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GENERATIVE AI-DRIVEN PROJECT MANAGEMENT: INTELLIGENT PLANNING, PREDICTIVE RESOURCE ALLOCATION, AND CONTEXT-AWARE STAKEHOLDER ENGAGEMENT

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Abstract

The integration of Generative Artificial Intelligence (GenAI) into project management is reshaping conventional management practices by enabling intelligent decision support, adaptive planning, and human–AI collaboration. This review examines the application of GenAI across project planning, resource allocation, scheduling, risk management, and stakeholder communication, synthesizing academic research, empirical evidence, and emerging enterprise platform architectures. It explores how transformer-based large language models (LLMs) can complement established project management methodologies by transforming static planning processes into dynamic, iterative workflows that respond to changing project requirements, resource constraints, and stakeholder expectations. Particular attention is given to hybrid architectures that integrate LLMs with retrieval-augmented generation (RAG), knowledge graphs, and deterministic scheduling techniques, including the Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT). These combinations offer a promising foundation for improving planning accuracy, resource utilization, schedule reliability, and managerial decision-making, although reported performance gains require careful interpretation in light of differences in study design, implementation context, and evaluation methods. The review also investigates multi-agent AI systems that coordinate specialized agents to automate administrative tasks, support cross-functional collaboration, and facilitate context-aware stakeholder engagement. Despite these opportunities, successful implementation remains constrained by hallucinations, data privacy risks, algorithmic bias, inadequate governance, overreliance on

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automated recommendations, and potential erosion of professional expertise. To address these challenges, this study proposes a socio-technical framework integrating human-in-the-loop oversight, transparent decision-making, secure data management, systematic AI evaluation, and continuous workforce development. The review establishes a research-oriented foundation for responsible GenAI adoption in project management and identifies priorities for future empirical validation, organizational readiness assessment, and the development of trustworthy human–AI project management ecosystems.

1. INTRODUCTION

Information Technology (IT) and complex engineering project management operate in environments defined by rapid technological changes, distributed hybrid work arrangements, and exponential growth in data volume (Durney & Donnelly, 2015). Despite substantial financial and structural investments in project management methodologies, project failure rates remain elevated across industries. Empirical estimates indicate that nearly 10% of total invested capital is lost due to project inefficiency (Aramali et al., 2025). Standard industry analyses reveal that typical causes of project failures center on budget overruns (55%), inadequate requirements management (47%), misalignment with overarching business goals (44%), insufficient sponsor support (41%), ambiguous initial scope definitions (37%), weak top management involvement (33%), and the absence of a unified project vision (31%) (Bento et al., 2022).

Traditional Artificial Intelligence (AI) solutions in project management relied on narrow machine learning models, deterministic optimization algorithms, and isolated natural language processing (NLP) pipelines focused primarily on task-specific predictive analytics, such as risk scoring or critical path calculation. While these legacy techniques enhanced quantitative forecasting, they functioned as static point solutions or administrative toolboxes, leaving qualitative, linguistic, and procedural synthesis to human project managers (Auth et al., 2021)

The emergence of Generative Artificial Intelligence (GenAI), driven by transformer-based Large Language Models (LLMs), represents a structural shift from passive analytical tools to active co-orchestrators across the project lifecycle. Capable of dynamic text synthesis, complex context reasoning, multi-modal code generation, and direct software ecosystem integration, GenAI redefines operational capabilities (Mundlamuri et al., 2025). Recent empirical assessments demonstrate that corporate adoption of GenAI has reached 88%, supported by significant private capital deployments, including over $33.9 billion in U.S. generative AI investments alone. On an individual level, work-related adoption has reached 28%, with 10.6% of workers utilizing generative AI daily (Vaswani et al., 2017). Within project management contexts, early evidence shows that GenAI integration can reduce execution time by 10–15%, decrease budget deviations by 10–20%, and increase overall project manager productivity by up to 63%, with 90% of adopting companies recording a positive return on investment within a year (Noy & Zhang, 2023).

This review article provides a comprehensive synthesis of current academic literature, empirical data, and industry architectures regarding GenAI applications in automated project planning, resource allocation, and stakeholder communication (Javadpour et al., 2026). By mapping transformer capabilities across established management process groups, examining Retrieval-Augmented Generation (RAG) and multi-agent orchestration frameworks, and analyzing commercial platform integrations, this paper outlines both the operational value and socio-technical governance requirements of

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modern AI-driven project management (Anghel & Cioara, 2026).

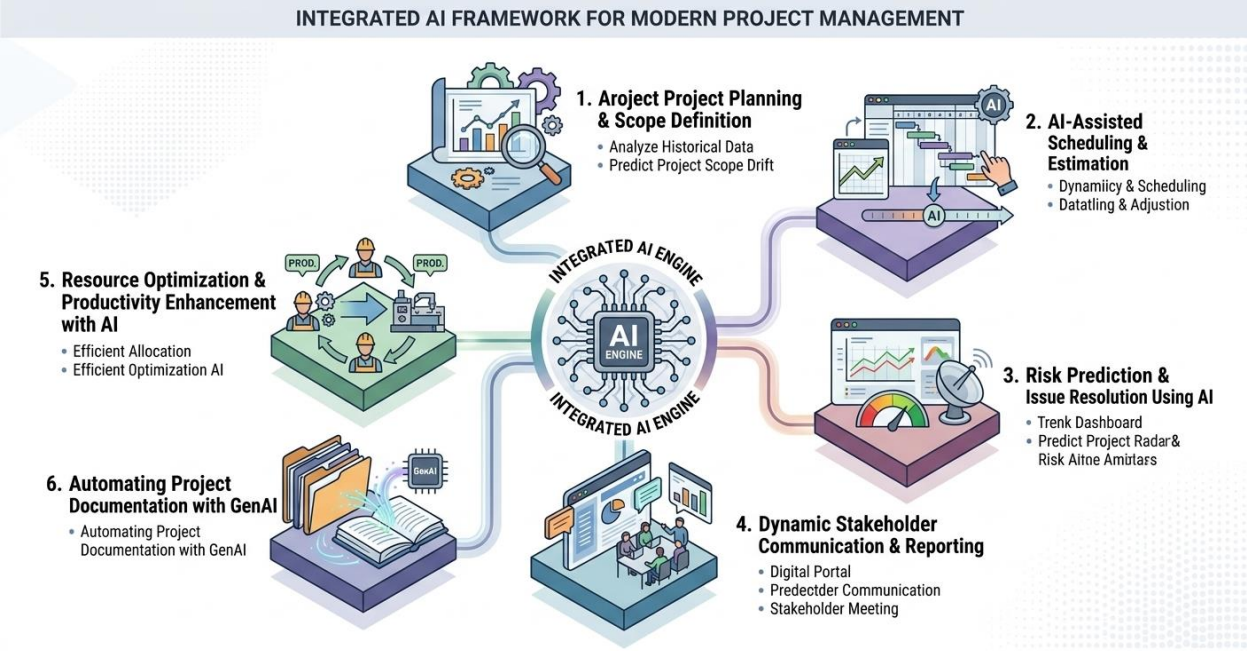


Figure [X]: Conceptual Framework for the Application of AI Across Key Project Management Domains

Figure 1: Conceptual Framework for the Integration of Artificial Intelligence Across Core Project Management Domains

2. Foundations and Process Group Mapping

To understand the systemic integration of GenAI across project lifecycles, applications can be mapped against standard process groups established by the Project Management Institute (PMI): Initiating, Planning, Executing, Monitoring and Controlling, and Closing. Academic literature demonstrates that practitioner consensus regarding GenAI's utility is strongest in the Planning (86%), Integration (83%), and Monitoring and Controlling (75%) process groups (Gupta & Chaudhuri, 2025).

Table 1: Mapping of Generative AI Capabilities and Core Artifacts Across Project Management Process Groups

Process Group	Core GenAI Capabilities	Primary Input Data	Generated / Managed Artifacts	Primary Operational Impact
Initiating	Semantic scope synthesis, ambiguity detection, feasibility analysis	Stakeholder interviews, business cases, charter templates	Project Charters, Stakeholder Registers, Initial Scope Statements	Reduces setup time; mitigates initial requirement ambiguities.
Planning	Dynamic Work Breakdown Structure (WBS) creation,	Unstructured requirements, historical sprint	WBS, PERT/Gantt schedules, Risk	Automates structural task breakdown;

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	automated cost/time estimation, risk register formulation	logs, domain handbooks	Registers, Resource Matrices	improves estimate baseline accuracy.
Executing	Code generation, automated task routing, cross-functional mediation	User stories, sprint backlogs, code repositories, team rosters	Code snippets, Test Scripts, Task Assignments, Briefings	Reduces boilerplate work by >50%; accelerates cycle times.
Monitoring & controlling	Real-time status reporting, anomaly detection, automated variance analysis	Time-tracking logs, git commits, budget burn rates, issue tickets	Interactive Dashboards, Earned Value Analyses, Risk Alerts	Proactively identifies scope creep and schedule bottlenecks.
Closing	Automated documentation synthesis, retrospective summarization, post-mortem extraction	Project archives, retrospective transcripts, issue resolution logs	Lessons Learned Registers, Final Project Reports, Closeout Summaries	Prevents knowledge decay; institutionalizes organizational memory.

Synthesizing cross-process group capabilities reveals a fundamental evolution: GenAI collapses the traditional chronological boundary between project planning and execution. In legacy frameworks, planning functioned as a discrete phase producing static milestone baselines. Under GenAI augmentation, real-time data inputs from execution tools continuously re-trigger planning algorithms. This transitions project lifecycles into dynamic loops, where schedule estimates, task dependencies, and resource allocations are iteratively recalculated as execution unfolds (Brynjolfsson et al., 2025).

3. Automated Project Planning: Artifact Generation and Structural Decomposition

Automated project planning relies on converting unstructured human intent, product visions, and client specifications into structured, executable project schedules. The foundational step requires decomposing high-level project objectives into a Work Breakdown Structure (WBS) and mapping logical task dependencies (Barcaui & Monat, 2023).

The core generative transformation follows an integrated multi-stage pipeline. Initially, unstructured project intent and raw requirements specifications are ingested by a Generative AI engine. This engine operates alongside domain-specific knowledge bases using Retrieval-Augmented Generation (RAG) and Knowledge Graphs (KG) to ground context. Next, structured reasoning techniques such as Chain-of-Thought (CoT) prompting guide the model to decompose the high-level scope into activity nodes and logical dependencies (Gao et al., 2026). Rather than relying on non-deterministic neural networks for final scheduling calculations, these structural task outputs are passed into deterministic optimization algorithms, such as the Critical Path Method (CPM) or Program Evaluation and Review Technique (PERT). The hybrid pipeline culminates in the automated output of executable schedules, Gantt charts, and preliminary risk registers (Lewis et al., 2020).

3.1 Prompting Paradigms and Retrieval Architectures

General-purpose foundation models frequently struggle with industry-specific task dependencies and technical constraints when evaluated in zero-shot configurations. Empirical evaluations demonstrate that zero-shot prompting produces incomplete project plans, achieving lower

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confidence scores (averaging 64% accuracy, or 1.91 out of 3.0). Conversely, applying Chain-of-Thought (CoT) prompting techniques wherein the LLM explicitly articulates its step-by-step reasoning regarding activity sequencing, safety dependencies, and resource constraints elevates planning accuracy to 84% (confidence score 2.52) while yielding significant improvements across BLEU, ROUGE-L, METEOR, content overlap, and semantic similarity metrics (Wei et al., 2022).

To prevent structural hallucinations and ground LLM outputs in verified technical constraints, systems deploy Retrieval-Augmented Generation (RAG). Modern planning frameworks utilize dual-tier Static RAG architectures:

- **Local Static RAG**: Retrieves localized definitions, taxonomy standards, and Work Breakdown Structure (WBS) node rules from private organizational data repositories.
- **Global Static RAG**: Pulls domain-wide technical standards, regulatory compliance manuals, and historical project performance logs from broader knowledge bases (Hiriyanna & Zhao, 2025).

Advanced planning frameworks combine static RAG with Knowledge Graphs (KG) to represent explicit structural relationships between activities, inspection protocols, and safety standards. In construction and complex software engineering, coupling LLMs with Knowledge Graphs through fine-tuning or Agentic RAG (ARAG) yields significant optimization gains, including performance improvements of up to +42.3% in missing value prediction, +79.1% in task dependency analysis, and +28.9% in automated plan generation compared to baseline models. (Hou et al., 2024)

Empirical evaluations in software requirements engineering highlight the nuances of model selection during initiation. In studies assessing zero-shot GPT-4 performance on medical ventilator software specifications, the model performed best at identifying requirement incompleteness with a precision of 0.61, while effectively spotting missing functional details (Gao et al., 2025). Comparative evaluations between GPT-4 and CodeLlama for student club management application specifications revealed that while ChatGPT generated significantly more precise and hallucination-resistant requirements, it still exhibited occasional information gaps requiring human verification (Krishna et al., 2024).

3.2 Integration with Deterministic Project Control Frameworks

While LLMs excel at linguistic parsing, qualitative scope decomposition, and semantic risk formulation, their internal architectures are non-deterministic and unreliable for direct mathematical scheduling. Consequently, state-of-the-art automated planning models adopt hybrid processing pipelines. The LLM performs structural task extraction and semantic dependency identification; these textual outputs are subsequently parsed into quantitative scheduling engines utilizing Critical Path Method (CPM) or PERT algorithms (Ma et al., 2026).

This integration bridges a long-standing operational divide: the gap between dynamic schedule delay monitoring and legal contractual risk management. Standard CPM systems calculate that an activity is delayed by a specific number of days, but cannot interpret the contractual implications. By linking CPM execution datasets back to contract documents via RAG-enabled LLMs, systems automatically detect operational delay anomalies, cross-reference contract clauses, and alert managers to financial or legal dispute exposure in real time. (Zhang et al., 2023)

4. Algorithmic Resource Allocation and Constraint Optimization

Resource allocation requires balancing resource demand against team capacity, individual skill sets, availability, project budgets, and deadline constraints. Traditional resource allocation methods rely on static allocation matrices and manual oversight, resulting in frequent resource

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bottlenecks, underutilized talent, and localized overwork (Raidén et al., 2006).

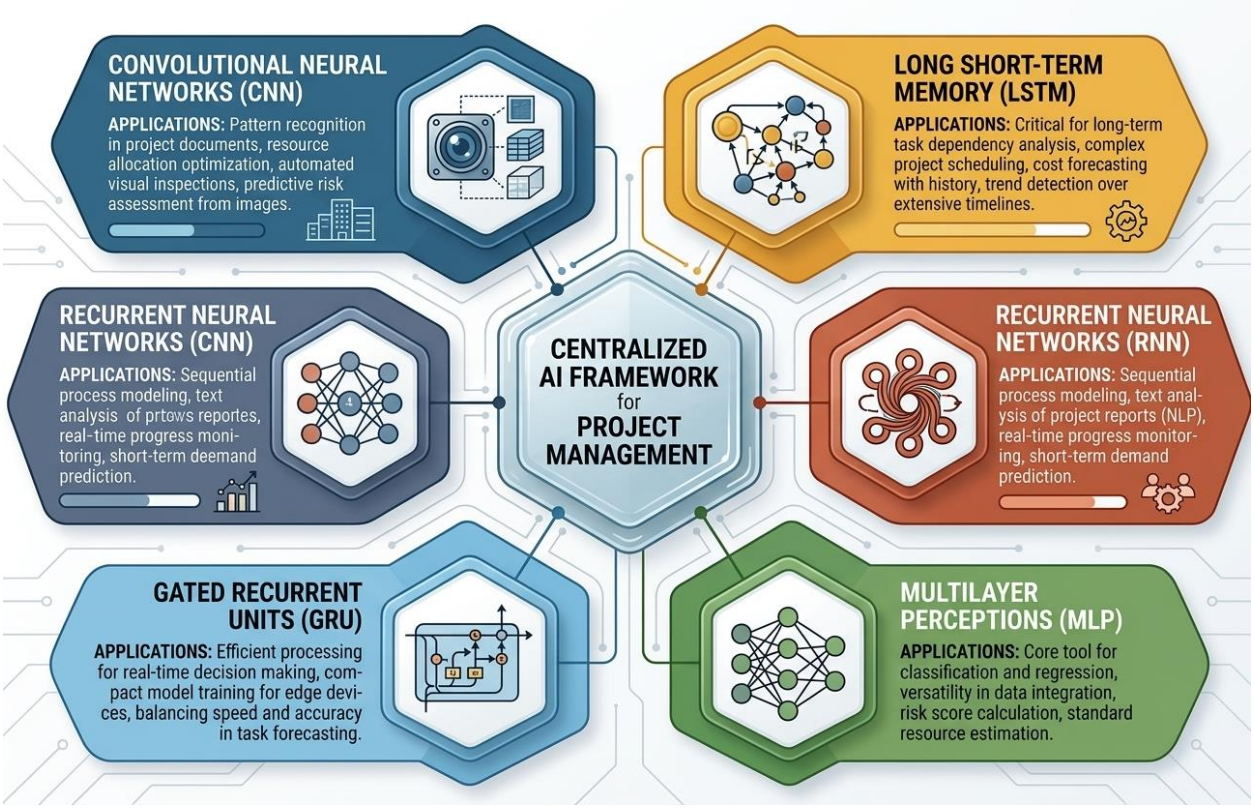


Figure 2: Architecture and Domain Applications of Neural Network Architectures in Centralized AI Project Management

4.1 Multi-Parameter Skill Matching and Capacity Analytics

GenAI transforms resource management by treating workforce capacity as a real-time operational variable. Rather than viewing team availability through binary calendar allocations, LLM-driven workforce frameworks ingest multi-dimensional employee profiles. These systems analyze contextual data including historical task execution speeds, technical code commit patterns, past performance evaluations, specialized certifications, and current task loads to compute contextual skill-fit scores. (Karmazinuk & Helik, 2026)

Through generative reasoning and contextual simulation, the system matches task requirements to the optimal team member based on technical competence, available capacity, and financial cost (Dell'Acqua et al., 2025).

Table 2: Comparative Analysis of Traditional vs. Generative AI-Driven Resource Allocation Paradigms

Dimension	Traditional Resource Allocation	Generative AI-Driven Allocation	Operational / Financial Impact

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Data Basis	Static skills inventories, manual self-assessments, fixed calendars	Dynamic commit histories, unstructured performance logs, real-time workload feeds	Eliminates skill profile obsolescence; improves matching precision.
Optimization Goal	Single-variable load balancing (e.g., hours assigned per week)	Multi-objective optimization (skills alignment, burnout risk, cost, delivery timeline)	Maximizes productivity while reducing employee fatigue and turnover.
Adaptability	Manual reassignment during weekly/bi-weekly status reviews	Continuous, real-time workload monitoring and dynamic auto-reallocation	Reduces schedule slippage caused by unexpected bottlenecks.
Forecast Horizon	Deterministic, reactive allocation based on current demand	Simulation-based predictive workforce planning and demand forecasting	Proactively flags talent deficits weeks before sprint execution.
Domain Constraint Handling	Dependent on human memory and spreadsheet complexity	Automated integration of regulatory, contractual, and labor policy constraints	Prevents compliance breaches and over-allocation penalties.

4.2 Dynamic Re-Allocation and Human Power-Skill Elevation

When execution deviations occur such as a critical developer taking unexpected leave or a technical task exceeding estimated effort GenAI allocation systems execute scenario simulations. The model evaluates alternative staffing permutations, calculates downstream impacts on the critical path, and presents optimized reallocation options to the project lead (Anghel & Cioara, 2026).

This automation yields a significant organizational side effect: as algorithmic models assume the burden of technical skill matching, task routing, and capacity accounting, the core competency requirements for human project managers undergo a fundamental shift. Technical assignment administration is automated, elevating human "power skills" specifically emotional intelligence (EI), stakeholder empathy, ethical judgment, and strategic business acumen as the primary determinants of project leadership success. (Huzooree, 2026)

5. Dynamic Stakeholder Communication and Multi-Agent Orchestration

Communication breakdown and fragmented stakeholder expectations represent primary drivers of project failure. GenAI addresses these friction points by automating administrative communication and serving as an intelligent orchestration layer across complex stakeholder networks (Pirozzi, 2026).

Multi-agent coordination in modern project management operates through a structured hub-and-spoke topology. A human project manager establishes strategic goals and retains oversight authority. The human manager interacts directly with a Centralized Supervisor Agent, powered by an LLM orchestrator. This supervisor agent uses inter-agent communication protocols such as Model Context Protocol (MCP) or Agent-to-Agent (A2A) protocols to delegate tasks to domain-specialized AI agents (Zhu et al., 2026). For instance, an *Initiating Specialist Agent* gathers requirements and drafts charters; a *Planning Specialist Agent* constructs schedules and allocates resources; and an *Executing Specialist Agent* monitors real-time code repositories and updates issue trackers. The supervisor agent consolidates agent outputs, verifies task completion against project constraints, and reports synthesized progress back to the human project manager. (Chen et al., 2024)

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5.1 Automated Stakeholder Engagement and Artifact Synthesis

GenAI tools streamline communication by processing multi-modal team inputs into targeted stakeholder outputs. Systems integrated into collaboration platforms (e.g., Zoom, Microsoft Teams, Notion) automatically transcribe technical discussions, isolate decisions, extract action items, and update project tracking platforms without human intervention (Wang et al., 2026).

Furthermore, LLMs allow status reporting to be dynamically tailored to distinct audience profiles:

- **Executive Leadership**: Synthesizes broad financial burn rates, high-level milestone completion percentages, and critical business risks.
- **Clients / External Stakeholders**: Translates technical progress into non-technical deliverables, contractual compliance markers, and milestone achievements.
- **Engineering Teams**: Generates detailed feature specifications, API requirements, bug triage queues, and immediate sprint priorities (Rahimzadeh et al., 2025).

5.2 Multi-Agent Orchestration Architectures

To move beyond basic prompt-and-response interaction models, advanced project environments deploy Multi-Agent Systems (MAS). In these architectures, specialized autonomous AI agents operate collaboratively, assuming distinct functional roles across the project lifecycle (Roumeliotis et al., 2026).

Three primary agentic topologies dominate current implementations:

1. **Process Group Specialized AI Agents**: Dedicated agents are bound to specific PMBOK process groups. An *Initiating Agent* processes intake forms to draft charters; a *Planning Agent* converts charters into WBS schedules; an *Executing Agent* tracks task completion and alerts a *Monitoring Agent* to deviations (Meng, 2025).
2. **Role-Based Simulation AI Agents**: Agents assume specialized project management personas (e.g., Virtual Project Manager, Risk Manager, Scrum Master, Lead Developer). These agents conduct simulated negotiations to stress-test project schedules and identify hidden dependencies prior to execution (Liu et al., 2024).
3. **Hybrid Centralized (Supervisor) Topologies**: A centralized supervisor agent acts as a hub-and-spoke router (implemented via frameworks such as LangGraph or AutoGen's GroupChatManager). The supervisor agent selects speaker turns using policies such as auto, round_robin, random, manual, or custom callback functions. It decomposes top-level goals, routes sub-tasks to specialized worker agents, aggregates results, and enforces structural execution policies (Zhu et al., 2026).

Inter-agent collaboration is operationalized through standardized communication protocols, notably **Model Context Protocol (MCP)** and **Agent-to-Agent (A2A)** protocols. These protocol standards define how agents register tools, exchange state variables, pass context windows, and request validation (Liu et al., 2024).

However, multi-agent orchestration introduces technical challenges. Dialogue context windows tend to saturate as conversation length scales, requiring aggressive token management strategies (e.g., MessageTokenLimiter, MessageHistoryLimiter, and TextMessageCompressor) to prevent performance degradation and escalating computational costs (Shi et al., 2023).

6. Commercial Platform Landscape and Empirical Performance Metrics

A clear operational gap exists between academic research and commercial technology platforms. While peer-reviewed academic studies remain predominantly focused on prompt engineering baseline LLMs (such as raw GPT-4 or CodeLlama evaluation), commercial and open-source software platforms have rapidly progressed toward embedding GenAI directly into operational workflows (Anjum, 2026).

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Table 3: Enterprise Project Management AI Feature Matrix and Operational Capabilities

Platform	Core AI Architecture	Standout AI Capabilities	Enterprise Security & Governance	Targeted Workflows / Best For
Asana	Asana AI / AI Studio	No-code agentic workflow builder, "AI Teammates" for automated intake processing and task routing	SAML SSO, Enterprise Key Management (EKM), strict data residency controls	Cross-functional enterprise teams requiring agentic workflow automation.
ClickUp	ClickUp Brain	Conversational workspace assistant, automated status report generation, wiki-to-task synthesis	Role-based access controls, data encryption in transit and at rest	Distributed agile software teams seeking integrated writing and task automation.
Monday.com	Monday AI	Dynamic document building, automated formula generation, workflow condition summaries	Enterprise-grade security policies, compliance audit logging	Operational project management requiring rapid low-code automation setup.
Atlassian Jira / Confluence	Atlassian Intelligence	Natural language JQL query synthesis, automated story point estimation, release summary generation	Enterprise SOC2 Type II, ISO27001 compliance, strict data isolation	Software engineering organizations deeply embedded in Agile/Scrum lifecycles.
Dify (Open-Source)	Open-Source LLMOps & Agent Orchestrator	Custom RAG pipeline builder, multi-model backend integration, visual workflow node orchestration	Self-hosted infrastructure option; complete local data sovereignty	Organizations requiring customized, self-hosted agentic project management pipelines.

6.1 Synthesized Empirical Metrics

Empirical evaluations across software engineering, IT project management, and corporate adoption surveys reveal consistent performance improvements alongside emerging operational trends (Conforto et al., 2014).

Table 4: Key Empirical Productivity and ROI Metrics from GenAI Integration

Metric Category	Quantitative Outcome	Empirical Context / Source Study
Project Manager Productivity	63% report increased productivity	Industry survey of project managers adopting AI tools.
Return on Investment (ROI)	90% of companies achieve positive ROI within 1 year	Corporate financial evaluation of AI tool adoption.
Schedule Compression	10% – 15% reduction in project execution time	Quantitative project lifecycle performance study.
Budget Variance Control	10% – 20% decrease in overall budget deviations	Financial efficiency and risk reduction analysis.

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Developer Task Acceleration	>50% time reduction on boilerplate code and documentation	Survey of 65 software developers across SDLC tasks.
Task-Specific Software Gains	Code optimization (+60%), Bug fixing (+26%), Documentation (+12%)	Empirical Software Development Lifecycle (SDLC) analysis.
Organizational Adoption Forecast	Adoption projected to rise from 46% (2024) to 85% (2026)	Capgemini Research Institute software engineering study.

7. Socio-Technical Challenges, Governance, and Future Research Agenda

Despite rapid adoption and measurable productivity gains, integrating GenAI into project management introduces technical, organizational, and socio-technical challenges. Interpreted through a socio-technical theoretical lens, current industry issues stem from a persistent misalignment between GenAI's rapidly evolving technical subsystem and the slower-adapting social subsystem of organizational routines, governance policies, and human skill sets (Gupta & Chaudhuri, 2025).

7.1 Technical Limitations and Vulnerabilities

Uncritical adoption of GenAI creates systemic risks due to model hallucinations, context saturation, and unverified outputs. LLMs regularly generate incorrect scope context, non-existent project dependencies, or overly optimistic resource estimates. Furthermore, as multi-agent dialogues expand, models frequently suffer from instruction decay or context saturation, leading to routing failures within supervisor architectures (Perez et al., 2022).

A significant measurement gap also persists across the industry: while software teams report high perceived productivity gains, most organizations lack objective quantitative frameworks to measure actual code quality, structural debt, or baseline project velocity improvements (Forsgren et al., 2018).

7.2 Human and Socio-Technical Dynamics

The automation of project artifacts alters team dynamics and skill requirements. Generating project plans, code, and documentation via AI risks degrading foundational technical and managerial skills among junior professionals. Furthermore, AI models lack emotional intelligence, situational empathy, dynamic intuition, and nuanced negotiation capabilities. Complex stakeholder conflicts, team morale issues, and delicate contract renegotiations remain resistant to automation (Lee et al., 2025).

Workplace adoption also exhibits pronounced demographic gradients. Survey data indicates that younger workers, degree holders, and computer-industry specialists adopt generative tools at significantly higher rates than older workers or those in non-technical sectors, threatening to create internal productivity divides (Leon, 2026).

7.3 Framework for Socio-Technical Alignment and Governance

Achieving sustainable alignment requires balancing technical innovations with social subsystem governance. On the technical side, organizations deploy multi-agent communication protocols (A2A, MCP), dual-tier RAG knowledge bases, and deterministic CPM scheduling bridges to ensure computational accuracy. On the social side, these tools must be enveloped in explicit governance policies (Hanafizadeh & Mehrasa, 2025).

Key governance mandates include:

- **Strict Human-in-the-Loop (HITL) Controls**: Autonomous agent recommendations for critical project artifacts such as budget reallocations, baseline schedule alterations, or external client deliverables must require explicit human authorization (Ipekci, 2026).
- **Data Anonymization and Privacy Pipelines**: Project management tools must de-identify personal employee data, proprietary source code, and confidential client details before feeding

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contextual payloads into external LLM endpoints, ensuring compliance with GDPR and corporate privacy standards (Sedayao et al., 2014).

• **Institutionalized Prompt Engineering Libraries**: Organizations should maintain centralized, security-vetted prompt registries to standardize artifact generation and minimize prompt injection vulnerabilities (Elgendy et al., 2026).

• **Power-Skill Upskilling Initiatives**: Organizations must reorient project leadership training toward interpersonal negotiation, emotional intelligence, and strategic business acumen to complement automated technical management (Bellarmino, 2024).

The tension between technical acceleration and organizational risk explains a critical industry projection: while analysts project that enterprise application penetration of agentic AI will reach 40% by 2026, over 40% of agentic AI projects are predicted to be canceled by 2027 due to spiraling compute/token costs, unclear value realization, and inadequate risk management (Antoniuk et al., 2025).

Conclusion

This systematic review has comprehensively examined the transformative role of Generative Artificial Intelligence in automating project planning, resource allocation, and stakeholder communication across complex IT and engineering domains. The evidence demonstrates that GenAI represents more than incremental improvement; it fundamentally restructures project management workflows through dynamic, iterative loops that collapse traditional boundaries between planning and execution phases. Hybrid architectures combining LLMs with RAG, Knowledge Graphs, and deterministic scheduling algorithms have proven effective in generating structured Work Breakdown Structures, optimizing resource assignments, and synthesizing stakeholder communications with measurable productivity gains, including 10-15% schedule compression, 10-20% budget deviation reduction, and 63% reported increases in project manager productivity. Multi-agent orchestration frameworks have emerged as particularly promising, enabling specialized AI agents to collaborate through standardized protocols (MCP, A2A) while maintaining human oversight through supervisor topologies. These systems automate routine administrative tasks, allowing human project managers to focus on higher-order responsibilities requiring emotional intelligence, strategic judgment, and stakeholder empathy. However, sustained adoption requires addressing persistent technical vulnerabilities model hallucinations, context saturation, and unverified outputs alongside socio-technical challenges including skill degradation, demographic adoption divides, and governance gaps. Our proposed framework emphasizes human-in-the-loop controls, institutionalized prompt engineering, data privacy pipelines, and targeted upskilling initiatives to ensure responsible integration. Looking forward, the trajectory of GenAI in project management will be shaped by the tension between rapid technical acceleration and organizational risk management. While enterprise adoption forecasts remain optimistic, the projected cancellation rate of 40% for agentic AI projects underscores the critical importance of governance, measurable value realization, and cost optimization. Future research must prioritize objective quantitative frameworks for measuring actual code quality and project velocity improvements, longitudinal studies on workforce skill evolution, and governance models balancing automation with human oversight. Ultimately, organizations that successfully navigate this socio-technical transition will achieve not only operational efficiency but also enhanced human capabilities, positioning GenAI as a genuine partner in project leadership rather than merely an automation tool.

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