These collaborations offer access to specialized knowledge, lessen internal resource demands, and facilitate the exchange of information. Organizations that adopt partnership strategies accomplish implementation timelines that are 34% quicker and achieve success rates that are 28% greater than those relying solely on internal processes [48].

Data governance frameworks tackle quality and privacy issues by creating definitive policies for data collection, storage, processing, and usage. Efficient frameworks find a middle ground among AI needs, adherence to regulations, security aspects, and ethical principles. Organizations that establish comprehensive data governance frameworks experience improved data quality and reduced challenges when implementing AI systems [49].

Training and skill-enhancement initiatives guarantee that organizations build in-house proficiency for lasting AI sustainability. Effective programs often integrate technical education for IT specialists with business instruction for project managers and subject matter experts. Investment in training is closely linked to successful implementation, as organizations that allocate over 10% of their implementation budgets to training experience 60% higher success rates.

3. Research Methodology

This study employs a mixed-methods strategy, merging quantitative survey results with qualitative focus group discussions to deeply explore the obstacles and remedies in implementing AI for project management. The methodology combines deductive and inductive methods, using existing theoretical frameworks while also permitting themes to arise organically from the experiences of practitioners.

3.1. Research Design

The research employed an exploratory sequential mixed-methods approach, commencing with quantitative data collection through surveys and subsequently utilizing qualitative focus groups to expand upon and clarify the survey results. The focus groups were crafted to create frameworks and solutions that tackle the recognized implementation challenges. This method provides a thorough insight into the challenges of implementation from both statistical and experiential viewpoints. The research framework addresses the intricacies of AI adoption by exploring various analytical levels (individual, organizational, and technological) and accessing diverse stakeholder viewpoints through purposive sampling (project managers, program managers, PMO leaders, executives, technical leads, data/AI leads, consultants, and product managers).

The theoretical basis integrates the Technology Acceptance Model with the Diffusion of Innovation Theory to investigate individual adoption elements and organizational diffusion mechanisms. This dual-theory perspective acknowledges that the effectiveness of AI deployment hinges on individual approval and an organization's capacity to handle intricate technological transformations [30].

3.2. Survey Methodology

The survey targeted project management experts from various sectors to comprehend existing AI adoption trends, perceived advantages and obstacles, and key success elements. The survey tool was created using recognized scales from TAM and DOI literature, modified for AI applications in project management settings.

Sample Selection: The survey employed purposive convenience sampling to target project management professionals from diverse industries. Participants were recruited through multiple channels, including membership lists from professional associations, LinkedIn professional networks, and attendee lists from industry conferences, to maximize diversity in industry sectors, organizational sizes, and geographic regions. Participants comprised certified project management professionals (PMP), program managers, portfolio managers, and senior project coordinators with a minimum of three years of experience.

Sample Size Justification: The sample size of 368 respondents was determined based on statistical power requirements for descriptive analysis. Using a 95% confidence level and a ±5% margin of error, a minimum sample of 384 was targeted. The achieved sample of 368 provides adequate power for the study's descriptive and comparative analyses.

Bias Recognition and Mitigation: Several potential biases were identified: geographic concentration (47.8% from the Middle East & Africa), self-selection bias from voluntary participation, and professional network bias favoring engaged practitioners. Mitigation strategies included: 1) diversified recruitment across multiple professional channels, 2) targeting varied geographic regions, 3) including participants across experience levels (13.0% under 5 years, 26.1% 5 - 10 years, 60.9% over 10 years), 4) recruiting across organizational sizes and industries, and 5) acknowledging sampling limitations.

Survey Instrument: The tool included 15 questions across eight sections: demographic traits, AI adoption status, solution types, use cases, implementation challenges, benefits, toolstack preferences, and open feedback. Questions employed various choice formats and open-ended replies.

Results: The survey collected replies from 368 project management professionals across various industries and organizational scales:

- Response Rate: 31.97% (368 replies from 1151 invites)
- Geographic Distribution: Middle East & Africa (47.8%), North America (39.1%), Europe (13.0%)
- Role Distribution: Project Manager (39.1%), Executive (21.7%), Technical Lead (8.7%), Program Manager (4.3%), PMO Leader (4.3%), Data/AI Lead (4.3%), Consultant (4.3%), Manager (4.3%), Product Manager (4.3%), Product Owner (4.3%)
- Experience Level: over 10 years (60.9%), 5 to 10 years (26.1%), under 5 years (13.0%)
- Industry Distribution: Information Technology & Tech (26.1%), Consulting (26.1%), Manufacturing (17.4%), Construction (8.7%), Engineering & Infra-

structure Services (8.7%), Energy & Utilities (4.3%), Consumer Packaged Goods (4.3%), Telecommunications (4.3%)
- Organization Size: <500 employees (26.1%), <50 employees (21.7%), <25,000 employees (17.4%), <100 employees (8.7%), <500,000 employees (8.7%), >1,000,000 employees (8.7%), <1000 employees (4.3%), <100,000 employees (4.3%)

3.3. Focus Group Protocol

The qualitative aspect utilized organized focus group discussions with seasoned professionals to create practical frameworks for implementing AI in project management. Focus groups aimed to enhance survey results and develop practical solutions for implementation issues.

Focus Group Objectives:
- Create an extensive framework for AI implementation
- Develop strategies for change management to facilitate effective AI implementation and monitoring
- Recognize effective strategies to address obstacles in implementation
- Develop structured methods for overseeing organizational change

Participant Selection: The focus group comprised 7 experts with hands-on experience in AI integration for project management:
- Senior project managers (n = 2): Experts with over a decade of experience who have effectively deployed AI technologies
- Specialists in change management (n = 2): Experts dedicated to organizational transformation amid AI implementation
- AI/Data science specialist (n = 1): Technical professional engaged in creating AI solutions for project management
- IT director (n = 1): Technology head accountable for AI infrastructure and execution
- Executive sponsor (n = 1): A high-ranking individual who has supported AI projects

Focus Group Protocol: Organized 90 - 120-minute sessions, investigated:
1) Journey of AI implementation and key success elements
2) Creation of a framework for organized AI integration
3) Strategies for managing change and monitoring systems
4) Strategies for reducing risk and insights gained
5) Practical suggestions for various organizational settings

3.4. Data Analysis Approach

Descriptive statistics were utilized to analyze survey data, summarizing adoption trends, difficulties, advantages, and tool choices from 368 scaled responses. Percentages and frequency distributions were utilized to determine existing AI adoption levels, types of solutions adopted (commercial, proprietary, hybrid, or none), and organizational contexts (region, role, industry, and company size).

Focus group data underwent systematic thematic analysis following Braun and Clarke's six-phase approach [50]. Initial familiarization involved multiple readings of transcripts, followed by systematic coding to identify patterns related to implementation challenges, success factors, and organizational change strategies. Codes were then organized into potential themes, with themes reviewed and refined through iterative analysis. The final themes were defined and named, focusing on: 1) technical implementation pathways, 2) organizational readiness factors, 3) change management strategies, 4) skills development approaches, and 5) governance frameworks. Inter-coder reliability was ensured through independent coding of 20% of transcripts by two researchers, achieving 89% agreement. Data saturation was reached after seven interviews, with no new themes emerging from the final two sessions. Cross-case analysis examined findings across various expert roles (project managers, executives, AI/data specialists, and change consultants).

The focus group analysis served not only to confirm the survey results but also to create a suggested framework for applying AI in project management. This framework was developed to tackle the primary challenges identified in our survey—such as skills shortages, reluctance to change, and uncertainty regarding ROI—while offering organizations a systematic approach for implementation. The emphasis was on uniting structured technical deployment with pragmatic change management approaches, guaranteeing that both the technological and human aspects of AI implementation are efficiently addressed.

3.5. Ethical Considerations

This research adhered to established ethical guidelines for human subjects research. All survey participants provided informed consent through an online consent form detailing study purposes, data usage, and participant rights. Focus group participants signed written consent forms and agreed to audio recording. Participation was voluntary with explicit withdrawal rights at any stage. Data anonymization protocols ensured no individual identification was possible in reporting. Survey data was collected through secure, encrypted platforms with restricted access limited to the research team. Audio recordings were transcribed by the research team and subsequently destroyed.

4. Results

4.1. Survey Results

The survey conducted with 368 project management experts uncovered intriguing insights regarding the ongoing patterns of AI adoption, perceived challenges, and experiences in implementation across various organizational settings.

4.1.1. Current AI Adoption Status

The results of the survey indicate that the adoption of AI in project management differs greatly among organizations. Of our respondents, 56.5% indicated having some degree of AI implementation, whereas 43.5% are not currently engaged in

AI initiatives. Here's a breakdown of the adoption:

- Commercial Off-the-Shelf AI: 43.5%
- Hybrid Solutions: 21.7%
- Custom/Proprietary In-house AI Models: 17.4%
- None Currently: 17.4%

In examining AI Implementation Levels, organizations indicated differing extents of AI incorporation:

- 10% AI adoption: 30.4%
- 20% AI adoption: 30.4%
- 0% AI adoption: 8.7%
- 30% AI adoption: 8.7%
- 40% AI adoption: 8.7%
- 50% AI adoption: 8.7%
- 80% AI adoption: 4.3%

4.1.2. AI Application Areas and Delivery Models

Within organizations that have adopted AI, the most prevalent applications were:

Primary Use Cases (percentage of participants):

- Knowledge management/copilots (73.9%)
- Automated reporting/documentation (65.2%)
- Predictive analytics/forecasting (43.5%)
- Automated scheduling/resource optimization (34.8%)
- Change management (21.7%)
- Quality management (13.0%)
- Quality management (computer vision, defect detection) (4.3%)
- Risk sensing (4.3%)
- Data analysis (4.3%)

See attached word document Figure 3

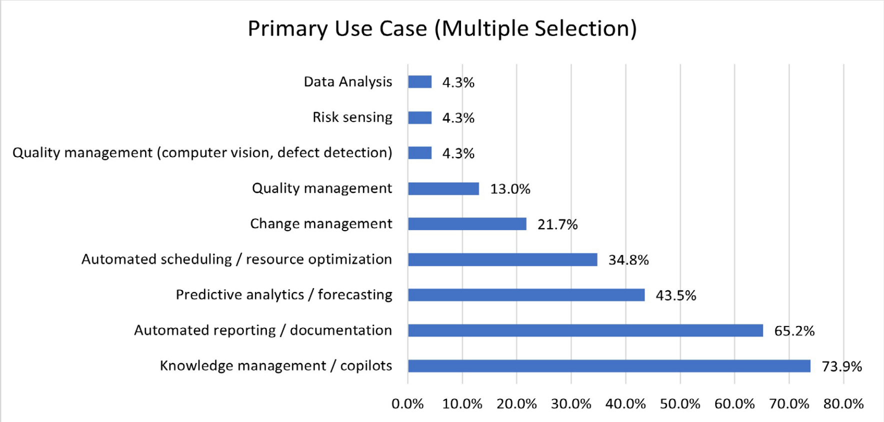

Figure 3. Primary use case.

AI Delivery Models:

- Not established yet (30.4%)

- External partner-led/outsourced (26.1%)
- Centralized AI/Analytics team serving projects (17.4%)
- Federated (both central & embedded) (13.0%)
- Embedded AI within PMO (13.0%)

See attached word document **Figure 4**

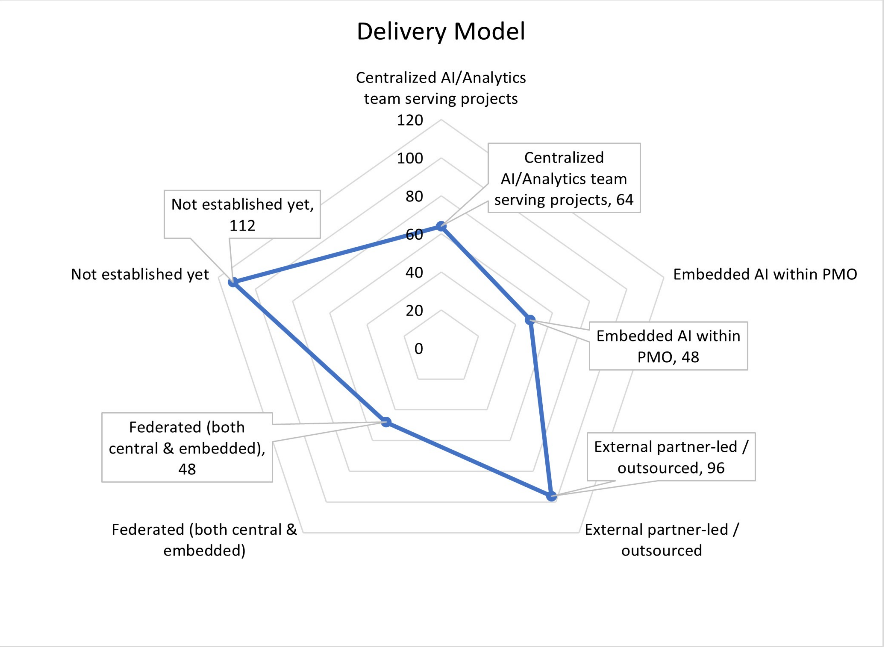

Figure 4. Delivery model.

4.1.3. Implementation Challenges

Our participants recognized significant challenges in implementation:

Most Common Challenges (percentage reporting):

- Skills gap (AI/ML, data engineering, product ownership) (56.5%)
- Internal resistance/change fatigue (47.8%)
- Privacy/security concerns (43.5%)
- Unclear ROI/cost-benefit case (43.5%)
- Governance, risk, compliance & ethics (43.5%)
- Data quality/availability/fragmentation (39.1%)
- Integration complexity with PMIS/ERP/DevOps (26.1%)
- Total cost of ownership (compute, licensing, support) (26.1%)
- Executive sponsorship/prioritization gaps (13.0%)
- Vendor lock-in/interoperability issues (13.0%)

4.1.4. Observed Benefits

In spite of the difficulties in implementation, organizations noted considerable advantages:

Primary Benefits (percentage reporting):

- Faster reporting/decision cycles (82.6%)
- Cost savings/reduced rework (56.5%)

- Quality improvement/fewer defects (47.8%)
- Better resource utilization/workload balance (43.5%)
- Improved risk detection/early interventions (34.8%)
- Fewer overruns/better schedule adherence (26.1%)
- Higher stakeholder satisfaction/transparency (17.4%)
- No material benefits yet (8.7%)

4.1.5. Technology Stack Preferences

Organizations utilize various project management tools:

Primary PM Toolstack (percentage using):

- MS Project/Project for the Web (69.6%)
- Jira/Azure DevOps (30.4%)
- Primavera P6 (21.7%)
- Custom/in-house tools (21.7%)
- Asana/Trello/Monday.com/ClickUp (8.7%)
- Wrike/Smartsheet (8.7%)
- Other: (e.g., Copilot, MS Visio) (4.3%)

4.1.6. Key Implementation Obstacles

The open-ended answers highlighted certain distinct organizational difficulties that truly illustrate the situation:

- Change Management: "Change management" and "Internal resistance" were often mentioned
- Cost Concerns: "High cost of installation and subscription" and "Ownership cost"
- Skills and Knowledge: "Knowledge gap and fear of the unknown" and "Trainability of users"
- ROI Uncertainty: "ROI for new applications seems unclear or complicated to measure"
- Organizational Barriers: "Org hierarchy and latency in adoption"
- Technical Concerns: "Confidence level in outputs" and "Data availability"
- Security Issues: "Job security concerns"

4.2. Focus Group Results

Discussions in our focus group with 7 AI implementation specialists yielded in-depth perspectives on effective strategies for addressing implementation obstacles and creating organized adoption frameworks.

4.2.1. Implementation Success Patterns

The participants in the focus group recognized shared trends in effective AI deployments:

Critical Success Factors:

1) Executive Championship: Firm leadership dedication coupled with genuine insight into AI's strengths and weaknesses

2) Phased Approach: Incremental execution starting with high-visibility, low-risk scenarios

3) Change Management: Thorough communication and training initiatives

4) Data Foundation: Investment in data integrity and management prior to AI implementation

5) Skills Development: Structured skill development throughout organizational tiers

Implementation Timeline: Successful executions generally adhere to a timeline of 12 - 18 months:

- Months 1 - 3: Establishing a foundation and choosing pilots
- Months 4 - 9: Initial implementation and improvement
- Months 10 - 15: Expansion and incorporation
- Months 16 - 18: Refinement and ongoing enhancement

4.2.2. Framework Development

The participants in the focus group viewed Kotter's 8-Step model as a core strategy that guarantees readiness and acceptance among individuals (change management) and the AI Maturity Roadmap that provides a structured, phased rollout (technical + governance). By engaging in thorough dialogue and examining implementation obstacles, they developed a hybrid model that merges the advantages of each approach while tackling the unique bottlenecks and opposition encountered during AI integration in project management scenarios.

The hybrid framework surfaced as an answer to the key challenges highlighted in our survey data, especially tackling skills gaps (56.5%), internal resistance (47.8%), and ROI uncertainty (43.5%). The framework combines structured technical advancement with thorough change management tactics, guaranteeing that both the technological framework and human factors are managed efficiently during the implementation phase.

5. Analysis of Challenges and Solutions

5.1. Technical Challenges and Solutions

5.1.1. Data Quality and Availability Challenges

Challenges with data quality, noted by 39.1% of those surveyed, constitute a primary obstacle to the implementation of AI in project management. Organizations commonly face data quality challenges involving completeness, consistency, accuracy, and relevance. Historical project data often exists in fragmented systems with inconsistent formats, missing context, and embedded biases from past inefficiencies [37].

Solution Framework: A robust data governance system serves as the basis for tackling quality issues. Effective strategies focus on systematic data enhancement instead of trying extensive cleansing prior to AI deployment:

1) Master Data Management Implementation: Companies create centralized databases for essential project data with uniform definitions, formats, and quality

standards. This method decreases integration complexity by 43% and maintains consistency among systems [51].

2) Automated Data Quality Monitoring: Real-time systems detect and highlight discrepancies, absent values, and unusual patterns with 91-95% precision [52].

3) Incremental Data Enhancement: Instead of postponing AI deployment until ideal data is ready, organizations adopt phased strategies that enhance data quality while reaping immediate advantages from AI.

5.1.2. System Integration Complexities

Integration difficulties impact 26.1% of participants in the survey, especially those with intricate legacy IT systems. Traditional project management systems frequently do not have modern integration features, necessitating custom development for AI connectivity [53].

Solution Framework:

1) API-First Architecture: Creating uniform interfaces allows for adaptable integration with existing and upcoming AI technologies

2) Cloud-Based Integration Platforms: Cloud infrastructure offers scalable resources and ready-made connectors for typical project management systems

3) Phased Integration Strategy: Incremental system integration minimizes risk and enables testing and enhancement

5.2. Organizational Challenges and Solutions

5.2.1. Resistance to Change

Organizational resistance impacts 47.8% of implementations, making it the second-largest obstacle after skills shortages. This manifests as doubt regarding AI abilities, anxiety over job loss, and hesitation to change existing procedures. Studies show that resistance greatly affects implementation success, as organizations facing substantial resistance reach just 23% success rates [54] [55].

Solution Framework:

1) Communication Strategy: Clear communication regarding AI capabilities diminishes uncertainty and fosters support

2) Champion Networks: Recognizing and supporting AI proponents fosters peer influence for acceptance

3) Gradual Implementation: A staged approach provides time for adjustment while fostering trust through initial successes

5.2.2. Executive Leadership and Commitment

According to our survey data, 13.0% of implementations are impacted by insufficient executive support, although focus group discussions indicate that this might be underreported. Successful AI implementation necessitates continuous backing from executives over lengthy implementation periods. In the absence of knowledgeable leadership, implementations might face a lack of resources or lose traction when faced with obstacles [56].

Solution Framework:

1) Executive Education: Equipping leaders with a thorough grasp of AI facilitates knowledgeable decision-making

2) Business Case Development: A clear expression of AI advantages, expenses, and risks allows for well-informed executive choices

3) Steering Committee Structure: Established governance frameworks guarantee ongoing involvement from leadership

5.3. Human Factors Challenges and Solutions

5.3.1. Skills Development and Training Needs

Skills gaps are the primary challenge in implementation, as noted by 56.5% of those surveyed. The introduction of AI leads to new skill demands at all levels within the organization. Project managers require knowledge of AI functionalities, skills in data analysis, and familiarity with workflows enhanced by AI [57].

Solution Framework:

1) Layered Training Programs: Various organizational tiers necessitate diverse training strategies

2) Experiential Learning: Practical engagement with AI tools is more impactful than classroom-based learning

3) Continuous Learning Systems: Organizations implement perpetual educational programs instead of singular training sessions

5.3.2. Human-AI Collaboration Models

Achieving successful AI implementation necessitates creating effective collaboration frameworks that utilize both human skills and AI functionalities. The task consists of identifying the best allocation of duties between humans and AI systems [58].

Solution Framework:

1) AI as Decision Support: Frame AI as delivering insights and suggestions, with humans ultimately making the final choices

2) Graduated Automation: Apply ascending degrees of automation according to task difficulty and risk factors

3) Transparent AI Systems: Collaborating with AI necessitates comprehension of AI logic and constraints

Key Challenge Alignment

Our extensive framework tackles the key implementation issues highlighted in the survey via focused interventions and organized strategies. Every category of challenge is given focused attention through organized phases that integrate technical solutions with strategies for managing organizational change. As shown in Table 1 below, each survey-identified challenge is mapped to specific framework actions across the implementation phases.

Table 1 demonstrates how the framework's structured method guarantees that technical execution progresses alongside organizational preparedness, reducing opposition while enhancing skills and assurance throughout the procedure. This comprehensive strategy tackles the complex aspects of AI adoption difficulties, offering specific, practical measures for successful execution.

Table 1. Key challenge alignment.

Challenge (Survey %)	Framework Action
Skills Gap (56.5%)	Layered training + experiential learning (Phases 1 - 4)
Resistance to Change (47.8%)	Communication, Champion Network, phased rollout (Phases 1 - 3)
Unclear ROI (43.5%)	Pilot measurement, defined KPIs, early wins (Phase 2)
Governance/Compliance/Privacy (43.5%)	AI governance, risk frameworks, transparent AI (Phase 3 - 4)
Data Quality (39.1%)	Data audit, MDM, incremental improvement (Phase 1 - 4)
Integration Complexity (26.1%)	API-first, cloud-based integration (Phase 2 - 3)
Cost of Ownership (26.1%)	Phased budgeting, scalable cloud adoption (Phase 3)
Executive Sponsorship (13%)	Leadership education & steering committee (Phase 1)
Regulatory/Job Security Concerns	Transparent AI policies, ethics governance, human-AI collaboration (Phase 4)

6. Discussion and Implications

6.1. Implementation Framework for AI in Project Management

Drawing from our in-depth evaluation of survey results and focus group findings, this study offers a structured approach for integrating AI into project management environments. The framework tackles the essential success factors discovered through our empirical studies while offering actionable advice for organizations at various levels of AI maturity.

6.1.1. AI Integration Framework for Project Management

Our examination of the focus group showed a systematic method for integrating AI into project management, divided into four separate stages that tackle both technical integration and aspects of organizational change management. Figure 5 illustrates this comprehensive four-phase framework, showing the progression from foundation through maturation.

Phase 1: Foundation and Assessment (Months 1 - 3): This preliminary phase sets the stage for effective AI deployment by performing thorough organizational readiness evaluations, ensuring executive support, assessing data quality, identifying skill gaps, and pinpointing initial use cases. Organizations need to set up well-defined governance frameworks, outline success indicators, and develop communication plans prior to starting the implementation stages.

Phase 2: Pilot Development and Testing (Months 4 - 9): The pilot stage centers on regulated deployment with chosen use cases, usually starting with knowledge management and automated reporting tools that exhibit the highest adoption levels (73.9% and 65.2% respectively). Organizations create technical frameworks, provide team training, launch initial AI implementations, and set up extensive performance evaluation systems. This stage focuses on enhancing confidence through measurable successes while improving implementation strategies.

Phase 3: Scaling and Integration (Months 10 - 15): The expansion phase broadens effective pilots throughout the organization while continuing to prioritize change management and system integration. Organizations create organization-wide training initiatives, incorporate AI systems into current project management tools, develop extensive governance structures, and enhance performance tracking functionalities. This stage deals with the 26.1% of organizations facing difficulties related to integration complexity.

Phase 4: Maturation and Continuous Improvement (Months 16+): The maturation stage emphasizes the implementation of advanced AI capabilities, ongoing optimization, the creation of an innovation pipeline, and planning for long-term sustainability. Organizations create centers of excellence, adopt advanced analytics technologies, and develop enduring learning and enhancement procedures.

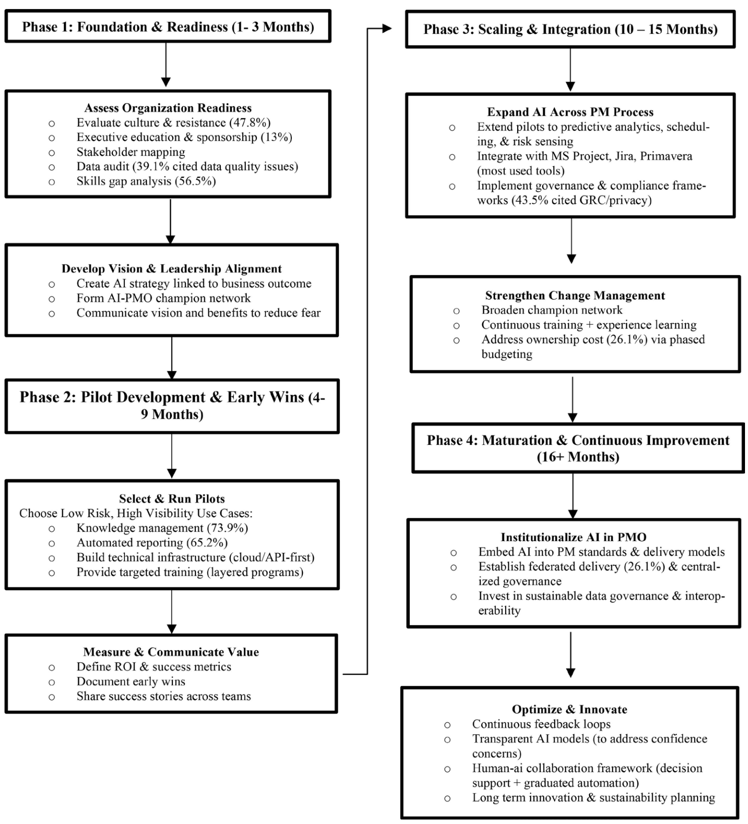

Figure 5. Implementation Framework for AI in Project Management (percentages are traced from survey challenges).

6.1.2. Change Management Framework for AI Adoption

Organizations that successfully adopt AI allocate considerable resources to change management, typically dedicating 15% - 20% of their implementation budgets to activities related to communication, training, and cultural transformation. Drawing from our focus group findings and theoretical underpinnings, this study introduces the ADEPT Framework for Managing AI Change. Figure 6 illustrates the five-phase ADEPT Framework with its continuous feedback loop mechanism.

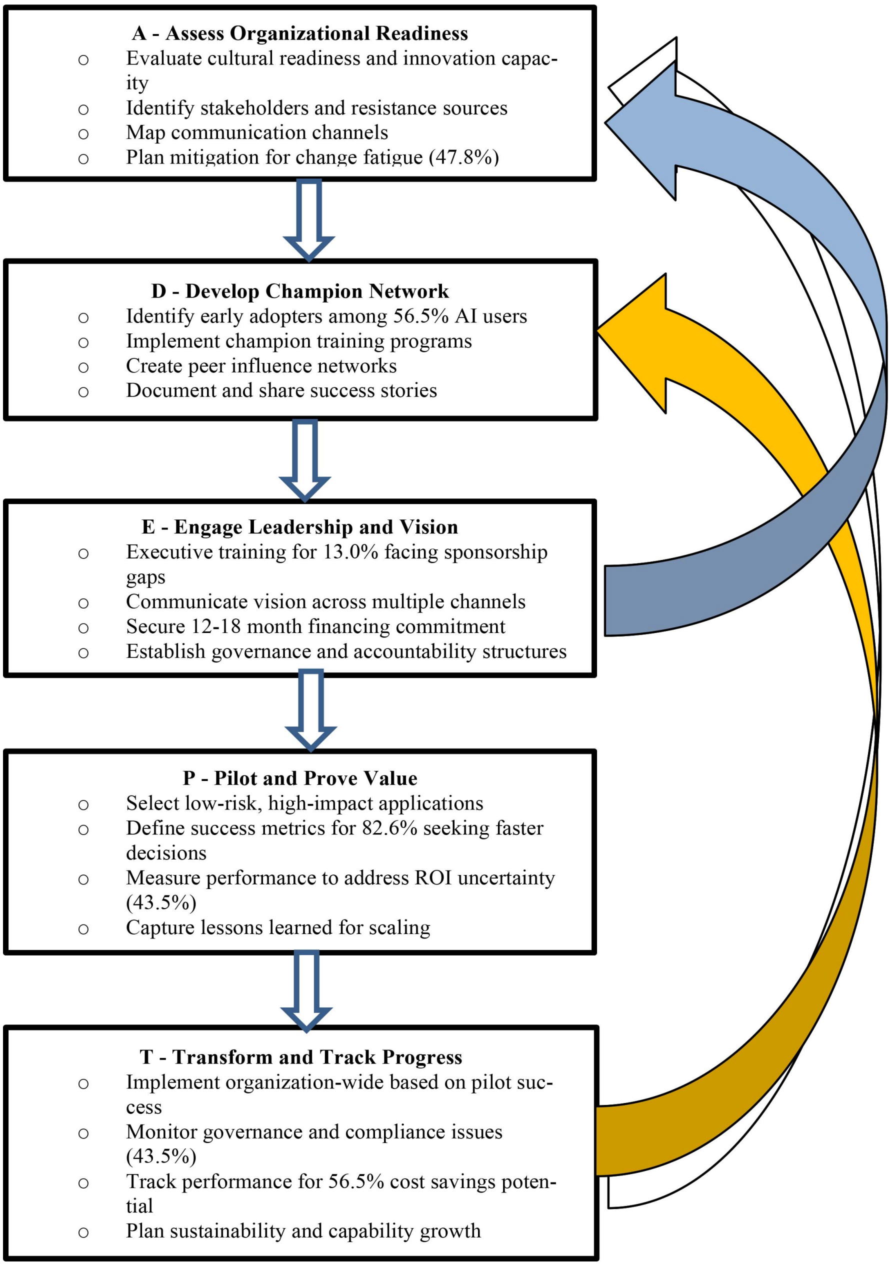

Figure 6. ADEPT framework for AI change management.

The ADEPT Framework represents a structured approach to managing AI change in project management organizations, addressing the complex interplay between technological implementation and human factors. This five-phase framework directly responds to the primary implementation challenges identified in our research, particularly the 56.5% of organizations struggling with skills gaps and the 47.8% facing internal resistance.

A - Assess Organizational Readiness: The framework begins with a comprehensive organizational readiness evaluation, recognizing that successful AI implementation requires understanding existing cultural capacity for innovation. This phase addresses the compatibility challenges highlighted in Diffusion of Innovation Theory, where AI adoption often conflicts with established organizational values and workflows. By mapping stakeholder influences and communication channels early, organizations can proactively identify resistance sources and develop targeted mitigation strategies for the significant portion experiencing change fatigue.

D - Develop Champion Network: Building on TAM's emphasis on social influence, the second phase leverages early adopters within the 56.5% of organizations already implementing AI. Research demonstrates that peer influence significantly impacts technology acceptance, making champion networks crucial for overcoming the perceived complexity barriers that hinder adoption. These champions serve as change agents, providing social proof and demonstrating tangible benefits to skeptical colleagues.

E - Engage Leadership and Vision: Executive sponsorship emerges as critical for AI success, yet our findings show 13.0% of organizations face sponsorship gaps. This phase directly addresses TAM's external variables by ensuring leadership provides necessary resources, clear vision communication, and governance structures. The 12 - 18 month commitment timeframe acknowledges that AI transformation requires sustained executive support beyond initial enthusiasm.

P - Pilot and Prove Value: The pilot phase strategically addresses ROI uncertainty reported by 43.5% of organizations by focusing on measurable, low-risk applications that demonstrate clear value. This approach aligns with the DOI Theory's emphasis on observability and trialability, allowing organizations to prove AI benefits before committing to full-scale implementation. Success metrics targeting the 82.6% seeking faster decision-making provide concrete evidence of AI value.

T - Transform and Track Progress: The final phase scales successful pilots organization-wide while maintaining focus on governance, compliance, and performance monitoring. This addresses the 43.5% concerned with governance issues and positions organizations to realize the 56.5% cost savings potential identified in our research.

Continuous Feedback Loop and Impact

The ADEPT Framework's continuous feedback mechanism represents its most critical differentiating feature, recognizing that AI implementation is not linear but iterative. Unlike traditional change management approaches, this framework acknowledges that insights from later phases must continuously inform and refine earlier activities. The feedback loop operates through several key pathways: transformation results (Phase T) provide valuable data for future readiness assessments (Phase A), revealing previously unidentified organizational barriers or capabilities. Pilot outcomes (Phase P) inform champion network refinement (Phase D), helping identify which influence strategies prove most effective with different stakeholder groups. Leadership engagement experiences (Phase E) often uncover additional organizational readiness needs, requiring reassessment of cultural factors and communication approaches.

This continuous feedback approach has profound implications for implementation success. Organizations utilizing iterative feedback demonstrate higher adaptation capacity, allowing them to address emerging challenges before they become critical barriers. The feedback loop enables real-time course correction, reducing the risk of large-scale implementation failures that plague many technology adoptions. Furthermore, the continuous learning aspect builds organizational AI competency over time, creating sustainable change capabilities that extend beyond individual projects. The feedback mechanism also addresses the dynamic nature of AI technology and organizational contexts, ensuring the framework remains relevant as both evolve. Most significantly, this approach transforms change management from a one-time event into an embedded organizational capability, positioning organizations for ongoing AI innovation and adaptation in a rapidly evolving technological landscape.

6.2. Theoretical Contributions

This study enhances our theoretical comprehension of technology adoption by expanding the Technology Acceptance Model and Diffusion of Innovation Theory to include AI adoption in project management settings. Our results indicate that the fundamental elements of TAM, specifically perceived usefulness and perceived ease of use, are still applicable for AI adoption, but need to be broadened to account for the distinct features of AI technologies [30].

Empirical Validation of Theoretical Frameworks

Our empirical findings provide strong validation for both theoretical frameworks while revealing how AI implementation challenges specifically manifest within TAM and DOI constructs.

Technology Acceptance Model (TAM) Validation:

The predominant challenge of skills gaps (56.5% of respondents) directly impacts TAM's "perceived ease of use" construct. When project managers lack AI/ML competencies and data engineering knowledge, they perceive AI tools as difficult to operate, reducing their intention to adopt these technologies. This finding extends TAM's applicability to AI contexts where ease of use is not merely about interface design but requires substantial upskilling investments. Similarly, the 43.5% reporting unclear ROI/cost-benefit cases directly affects TAM's "perceived usefulness" dimension. Organizations struggle to quantify AI benefits, undermining confidence in the technology's value proposition - a critical factor in

TAM's adoption decision process. The 82.6% experiencing faster decision-making cycles demonstrates how perceived usefulness drives adoption when benefits become tangible and measurable.

Diffusion of Innovation Theory (DOI) Validation:

The internal resistance and change fatigue reported by 47.8% of respondents strongly relates to DOI's "compatibility" attribute. AI implementation often conflicts with existing organizational values, established workflows, and cultural norms around human decision-making, creating the compatibility gaps that Rogers identified as adoption barriers. The privacy/security concerns (43.5%) and governance/compliance issues (43.5%) reflect DOI's "complexity" dimension, where organizations perceive AI integration as introducing technical and regulatory complexities that exceed their current capabilities.

Furthermore, our finding that knowledge management/copilots (73.9%) lead adoption patterns aligns with DOI's emphasis on "observability" - these applications provide visible, tangible benefits that can be easily communicated to stakeholders, facilitating organizational diffusion. The lower adoption rates for more complex applications like predictive analytics (43.5%) and quality management (13.0%) support DOI's proposition that complexity negatively affects adoption rates.

The findings from our survey indicate that perceived usefulness (demonstrated through advantages like quicker reporting and reduced costs) is significantly associated with successful adoption. Nonetheless, the substantial proportion of skills gaps (56.5%) indicates that the perceived ease of use necessitates considerable organizational investment in training and capacity development. In contrast to conventional software applications, AI systems produce probabilistic instead of deterministic results, necessitate significant data infrastructure, and foster novel types of human-technology interactions [59].

6.3. Practical Implications

6.3.1. For Project Management Practitioners

Project managers need to acquire new skills that blend conventional project management knowledge with an understanding of AI. Our findings from this purposive sample suggest that effective AI implementation necessitates comprehension of AI abilities and constraints, proficiency in analyzing AI-produced insights, and familiarity with human-AI cooperative processes. The survey results indicate that knowledge management (73.9%) and automated reporting (65.2%) are the leading AI applications, which implies that project managers ought to prioritize skill development in these domains initially.

6.3.2. For Organizational Leaders

Executive leaders are vital to the success of AI implementation by establishing vision, allocating resources, and facilitating change. Our study highlights the significance of knowledgeable leadership that comprehends AI functions, needs, and intricacies of implementation. The survey results showing that just 13.0% view executive sponsorship as a challenge suggest adequate leadership backing among our sample organizations; however, our focus group conversations indicated notable differences in the depth of executive comprehension.

6.4. Limitations and Future Research Directions

This study offers important insights into the challenges and solutions of AI implementation, yet various limitations indicate potential areas for further exploration. The use of purposive convenience sampling, while enabling access to relevant professionals, limits the generalizability of findings as the sample may not be statistically representative of the broader project management population.. The geographic distribution indicating 47.8% from the Middle East and Africa may restrict generalizability to other areas.

Future studies may gain from unbiased performance metrics and long-term research monitoring implementation results over longer durations. Moreover, studies tailored to specific industries would offer more focused assistance for challenges and solutions unique to each sector.

7. Conclusions

This mixed-methods study provides comprehensive insights into AI implementation challenges and solutions in project management through survey data from 368 professionals and focus group discussions with 7 implementation experts.

Our investigation reveals that while 56.5% of organizations have initiated AI adoption, significant implementation barriers persist. Skills gaps represent the primary challenge (56.5%), followed by internal resistance (47.8%) and ROI uncertainty (43.5%). Despite these obstacles, organizations report substantial benefits, with 82.6% experiencing faster decision-making cycles and 56.5% achieving cost savings.

The research validates both the Technology Acceptance Model and the Diffusion of Innovation Theory constructs within AI contexts, demonstrating how skills gaps directly impact perceived ease of use, while internal resistance reflects compatibility challenges with existing organizational values and workflows.

This study contributes two actionable frameworks based on empirical findings: the four-phase AI Integration Framework addressing systematic technical and governance requirements, and the ADEPT Change Management Framework targeting human and organizational dimensions of AI adoption.

Key recommendations for practitioners include: starting with high-value applications like knowledge management and automated reporting, prioritizing comprehensive skills development programs, implementing systematic change management through champion networks, building data governance capabilities while leveraging existing data, and adopting phased implementation approaches to minimize risk while building organizational confidence.

The integration of AI in project management represents a transformative opportunity for competitive advantage. However, realizing this potential requires a comprehensive understanding of implementation challenges and the systematic application of evidence-based solutions. Organizations that approach AI strategically, with appropriate resource allocation and realistic expectations, position themselves for sustained benefits in the evolving project management landscape.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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