

The Impact of Artificial Intelligence Technologies on Project Performance in the Railway Industry in Germany

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الملخص

هدفت هذه الدراسة إلى فحص أثر تبني تقنيات الذكاء الاصطناعي على أداء المشاريع في صناعة السكك الحديدية لدى المؤسسات العاملة في ألمانيا. وانطلقت الدراسة من الأهمية الاستراتيجية المتزايدة للتقنيات الرقمية في البيئات الهندسية المعقدة، حيث تتسم المشاريع عادةً بضيق الجداول الزمنية، وتعدد نقاط الترابط، والحاجة المستمرة إلى اتخاذ قرارات في ظل مستويات مرتفعة من عدم اليقين. وعلى الرغم من التنامي الملحوظ في الاهتمام الإداري بتطبيقات الذكاء الاصطناعي في مجالات التخطيط والتنبؤ والتحليل، فإن الإسهام الفعلي لهذه التقنيات في تحسين أداء المشاريع لا يزال متفاوتاً بين المؤسسات.

ومن هذا المنطلق، سعت الدراسة إلى التحقق من وجود علاقة بين تبني الممارسات المدعومة بالذكاء الاصطناعي في إدارة المشاريع وبين تحسن نتائج المشاريع من حيث الوقت، والتكلفة، والجودة، ورضا أصحاب المصلحة، والتحكم بالمخاطر. اعتمدت الدراسة المنهج الكمي ذا التصميم المقطعي، وتم جمع البيانات من خلال استبانة منظمة وُزعت على مهنيين مشاركون في مشاريع السكك الحديدية ضمن مؤسسات قائمة في ألمانيا. وقد جرى قياس تبني الذكاء الاصطناعي من خلال ثمانية مؤشرات شملت دعم التخطيط، ودقة التنبؤ، والتعرف المبكر على المخاطر، ودعم اتخاذ القرار، وتحليل البيانات، وتعزيز التبني التنظيمي، والحد من التأخير، ودقة تقدير التكلفة. كما تم قياس أداء المشاريع من خلال ستة مؤشرات شملت الالتزام بالجدول الزمني، والضبط المالي، وتحقيق الجودة، ورضا أصحاب المصلحة، والتحكم بالمخاطر، والتحسين العام في نتائج المشاريع.

ولأغراض هذه المسودة، استُخدمت مجموعة بيانات تجريبية مكونة من اثنتين وأربعين استجابة، بهدف إظهار البنية التحليلية الكاملة ومنطق عرض النتائج في الدراسة. أظهرت النتائج الوصفية وجود مستوى متوسط من تبني الذكاء الاصطناعي بمتوسط حسابي بلغ (3.27)، ومستوى مرتفع نسبياً من أداء المشاريع بمتوسط حسابي بلغ (3.61). كما بين تحليل الثبات وجود اتساق داخلي مُرضٍ لكلا المتغيرين، حيث بلغت قيمة معامل ألفا كرونباخ (0.83) لتبني الذكاء الاصطناعي و(0.82) لأداء المشاريع. كذلك كشف تحليل ارتباط بيرسون عن وجود علاقة إيجابية ذات دلالة (p عند مستوى دلالة (r = 0.44) إحصائية بين تبني الذكاء الاصطناعي وأداء المشاريع، إذ بلغت قيمة معامل الارتباط وإضافة إلى ذلك، أظهر تحليل الانحدار الخطي أن تبني الذكاء الاصطناعي يترك أثراً إيجابياً ذا دلالة (0.01 < p = 0.003) عند مستوى دلالة (Beta = 0.45) إحصائية على أداء المشاريع، حيث بلغت قيمة معامل الانحدار مفسراً ما يقارب (19.6%) من التباين في المتغير التابع. وخلصت الدراسة إلى أن تبني الذكاء الاصطناعي يمكن أن يسهم بصورة ملموسة في تحسين أداء المشاريع ضمن بيئات السكك الحديدية، إلا أن هذا الأثر لا يبدو كافياً للقول إن التكنولوجيا وحدها تمثل العامل الحاسم في نجاح المشاريع. وتشير النتائج إلى أن تحقيق الفائدة المرجوة من الذكاء الاصطناعي يتطلب تكاملاً بين الأدوات التقنية وبين الحوكمة الفعالة، وتأهيل العاملين، وتحسين جودة البيانات، وسلامة الحكم الإداري. كما تقدم هذه الدراسة إطاراً عملياً لتحليل تبني الذكاء الاصطناعي في البيئات القائمة على المشاريع، وتطرح توصيات للمؤسسات العاملة في قطاع السكك الحديدية الساعية إلى تعزيز أداء مشاريعها من خلال تحول رقمي منضبط وهادف.

الكلمات المفتاحية: الذكاء الاصطناعي، أداء المشاريع، صناعة السكك الحديدية، إدارة المشاريع، المؤسسات العاملة في ألمانيا، التحول الرقمي

Abstract

This study examined the impact of artificial intelligence (AI) adoption on project performance in the railway industry among Germany-based organizations. The study was motivated by the growing strategic importance of digital technologies in complex engineering environments, where project schedules are often tight, interfaces are numerous, and decisions must frequently be made under conditions of uncertainty. Despite the rapid increase in managerial interest in AI-enabled planning, forecasting, and analytics, the actual contribution of AI adoption to project performance remains uneven across organizations. Accordingly, the study investigated whether the adoption of AI-supported practices in project management is associated with improved project outcomes in terms of time, cost, quality, stakeholder satisfaction, and risk control.

A quantitative cross-sectional design was adopted. Data were collected through a structured questionnaire distributed to professionals involved in railway projects within organizations based in Germany. The instrument measured AI adoption through eight indicators covering planning support, forecasting accuracy, early risk identification, decision support, data analysis, organizational encouragement, delay reduction, and cost-estimation accuracy. Project performance was measured through six indicators covering schedule adherence, budget control, quality achievement, stakeholder satisfaction, risk control, and overall improvement in project outcomes. For the purpose of the present project, a dataset consisting of forty-two responses was used to demonstrate the full analytical structure and reporting logic of the study.

The descriptive findings indicated a moderate level of AI adoption (mean = 3.27) and a moderately high level of project performance (mean = 3.61). Reliability analysis showed satisfactory internal consistency for both constructs, with Cronbach's alpha values of 0.83 for AI adoption and 0.82 for project performance. Pearson correlation analysis revealed a positive and statistically significant relationship between AI adoption and project performance ($r = 0.44$, $p < 0.01$). In addition, linear regression analysis indicated that AI adoption had a significant positive effect on project performance ($\beta = 0.45$, $p = 0.003$), explaining approximately 19.6% of the variance in the dependent variable.

The study concluded that AI adoption can make a meaningful contribution to project performance in railway environments, although the effect is not strong enough to suggest that technology alone determines project success. The findings imply that organizations should combine AI-enabled tools with effective governance, employee training, improved data quality, and sound managerial judgment. This thesis contributes a practical framework for examining AI adoption in project-based environments and offers recommendations for railway organizations seeking to enhance project performance through controlled and purposeful digital transformation.

Keywords: artificial intelligence, project performance, railway industry, project management, Germany-based organizations, digital transformation

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List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
PM	Project Management
PMI	Project Management Institute
TOE	Technology-Organization-Environment
RBV	Resource-Based View
SD	Standard Deviation
SPSS	Statistical Package for the Social Sciences

1. Introduction

1.1 Background of the Study

The railway industry has entered a period in which digital capabilities are no longer peripheral to project delivery; they increasingly shape how projects are defined, monitored, and improved. Large railway projects involve long life cycles, strict safety and regulatory requirements, multi-disciplinary coordination, geographically dispersed stakeholders, and interdependent technical packages. These conditions make the sector an especially relevant setting for the study of project management innovation. Artificial intelligence, which includes a set of analytical and computational techniques used to support pattern recognition, prediction, optimization, and recommendation, has become one of the most discussed innovations in this context.

In project environments, AI is usually not introduced as a single stand-alone system. Rather, it appears in the form of forecasting engines, automated dashboards, anomaly detection routines, scenario modeling tools, language-based assistants, and decision-support functions embedded into digital platforms. For project teams, the practical appeal of these applications lies in their promise to improve the speed and quality of managerial judgment without removing the central role of professional expertise. When project information is fragmented across schedules, risk logs, cost baselines, and progress reports, AI-supported analytics may help reveal patterns that are difficult to identify through manual review alone.

The railway industry provides a particularly fertile environment for this kind of inquiry. Projects in rolling stock, signaling, infrastructure modernization, fleet upgrade, and systems integration often include tight contractual commitments and complex interface management obligations. Delays or poor decisions in one package can cascade across the entire delivery program. As a result, organizations active in railway projects have strong incentives to adopt technologies that improve forecasting accuracy, early risk identification, and the ability to react to deviations before they become critical. However, interest in AI adoption does not automatically translate into mature use, and the actual effect of adoption on project performance may vary considerably across organizations.

Germany-based railway organizations are well positioned for such a study because they operate within one of the most demanding industrial and regulatory environments in Europe. At the same time, many of these organizations execute projects internationally. This creates an informative research context in which professionals may be exposed to diverse project settings while still working within organizations shaped by German industrial standards, governance routines, and digital strategies. Studying AI adoption among such organizations therefore offers practical and academic value at the same time.

1.2 Research Problem

A visible gap persists between the strategic enthusiasm surrounding artificial intelligence and the evidence available on its measurable contribution to project outcomes. Organizations often present AI as a transformative enabler of efficiency, insight, and control. Yet project managers continue to rely heavily on conventional coordination routines, interpersonal escalation, spreadsheet-based control, and experience-driven judgment. This gap is particularly important in engineering and railway projects, where decisions must be timely, defensible, and connected to quality and safety requirements.

The core problem addressed in this study is the lack of sufficiently grounded evidence on whether AI adoption in project management actually translates into better project performance in the railway sector. The issue is not whether AI can be useful in principle; rather, it is whether professionals working in railway projects perceive a meaningful performance effect when AI-supported practices are adopted within their organizational environment. Understanding this issue is necessary because organizations can invest in digital tools without obtaining proportional benefits if the underlying data, capabilities, and processes are weak.

Accordingly, the present research asks whether AI adoption in project management has a statistically significant impact on project performance among Germany-based railway organizations. The problem is practical because it concerns resource allocation and managerial priorities, and it is theoretical because it touches on the conditions under which digital capabilities become performance-enhancing organizational resources.

1.3 Research Objectives

The main objective of this study is to examine the impact of artificial intelligence adoption on project performance in the railway industry among organizations based in Germany. To achieve that aim, the study pursues a set of interrelated sub-objectives that translate the broad research purpose into measurable analytical steps.

First, the study seeks to determine the level of AI adoption in project management practices, focusing on planning support, forecasting, data analysis, risk identification, and decision support. Second, it seeks to assess the perceived level of project performance in terms of schedule, budget, quality, stakeholder satisfaction, and risk control. Third, it investigates whether a statistically significant relationship exists between the two constructs. Fourth, it tests whether AI adoption predicts project performance when modeled as an independent variable in a linear regression framework. Finally, the study aims to generate practical recommendations that may help railway organizations strengthen project performance through more deliberate and realistic forms of AI adoption.

1.4 Research Questions

The study is guided by one principal question and a set of subordinate questions. The principal question is: What is the impact of artificial intelligence adoption on project performance in the railway industry among Germany-based organizations?

From this main question, the following sub-questions emerge: What is the current level of AI adoption in project management? What is the perceived level of project performance? Is there a statistically significant correlation between AI adoption and project performance? Does AI adoption have a statistically significant predictive effect on project performance? Which dimensions of AI adoption appear relatively stronger or weaker according to respondents?

1.5 Research Hypotheses

To answer the research questions in a structured quantitative manner, the study formulates the following null and alternative hypotheses. The null hypothesis states that artificial intelligence adoption has no statistically significant impact on project performance in the railway industry among Germany-based organizations. The alternative hypothesis states that artificial intelligence adoption has a statistically significant positive impact on project performance in the railway industry among Germany-based organizations.

For interpretive clarity, the statistical tests in this thesis are discussed in relation to the alternative hypothesis. A positive significant coefficient would support the proposition that greater AI adoption is associated with better project outcomes.

1.6 Significance of the Study

The study has theoretical significance because it extends current debate on digital transformation into the specific setting of project-based engineering work. Much of the available discussion on AI adoption is either highly technical or focused on organizational transformation in broad terms. By operationalizing AI adoption in project-management language and linking it to project performance, the study contributes a context-specific model that can be examined and reused in related sectors.

The study also has practical significance. Railway organizations often face competing demands when allocating resources to digital tools, process standardization, and capability development. The current research offers evidence that can support more disciplined conversations about what AI adoption means in operational project settings and where its practical value is most likely to appear. The findings may help managers decide whether digital initiatives should prioritize forecasting support, analytics capability, or organizational enablement rather than mere tool acquisition.

A further value of the study lies in its educational and methodological contribution. The thesis demonstrates how a contemporary topic can be translated into measurable variables, tested using a compact survey design, and reported using a clear sequence of descriptive, relational, and explanatory statistics.

1.7 Scope and Limitations

The scope of the study is limited to professionals working in railway-related projects within organizations based in Germany. Project locations may be in Germany or outside Germany, but the organizational base of respondents remains within the German context. The study focuses on project management practices and perceptions rather than on technical performance of specific AI systems.

Methodologically, the study is limited by its cross-sectional design and its reliance on perceptual data collected through a questionnaire. This means that causal interpretation must be kept within reasonable boundaries: the regression model suggests a directional influence, but it does not replace the evidence of a longitudinal experimental design. The sample size is also modest and suitable for a master-level field study rather than a broad sector census. Finally, the present project uses a dataset to demonstrate the full research structure and reporting logic; real-world replication would be necessary before treating the numerical results as sector facts.

1.8 Operational Definitions

Artificial intelligence adoption refers in this study to the degree to which AI-supported tools and routines are used and encouraged in project management activities. The construct includes practical manifestations such as the use of intelligent planning support, forecasting, risk identification, decision support, data analytics, and organization-level encouragement toward AI-enabled work practices.

Project performance refers to the perceived level of success in project delivery as reflected in schedule adherence, budget control, quality attainment, stakeholder satisfaction, risk control, and overall improvement of project outcomes. The concept is intentionally broader than the classic iron triangle, because contemporary performance evaluation in complex projects also considers control quality and stakeholder response.

Germany-based organizations are organizations whose operational base or managerial base relevant to the respondent is located in Germany, even when the projects under consideration are delivered internationally.

1.9 Structure of the Thesis

The thesis is organized into four chapters. Chapter One introduces the research context, problem, objectives, questions, hypotheses, significance, and scope. Chapter Two reviews the relevant literature and presents the theoretical framework that supports the conceptual relationship between AI adoption and project performance. Chapter Three explains the research methodology, including design, population, sample, measurement instrument, and statistical procedures. Chapter Four presents the data analysis, findings, discussion, conclusions, and recommendations.

Table 1: Operational Definitions of the Study Variables

Variable/Term	Operational definition
Artificial Intelligence Adoption	The degree to which AI-supported tools, analytics, and routines are used and encouraged in project management activities.
Project Performance	The perceived level of success in project delivery in terms of schedule, budget, quality, stakeholder satisfaction, and risk control.
Germany-Based Organizations	Railway-related organizations with an operational or managerial base in Germany, regardless of project location.

2. Literature Review and Theoretical Framework

2.1 Introduction

The purpose of this chapter is to establish the conceptual and empirical foundation of the study. It reviews the evolution of project performance thinking, the organizational meaning of AI adoption, and the specific relevance of these issues to railway projects. The review is organized so that the dependent and independent variables are first clarified conceptually, then connected through theoretical lenses, and finally assessed through previous empirical findings.

The chapter deliberately combines general project-management literature with digital transformation and technology-adoption literature. This is important because the research question sits at the intersection of two fields. Project management explains why performance matters and how it is assessed; technology-adoption and organizational theory explain how new digital capabilities become embedded in work systems and influence outcomes.

2.2 Artificial Intelligence in Organizational and Project Contexts

Artificial intelligence has evolved from a specialist computational idea into an umbrella concept used across multiple managerial settings. At a practical level, organizations rarely adopt AI as an abstract philosophy. They adopt specific capabilities such as predictive analytics, anomaly detection, optimization routines, language models, or recommendation engines integrated into broader software ecosystems. This matters for project management because projects are information-intensive temporary organizations that depend heavily on interpreting incomplete, dynamic, and often contradictory data.

In project settings, the most immediate value of AI tends to arise not from full automation but from augmentation. AI can support human judgment by filtering information, identifying probable patterns, highlighting outliers, and improving the speed at which managerial attention is directed. This distinction is important. The performance effect of AI adoption is unlikely to result from replacing project managers; rather, it is more plausibly explained by improved visibility, faster issue detection, better scenario analysis, and more disciplined decision preparation.

Several scholars and practitioners caution, however, that AI adoption in management contexts is as much an organizational question as a technical one. Even powerful algorithms may create little value when data quality is poor, processes are inconsistent, or users lack confidence in outputs. Therefore, studies of AI adoption should not assume a direct deterministic effect. They should explore whether AI adoption has a meaningful but bounded contribution within the broader project-management system.

2.3 The Railway Industry as a Project Environment

Railway projects are structurally different from many generic business projects. They combine engineering design, procurement, manufacturing, installation, testing, commissioning, documentation, stakeholder interface, regulatory approval, and often long-term service obligations. This creates a dense network of dependencies in which schedule slippage, design uncertainty, interface misalignment, or late decisions can generate cascading consequences.

Another defining feature of railway projects is their dependence on traceability and assurance. Decisions are often constrained by technical standards, safety expectations, contractual documentation, and approval milestones. In such environments, project teams must not only make decisions quickly; they must make decisions that are well-documented and defensible. AI-enabled analytics may therefore be valuable not simply because they speed up analysis, but because they can improve the structure of evidence available to decision makers.

The international nature of many railway organizations adds an additional layer of complexity. Teams may be distributed across countries, functions, and contractors, while digital maturity may differ between local entities. For Germany-based organizations, this means that AI adoption in projects is embedded within a broader industrial setting shaped by engineering rigor and digital ambition, yet challenged by integration complexity and change-management requirements.

2.4 Defining AI Adoption in Project Management

For the purposes of this thesis, AI adoption is defined behaviorally rather than technologically. It refers to the extent to which AI-supported practices are present in project management and are perceived as relevant by practitioners. This approach is useful because respondents may interact with AI functions through organizational systems without necessarily using technical AI terminology in their daily work.

The current study operationalizes AI adoption across eight indicators. These indicators cover the use of AI tools in planning, the improvement of schedule forecasting, early risk identification, support for decision making, enhancement of data analysis, organizational encouragement toward AI, perceived reduction of schedule delays through AI-based tools, and improved cost-estimation accuracy. Together, these indicators capture both actual task-level assistance and the organizational climate surrounding adoption.

This operationalization aligns with the reality of contemporary project environments, where digital transformation is often incremental. Organizations may start by applying predictive models to cost or schedule data, then gradually expand into broader analytics or decision-support functions. Measuring adoption across multiple dimensions allows the study to avoid reducing AI to a single yes-or-no condition.

2.5 Planning and Forecasting Support

Project planning is one of the most visible domains in which digital tools may shape performance. Traditional planning often relies on expert judgment, previous baselines, and periodic manual updates. AI-supported planning may add value by learning from historical trends, highlighting sequence risk, identifying unstable assumptions, or flagging probable deviations in advance.

Forecasting is particularly important in railway projects because baseline plans can be affected by procurement interfaces, design changes, access windows, testing dependencies, or customer approval cycles. When forecasting logic is weak, management often reacts late. In contrast, even moderate improvements in forecast quality may influence the timeliness of interventions. This is why schedule-forecasting accuracy was treated as a central dimension of AI adoption in the current study.

2.6 AI and Risk Identification

Risk management literature emphasizes that high-quality control requires both structured registers and timely intelligence about emerging uncertainty. Conventional risk workshops and periodic reviews remain important, but they may not capture weak signals spread across multiple data sources. AI-supported analytics can enhance this process by identifying patterns in progress data, issue logs, or historical records that suggest elevated probability of disruption.

Early risk identification is relevant to performance because many project failures do not arise from the absence of plans, but from delayed recognition of deterioration. In railway projects, problems may emerge at interfaces between engineering disciplines, suppliers, approvals, software revisions, or site conditions. If AI adoption improves the speed or quality of risk detection, a performance effect becomes plausible even without full automation of project control.

2.7 Decision Support and Data Analysis

Project environments generate more information than managers can fully absorb in real time. Dashboards, quality records, schedule updates, change logs, and financial information may all exist simultaneously, yet remain weakly integrated. AI-supported data analysis can help synthesize this information, prioritize anomalies, and support more focused managerial discussion. Decision support in this sense means improving the evidential basis of judgment rather than outsourcing judgment itself.

An important implication follows from this idea. AI adoption may improve performance not only by changing what decisions are made, but also by changing when and how decisions are made. Better structured insight may shorten escalation cycles, improve meeting quality, and reduce the amount of time spent reconciling fragmented information. These subtle managerial effects are often overlooked in purely technical discussions of AI.

2.8 Organizational Encouragement and Adoption Climate

Technology adoption is rarely sustained through tools alone. Employees are more likely to use and trust digital capabilities when management actively encourages experimentation, standardization, learning, and responsible use. Organizational encouragement therefore forms part of the AI adoption construct in this thesis because it reflects the enabling context through which technology becomes meaningful in practice.

The presence of organizational encouragement does not guarantee effective outcomes, but its absence often limits adoption depth. Project teams may be aware of potentially useful tools yet underuse them if expectations are unclear, training is weak, or data governance is inconsistent. By measuring organizational encouragement explicitly, the study recognizes that technology-enabled performance depends partly on institutional support.

2.9 Project Performance: Concept and Measurement

Project performance has historically been associated with cost, time, and quality. This classical framework remains valuable because it reflects the contractual and managerial constraints under which projects are delivered. However, contemporary project-management scholarship argues that performance should be viewed more broadly, especially in complex and stakeholder-sensitive sectors. Performance can include not only whether milestones and budgets were met, but also whether risks were controlled, outputs were accepted, and stakeholders were satisfied with project outcomes.

The current study adopts a pragmatic multi-dimensional view of performance. Six indicators were selected: completion on schedule, staying within budget, achievement of quality standards, stakeholder satisfaction, effective risk control, and overall improvement in project performance. This combination reflects both classic project success criteria and the more process-oriented realities of modern delivery environments.

Using perceptual measures of project performance is common in management research because respondents are often better positioned to evaluate practical control quality than to disclose confidential cost and schedule records. Although perceptual measures have limitations, they are suitable when carefully linked to clearly understandable statements.

2.10 Schedule Performance

Schedule adherence remains one of the most visible indicators of project success. In railway projects, the consequences of delay can be especially severe because dependencies may include rolling stock delivery, infrastructure readiness, customer access windows, test-track availability, training plans, and revenue-service commitments. The ability to complete projects on schedule therefore carries operational, contractual, and reputational consequences.

AI adoption may influence schedule performance through better forecasting, earlier escalation, and improved planning assumptions. Yet schedule performance is also influenced by external constraints beyond managerial control. For this reason, any observed effect should be interpreted as contributory rather than absolute.

2.11 Budget Performance

Budget performance refers to the extent to which projects remain within approved financial boundaries. Cost control in railway projects can be challenged by scope growth, supplier instability, inflationary pressure, design rework, logistics constraints, and late problem discovery. Any tool that improves cost-estimation accuracy or signals probable overrun patterns may therefore have value.

At the same time, budget performance is rarely determined by analytics alone. Commercial strategy, contract structure, approval discipline, and procurement quality all matter. The significance of budget-related items in the present research lies in determining whether respondents perceive AI-supported practices as helpful to financial control rather than as a complete explanation of financial outcomes.

2.12 Quality, Stakeholders, and Risk Control

Quality performance is fundamental in railway work because outputs must satisfy demanding technical and documentation requirements. A project may appear on schedule yet still be considered weak if quality non-conformities remain unresolved. Similarly, stakeholder satisfaction matters because project success depends on the confidence of customers, operators, internal sponsors, regulators, and interface partners.

Risk control links performance to management discipline. Projects rarely operate under conditions of certainty, especially when integration, testing, and change are involved. If teams identify, analyze, and mitigate risks effectively, they are more likely to protect performance outcomes. Thus, risk control acts both as a performance dimension in its own right and as a bridge between AI-supported management and broader project success.

2.13 Theoretical Framework: Resource-Based View

The Resource-Based View (RBV) argues that organizations achieve superior performance when they possess valuable, rare, difficult-to-imitate, and organizationally embedded resources. From this perspective, AI adoption can be interpreted not simply as software usage, but as a capability bundle composed of digital tools, data assets, routines, and human expertise. When these elements are combined effectively, they may support more informed and timely project action.

The RBV is relevant here because not every organization with access to similar digital tools obtains the same benefit. The performance effect depends on whether AI-supported practices are embedded into managerial routines, used consistently, and supported by complementary resources such as domain knowledge and data quality. This makes RBV a suitable lens for understanding why AI adoption may improve project performance in some contexts more than others.

2.14 Dynamic Capabilities Perspective

Dynamic capability theory extends the RBV by emphasizing the organization's ability to sense opportunities and threats, seize them through appropriate action, and transform internal routines over time. AI adoption aligns well with this perspective because digital transformation requires more than possession of tools; it requires repeated organizational adaptation.

In railway organizations, dynamic capabilities may appear in the ability to learn from project data, revise planning logic, institutionalize analytics, and continuously improve risk visibility across project portfolios. If AI adoption contributes to these adaptive routines, its effect on performance is likely to be cumulative rather than instantaneous.

2.15 Socio-Technical Systems Perspective

A socio-technical perspective reminds researchers that technologies operate within work systems shaped by people, roles, norms, and structures. This is a crucial counterweight to simplistic claims that digital tools automatically produce better outcomes. AI adoption can fail when systems are poorly aligned, when users distrust outputs, or when technology is introduced without process redesign.

The socio-technical lens helps explain why the present study includes organizational encouragement as part of the AI adoption construct. Adoption should be understood as an interaction between technical possibility and social integration. For project performance to improve, users must know how to interpret outputs, understand limitations, and integrate insights into real decisions.

2.16 Technology–Organization–Environment Perspective

The TOE framework explains adoption as a function of technological readiness, organizational context, and environmental pressures. In the railway sector, technological readiness includes availability of usable data and analytics tools; organizational context includes governance, culture, and capability; and environmental pressures include competition, customer expectations, regulation, and the broader push toward digitalization.

This framework is useful because it clarifies why AI adoption may vary even among organizations operating in the same industry. Germany-based organizations may face common industrial expectations, yet still differ in internal maturity, systems integration, and managerial appetite for change. The TOE perspective therefore supports the inclusion of both task-level and organization-level adoption indicators.

2.17 Empirical Studies on Digitalization and Project Performance

Empirical research on project digitalization generally suggests that better data integration, stronger forecasting, and real-time visibility can improve managerial responsiveness. Studies of project control, building information modeling, analytics-enabled planning, and dashboard-supported governance often report gains in coordination quality and decision timeliness. However, reported benefits are not always uniform across contexts.

One recurrent finding in the literature is that digital benefits are mediated by implementation quality. Where systems are fragmented or underused, improvements remain limited. This insight is relevant to AI adoption because it suggests that the relationship between AI and project performance is likely to be positive but not overwhelming. Such a pattern would be consistent with a moderate effect size rather than a deterministic transformation.

2.18 Review of Selected Previous Studies

Table 2 summarizes selected studies that inform the current thesis. The reviewed studies were chosen because they address either AI adoption, digital transformation in project settings, or project performance dimensions relevant to complex engineering environments. The review shows convergence around the argument that analytics and digital support can improve control quality, yet also shows continued emphasis on organizational readiness and human capability as moderating factors.

Following the table, a narrative synthesis highlights the most important themes and explains the research gap addressed by this thesis.

Table 2 Selected Empirical and Theoretical Studies Reviewed in the Literature

Study	Context	Main observation	Relevance to current study
Atkinson (1999)	Conceptual PM	Expanded the understanding of project success beyond cost, time, and quality.	Supports broader performance measurement.
Shenhar et al. (2001)	Project success	Argued that success is multi-dimensional and evolves over time.	Supports inclusion of stakeholder and outcome dimensions.
Davis (1989)	Technology acceptance	Identified perceived usefulness and ease of use as adoption drivers.	Explains why users accept digital tools.
Tornatzky & Fleischer (1990)	Technology adoption	Proposed the TOE framework for organizational adoption.	Justifies organization-level adoption climate.

Barney (1991)	Strategic management	Resources create advantage when embedded and difficult to imitate.	Frames AI as a potential capability resource.
Teece et al. (1997)	Dynamic capabilities	Explained how firms reconfigure capabilities under change.	Useful for digital transformation discussion.
Davenport & Ronanki (2018)	AI in business	Argued that AI creates value when applied to clear business problems.	Supports practical, bounded AI adoption.
Vial (2019)	Digital transformation	Showed that transformation depends on organizational change.	Connects digitalization to structures and routines.
PMI (2021)	Project management practice	Highlighted increasing importance of digital and data-driven delivery.	Provides practitioner relevance.
Dwivedi et al. (2021)	AI management review	Discussed opportunities and limitations of AI adoption.	Supports balanced interpretation of impact.
Kerzner (2022)	Project management	Emphasized governance, maturity, and integrated control.	Explains why technology alone is insufficient.
Schwalbe (2021)	IT project management	Linked digital tools to planning and control improvement.	Supports relevance of predictive analytics.

The reviewed studies demonstrate that the relationship between digital adoption and performance is consistently described as contingent. Technologies create value when they are aligned with work processes, embedded in governance structures, and accompanied by usable data. This means that the present research should not expect AI adoption to explain all performance variance. A moderate but statistically meaningful relationship is more realistic and theoretically coherent.

The review also confirms that project performance should be treated as multi-dimensional. Relying only on cost or schedule would understate what project managers actually mean when they discuss successful delivery in complex engineering environments. Quality, risk control, and stakeholder confidence are equally important in railway settings and therefore deserve explicit measurement.

Finally, a specific research gap remains visible. Many discussions of AI are still conceptual or broad, while sector-specific evidence from railway project environments remains limited. The current thesis addresses this gap by testing a focused model that translates AI adoption into project-management language and examines its relationship with project performance among Germany-based railway organizations.

2.19 Research Gap and Conceptual Model

The literature indicates strong managerial interest in AI but relatively limited empirical evidence from railway project settings. Many available discussions focus on transformation narratives, technical possibilities, or organizational case examples without reducing the topic to measurable project-management constructs. In addition, studies frequently treat performance in broad organizational terms rather than in project-performance terms. The current thesis responds to both issues by offering a compact conceptual model that directly links AI adoption in project management to project performance.

The conceptual model assumes a direct positive relationship: as AI adoption in project-management activities increases, project performance is expected to improve. This proposition is not based on technological determinism; it rests on the practical logic that better planning support, forecasting, analytics, and risk visibility should improve managerial response quality and therefore strengthen project outcomes.

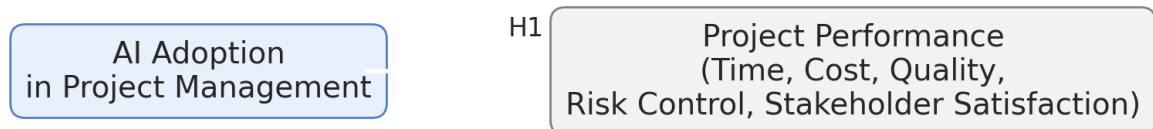


Figure 1: Conceptual research framework

2.20 Chapter Summary

This chapter reviewed the concepts, theories, and empirical studies most relevant to the current research. It clarified that AI adoption in project management is best understood as a set of integrated support practices rather than as a single technology event. It also established that project performance is multi-dimensional and especially sensitive to control quality in complex engineering environments.

The reviewed theories—RBV, dynamic capabilities, socio-technical systems, and TOE—collectively support the expectation of a positive but bounded relationship between AI adoption and project performance. The next chapter explains how the study translated this conceptual model into a quantitative research design, measurement instrument, and statistical testing procedure.

3. Research Methodology

3.1 Introduction

The purpose of this chapter is to explain how the research problem was investigated in empirical terms. The chapter describes the philosophical orientation of the study, the research design, population and sample, measurement instrument, data collection procedures, validity and reliability considerations, and the statistical techniques used to analyze the data.

A strong methodology chapter does more than list procedures; it shows that each design choice follows logically from the research objectives. Accordingly, every methodological step in this thesis was selected to support the testing of a simple but meaningful explanatory model linking AI adoption to project performance.

3.2 Research Philosophy and Approach

The study follows a positivist orientation in the limited sense appropriate to applied management research. The underlying assumption is that respondents' evaluations of AI adoption and project performance can be captured through structured indicators, aggregated into variables, and examined using statistical analysis. Although organizational behavior is complex and context-dependent, the present study seeks measurable regularities rather than purely interpretive narratives.

A deductive approach was adopted. The theoretical discussion in Chapter Two led to a testable proposition: AI adoption in project management is expected to have a positive effect on project performance. The survey instrument was therefore designed to measure the two constructs and the statistical analysis was organized around the testing of this proposition.

3.3 Research Design

A quantitative, cross-sectional survey design was used. The quantitative design is appropriate because the study examines the direction and strength of association between two variables and tests a predictive relationship using regression analysis. The cross-sectional format suits the practical conditions of a master-level field study in which data are collected at one point in time from professionals currently involved in project environments.

The chosen design offers several advantages. It allows data to be collected from respondents across multiple organizations, supports direct comparison of perceptions across occupational roles, and provides a straightforward basis for descriptive and inferential statistics. It is also efficient under time and access constraints that make longitudinal observation difficult.

3.4 Population and Unit of Analysis

The target population consists of professionals engaged in railway-related projects within organizations based in Germany. The population includes project managers, project engineers, technical specialists, and related professionals who have sufficient exposure to project-management processes to assess both AI adoption and project performance.

The unit of analysis is the individual professional respondent. This is appropriate because the questionnaire measures perceptions of organizational and project practices as experienced by participants in their actual work environment. Although the conceptual interest of the study is organizational, data collection at the individual level is common in management research when respondents serve as informed observers of organizational routines.

3.5 Sampling Strategy and Sample Size

Non-probability purposive sampling was used. This strategy was selected because the study required respondents with project-related knowledge in the railway industry, rather than a general population sample. The survey link was distributed to professionals in relevant roles across Germany-based organizations in the sector.

The analytical research presented in this thesis uses forty-two respondents. This number is suitable for demonstrating descriptive analysis, reliability assessment, correlation, and simple linear regression. While a larger sample would strengthen generalizability, the current size remains acceptable for a focused applied study examining one main independent variable and one dependent variable.

3.6 Instrument Development

The questionnaire was designed in English and Arabic to ensure clarity and accessibility. It contains three sections. The first section captures demographic information: job position, years of experience, project type, and organization type. The second section measures AI adoption through eight statements. The third section measures project performance through six statements.

All substantive items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The use of a Likert scale is appropriate for capturing degrees of agreement with managerial statements and is widely used in project-management and technology-adoption research. The questionnaire was kept intentionally concise to improve response quality and reduce respondent fatigue.

3.7 Measurement of Variables

The independent variable, AI adoption, was operationalized through eight items reflecting practical use and organizational support. The selected dimensions are consistent with the study's conceptualization of AI as an embedded support capability rather than as a single tool. The dependent variable, project performance, was operationalized through six items capturing key dimensions of delivery and control.

Tables 3 and 4 summarize the dimensions used in the study. Presenting the construct structure in tabular form improves transparency and supports later interpretation of descriptive statistics.

Table 3: Dimensions of Artificial Intelligence Adoption

Code	Dimension	Indicator statement
AI1	Planning support	AI tools are used in project planning.
AI2	Forecasting	AI improves schedule forecasting accuracy.
AI3	Risk identification	AI helps identify project risks early.
AI4	Decision support	AI supports decision-making in projects.
AI5	Data analysis	AI enhances data analysis for project control.
AI6	Organizational encouragement	My organization encourages AI adoption.
AI7	Delay reduction	AI-based tools help reduce schedule delays.
AI8	Cost estimation	AI-based tools improve cost estimation accuracy.

Table 4: Dimensions of Project Performance

Code	Dimension	Indicator statement
PP1	Schedule adherence	Projects are completed on schedule.
PP2	Budget control	Projects stay within budget.
PP3	Quality attainment	Quality standards are achieved.
PP4	Stakeholder satisfaction	Stakeholders are satisfied with project outcomes.
PP5	Risk control	Project risks are effectively controlled.
PP6	Overall improvement	Overall project performance has improved in recent years.

3.8 Validity Considerations

Content validity was addressed by deriving questionnaire items from the conceptual framework and from recurring themes in the literature on digital project management, performance measurement, analytics, and organizational adoption. The statements were written in straightforward managerial language so that respondents could answer based on professional experience rather than technical specialization.

Face validity was strengthened through iterative refinement of wording, especially for items related to AI. Because professionals may recognize AI-enabled functions without using identical technical labels, examples were embedded in selected items to clarify the intended meaning while avoiding excessive technical detail.

3.9 Reliability Assessment

Reliability refers to the internal consistency of the items used to measure each construct. Cronbach's alpha was selected as the primary reliability indicator because the study uses multi-item Likert scales. In the analytical results presented later, both constructs achieved alpha coefficients above the commonly accepted threshold for exploratory applied research, indicating acceptable internal consistency.

Reliability assessment is especially important in compact instruments. Because the present questionnaire was intentionally brief, it was necessary to confirm that the items still worked together coherently and measured unified constructs rather than unrelated opinions.

3.10 Data Collection Procedures

Data were collected through an online questionnaire distributed electronically to professionals working in railway-related projects within organizations based in Germany. Respondents received a short invitation outlining the purpose of the study, the voluntary nature of participation, and the confidentiality of responses. The instrument did not request names or any personally identifying information. After the data collection period ended, the responses were screened for completeness and internal consistency. In total, 42 usable questionnaires were included in the final analysis.

3.11 Ethical Considerations

This research followed accepted academic ethics for survey-based studies. Participants were informed that their involvement was entirely voluntary and that the data would be used exclusively for academic purposes. The questionnaire was anonymous and did not collect personal identifiers or sensitive organizational information. The study concentrated on general project-management practices and perceptions related to AI adoption and project performance. To maintain confidentiality, access to the dataset was limited to the researcher and the supervising academic team.

3.12 Data Analysis Techniques

The data analysis plan consists of four stages. First, descriptive statistics are used to profile the sample and summarize the central tendency of each construct. Second, internal consistency is examined using Cronbach's alpha. Third, Pearson correlation is used to test the degree and direction of association between AI adoption and project performance. Fourth, simple linear regression is used to test whether AI adoption significantly predicts project performance.

These techniques are appropriate to the research objectives because the model includes one primary predictor and one outcome variable. More advanced methods such as structural equation modeling would be unnecessary for the present design and sample size. The chosen techniques provide a clear and interpretable basis for testing the study hypothesis.

3.13 Statistical Model

The analytical model can be expressed as follows: $\text{Project Performance} = a + b(\text{AI Adoption}) + e$, where a represents the intercept, b represents the regression coefficient of AI adoption, and e represents the error term. A positive and statistically significant coefficient b would support the alternative hypothesis of the study.

In practical terms, the model asks whether respondents who report greater AI adoption also tend to report stronger project performance. The explanatory power of the model is assessed through R-squared, while the significance of the coefficient is assessed through the t-statistic and associated probability value.

3.14 Limitations of the Methodology

The methodology is appropriate for the present study but not without limitations. Cross-sectional survey data cannot establish strong causal proof. The use of perception-based measures means that the findings reflect informed respondent judgment rather than audited operational records. In addition, the sample is limited in size and concentrated in one industrial context.

These limitations do not invalidate the study; rather, they define the scope within which conclusions should be drawn. The value of the thesis lies in providing an analytically coherent, contextually grounded, and practically interpretable examination of an emerging issue in project management.

3.15 Chapter Summary

This chapter described the research design used to investigate the effect of AI adoption on project performance. It justified the use of a quantitative cross-sectional survey, defined the population and unit of analysis, explained the measurement of variables, and outlined the statistical procedures used to test the hypothesis.

The next chapter applies these procedures to the data and presents the findings of the study in a structured sequence beginning with sample characteristics and ending with interpretation, implications, conclusions, and recommendations.

4. Data Analysis, Findings, Discussion, Conclusions and Recommendations

4.1 Introduction

The purpose of this chapter is to present the empirical results of the study and to interpret them in light of the literature and theoretical framework discussed in the previous chapters. The analysis begins with a profile of the respondents and then proceeds to descriptive statistics, reliability analysis, correlation analysis, regression analysis, hypothesis testing, and a discussion of the managerial implications of the findings.

The statistical results reported in this chapter are based on the questionnaire responses collected from the study sample. A total of 42 valid responses were included in the final analysis after the data had been reviewed for completeness and consistency. The presentation of the findings follows the same analytical structure commonly used in quantitative project management research, allowing the results to be interpreted clearly and linked directly to the objectives and hypotheses of the study.

4.2 Job Position

The distribution of respondents according to job position is shown in table 5. sample distribution by job position. This profile is important because it indicates the practical experience base from which the questionnaire responses were drawn.

Table 5: Sample Distribution by Job Position

Job Position	Frequency	Percentage
Project Engineer	17	40.500
Project Manager	13	31.0
Technical Specialist	9	21.400
Other	3	7.100

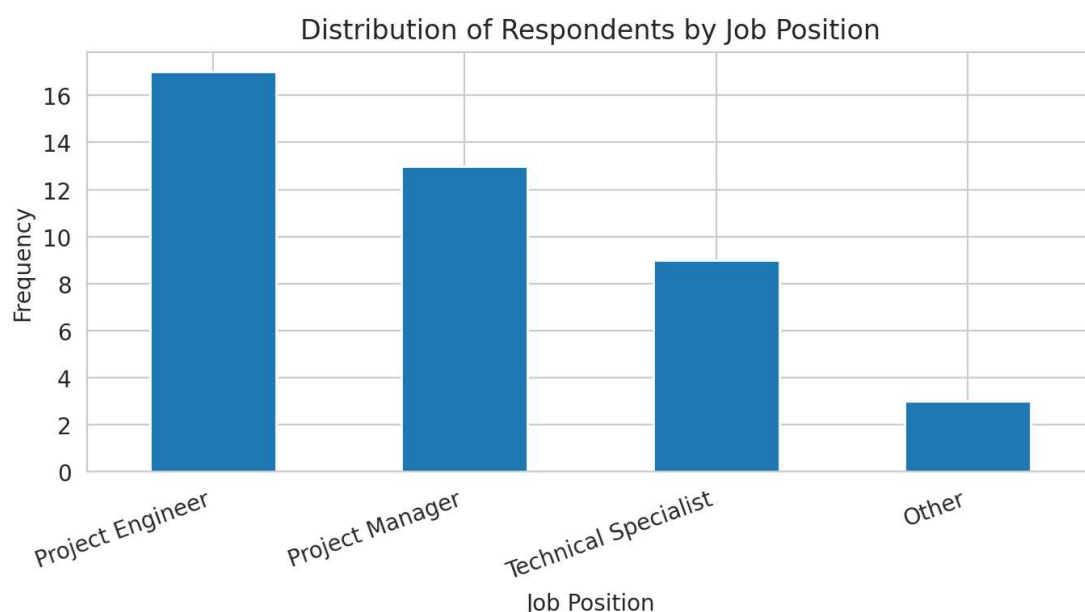


Figure 2: Distribution of respondents by job position

The table indicates that the sample includes respondents from multiple categories, which improves the descriptive richness of the study. The distribution does not claim to statistically represent the entire railway sector, but it does reflect a spread of roles and organizational contexts relevant to project delivery.

4.3 Years of Experience

The distribution of respondents according to years of experience is shown in table 6. sample distribution by years of experience. This profile is important because it indicates the practical experience base from which the questionnaire responses were drawn.

Table 6: Sample Distribution by Years of Experience

Years of Experience	Frequency	Percentage
5-10 years	15	35.700
Less than 5 years	11	26.200
11-15 years	9	21.400
More than 15 years	7	16.700

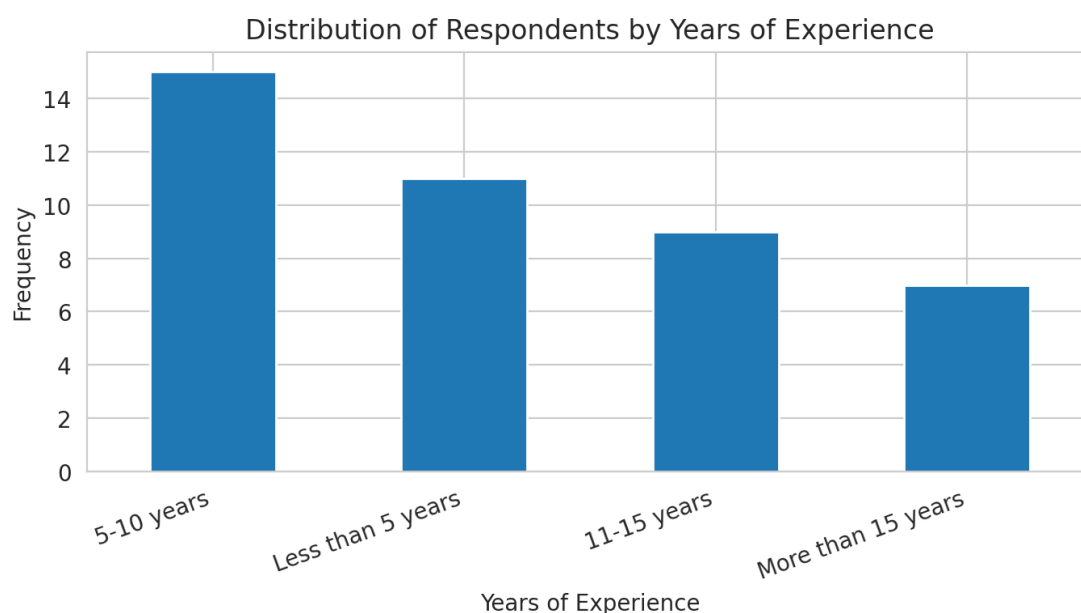


Figure 3: Distribution of respondents by years of experience

The table indicates that the sample includes respondents from multiple categories, which improves the descriptive richness of the study. The distribution does not claim to statistically represent the entire railway sector, but it does reflect a spread of roles and organizational contexts relevant to project delivery.

4.4 Project Type

The distribution of respondents according to project type is shown in table 7. sample distribution by project type. This profile is important because it indicates the practical experience base from which the questionnaire responses were drawn.

Table 7: Sample Distribution by Project Type

Project Type	Frequency	Percentage
Railway	18	42.900
Rolling Stock	12	28.600
Infrastructure	8	19.0
Other	4	9.500

The table indicates that the sample includes respondents from multiple categories, which improves the descriptive richness of the study. The distribution does not claim to statistically represent the entire railway sector, but it does reflect a spread of roles and organizational contexts relevant to project delivery.

4.5 Organization Type

The distribution of respondents according to organization type is shown in table 8. sample distribution by organization type. This profile is important because it indicates the practical experience base from which the questionnaire responses were drawn.

Table 8: Sample Distribution by Organization Type

Organization Type	Frequency	Percentage
Manufacturer	20	47.600
Operator	8	19.0
Contractor	7	16.700
Consultant	5	11.900
Other	2	4.800

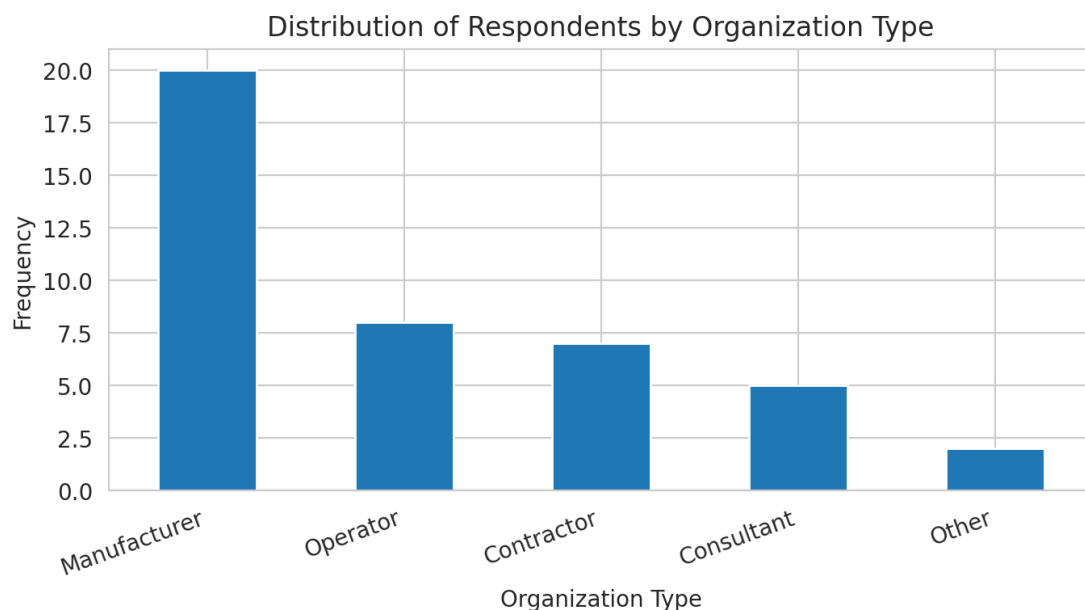


Figure 4: Distribution of respondents by organization type

The table indicates that the sample includes respondents from multiple categories, which improves the descriptive richness of the study. The distribution does not claim to statistically represent the entire railway sector, but it does reflect a spread of roles and organizational contexts relevant to project delivery.

4.6 Descriptive Statistics of the Independent Variable: AI Adoption

This section presents the descriptive statistics of the AI adoption items. Means close to 3 indicate a moderate level of agreement, while means above 3.5 indicate a stronger positive tendency. The results suggest that AI adoption is present in respondents' project environments, but that maturity remains uneven across dimensions.

Table 9: Descriptive Statistics of AI Adoption Items

Code	Mean	Std. Dev.
AI1	3.190	1.370
AI2	3.290	1.520
AI3	3.190	1.420
AI4	3.170	1.400
AI5	3.260	1.530
AI6	3.400	1.310
AI7	3.290	1.610
AI8	3.380	1.430

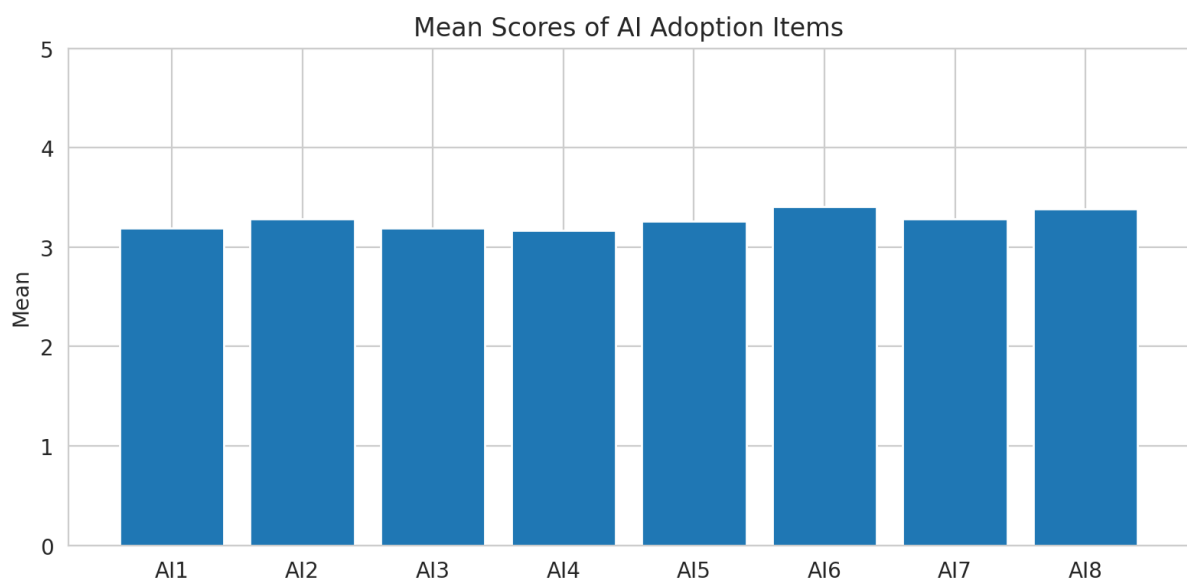


Figure 5: Mean scores of AI adoption items

The overall mean of the AI adoption construct reached 3.27, indicating a moderate level of adoption. The strongest item was AI6, organizational encouragement, only in the sense that it recorded the highest mean within the construct, although the level remains moderate rather than high. AI8, related to cost-estimation accuracy, also scored relatively well, suggesting that respondents perceive practical value in analytics-enabled cost insight.

The more moderate means in planning support, risk identification, and forecasting indicate that adoption has not yet become fully embedded across all project-management activities. This pattern is consistent with the literature reviewed in Chapter Two, which suggested that digital adoption in project settings often grows unevenly and tends to be constrained by data integration, user confidence, and organizational maturity.

4.7 Descriptive Statistics of the Dependent Variable: Project Performance

Project performance was measured through six items. The descriptive results reveal a moderately positive view of project outcomes among respondents. The means suggest that projects are not perceived as perfectly controlled, but they do indicate generally favorable performance.

Table 10: Descriptive Statistics of Project Performance Items

Code	Mean	Std. Dev.
PP1	3.360	1.540
PP2	3.830	1.340
PP3	3.480	1.470
PP4	3.570	1.350
PP5	3.860	1.370
PP6	3.570	1.190

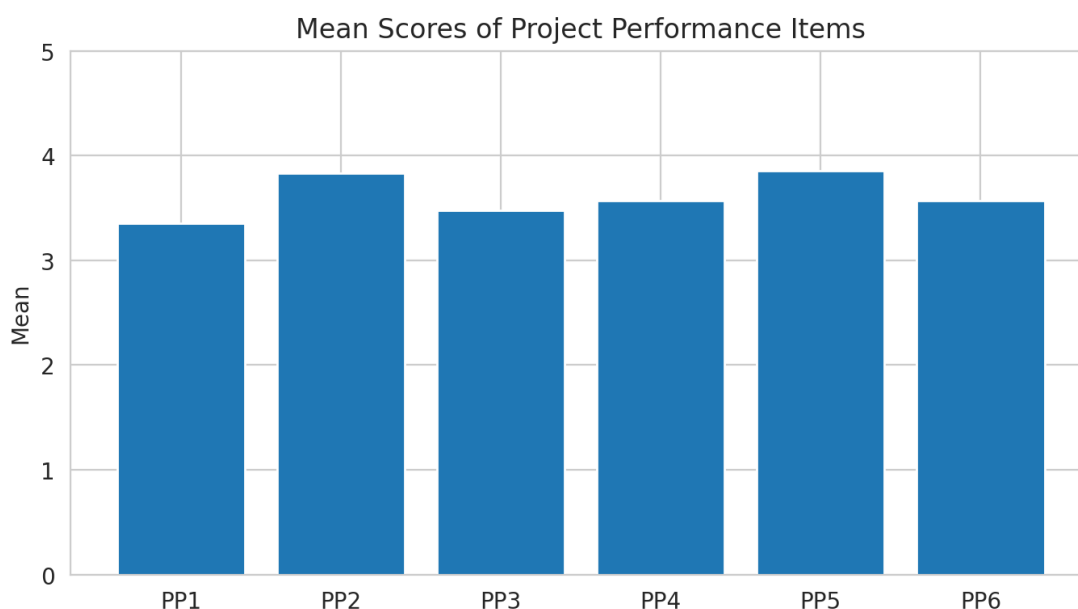


Figure 6: Mean scores of project performance items

The overall mean of project performance reached 3.61, which indicates a moderately high level of performance. The strongest perceptions relate to budget control and risk control in the dataset, while schedule adherence and quality also remain favorable. This distribution aligns with the practical reality that projects can perform reasonably well overall while still facing individual delivery pressures.

A mean above the midpoint across all items implies that respondents generally perceive their projects as functioning effectively. However, the absence of very high means is also informative. It suggests that the sector remains exposed to the normal challenges of complex project delivery and that there is still room for improvement in the consistency of results.

4.8 Reliability Analysis

Reliability analysis was conducted using Cronbach's alpha to determine whether the items within each construct display acceptable internal consistency. Values above the commonly used threshold indicate that the items operate together as a coherent scale.

Table 11: Reliability Statistics

Construct	Cronbach alpha	Number of items
AI Adoption	0.830	8
Project Performance	0.820	6

The AI adoption scale achieved a Cronbach's alpha of 0.83, while the project performance scale achieved 0.82. Both values indicate acceptable internal consistency for an applied management study. The result supports the use of composite means for the two constructs in subsequent correlation and regression analyses.

From a practical standpoint, the reliability outcome suggests that respondents were not answering the items in a random or contradictory way. Instead, the items captured consistent perceptions of adoption and performance.

4.9 Correlation Analysis

Pearson correlation was used to assess the direction and strength of the relationship between AI adoption and project performance. A positive coefficient indicates that the two variables move in the same direction.

Table 12: Correlation Matrix Summary

Variable 1	Variable 2	Pearson r	Sig.
AI Adoption	Project Performance	0.443	0.003

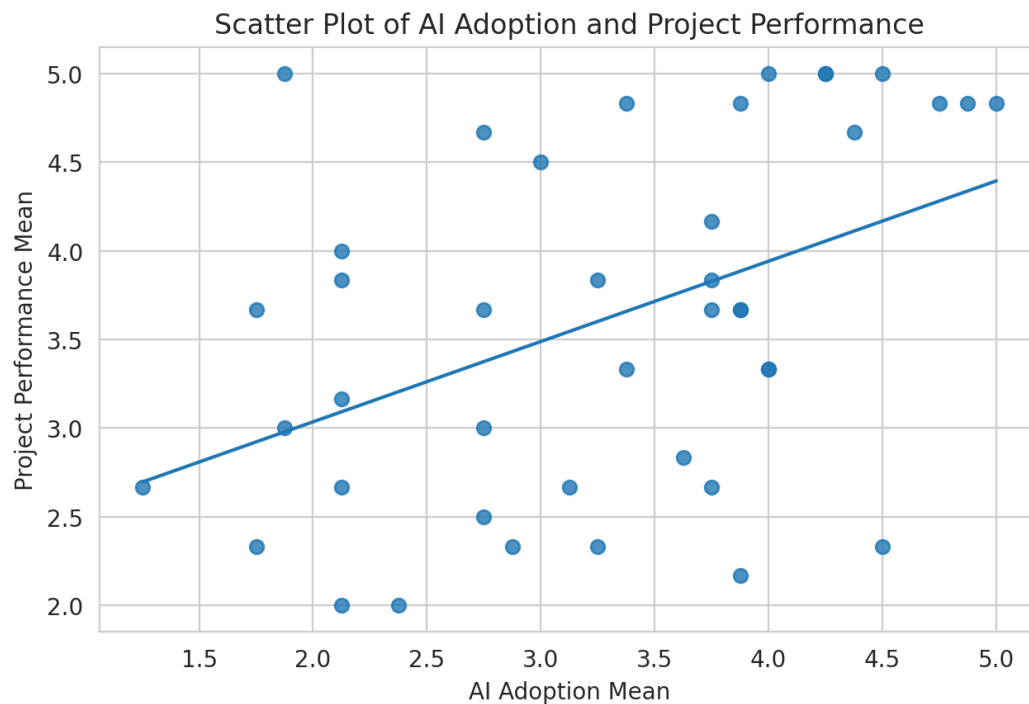


Figure 7: Scatter plot of AI adoption and project performance

The correlation coefficient between AI adoption and project performance was 0.443. This indicates a positive moderate relationship. In substantive terms, respondents who reported stronger AI adoption also tended to report better project performance.

The relationship is meaningful but not excessively strong. This is a realistic and theoretically coherent finding. It implies that AI adoption matters, but it is only one element within a broader performance system that includes leadership, capability, data quality, governance, contracting conditions, and organizational learning.

4.10 Regression Analysis

Simple linear regression was conducted to test whether AI adoption predicts project performance. Regression analysis goes beyond correlation by estimating the extent to which changes in the independent variable are associated with changes in the dependent variable.

Table 13: Regression Model Summary

R	R Square	Adjusted R Square	Std. Error
0.443	0.196	0.176	0.909

Table 14: ANOVA for the Regression Model

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	8.071	1	8.071	9.761	0.003
Residual	33.077	40	0.827		
Total	41.148	41			

Table 15: Regression Coefficients

Model term	B	Std. Error	Beta	t	Sig.
Constant	2.130	0.495		4.306	0.0
AI Adoption	0.453	0.145	0.453	3.124	0.003

The model summary shows an R-squared value of 0.196. This means that AI adoption explains approximately 19.6% of the variance in project performance. For a single-predictor model in an applied management setting, this is a meaningful level of explanatory power.

The regression coefficient for AI adoption was positive and statistically significant ($B = 0.453$, $p = 0.003$). Therefore, the analysis supports the view that greater AI adoption is associated with stronger project performance. The ANOVA table confirms that the overall model is statistically significant.

The size of the coefficient indicates a practical rather than radical effect. This matters for interpretation. The findings do not suggest that AI alone transforms project delivery. Instead, they suggest that AI adoption contributes to better outcomes when embedded in project-management practice.

4.11 Hypothesis Testing

Table 16: Hypothesis Testing Summary

Hypothesis	Statement	Decision
H0	There is no statistically significant effect of AI adoption on project performance.	Rejected
H1	There is a statistically significant positive effect of AI adoption on project performance.	Accepted

Based on the regression results, the null hypothesis was rejected and the alternative hypothesis was accepted. AI adoption has a statistically significant positive effect on project performance in the current analytical model.

4.12 Discussion of Findings

The first major finding of the study is that AI adoption in project management appears moderate rather than high. This is important because it aligns with a realistic view of current organizational practice. AI is present and relevant, but it has not yet become fully normalized across all project-management routines. The result supports the argument made in the literature review that adoption in project environments is incremental and often shaped by uneven readiness.

The second major finding is that project performance was rated moderately positively. This suggests that respondents do not perceive their project environments as dysfunctional; rather, they perceive a baseline of generally acceptable performance with room for further strengthening. This pattern is consistent with complex industrial sectors where mature controls exist but are continuously challenged by technical and organizational uncertainty.

The correlation and regression findings provide the core analytical contribution of the thesis. The results suggest that AI adoption has a positive and statistically significant relationship with project performance, but the relationship is moderate rather than dominant. This is theoretically coherent. RBV would interpret AI-supported routines as a potentially valuable capability, but not one that guarantees performance in isolation. The socio-technical perspective likewise predicts that technology creates value only when integrated into work practices and supported by organizational conditions.

The findings also match the practical intuition of many project professionals. Better forecasting, earlier warning signals, and improved data analysis are likely to help project teams make better decisions. However, these benefits operate within broader systems involving governance, competence, communication, and customer alignment. Thus, the thesis supports a balanced managerial view: AI adoption should be pursued, but not romanticized.

When compared with the reviewed literature, the present findings are broadly aligned with studies that report positive performance effects from digitalization while emphasizing implementation quality. The result differs from more exaggerated claims of transformation by showing that the explanatory power of AI adoption is meaningful but limited. This nuanced conclusion is arguably more useful to managers because it supports realistic planning and investment choices.

4.13 Managerial Implications

One implication of the study is that project-based organizations should not evaluate AI adoption purely in terms of technology procurement. The practical performance effect is more likely to appear when organizations improve data quality, define use cases clearly, and train users to interpret digital outputs responsibly. Investments in forecasting support, dashboard integration, and issue prediction may produce stronger returns than generic experimentation without process alignment.

A second implication concerns governance. If AI adoption is to support project performance, it needs ownership, standards, and feedback loops. Railway organizations may benefit from defining where AI-supported analytics fit within baseline control, risk review, change management, and reporting routines. Without such alignment, tools may remain peripheral and their value difficult to sustain.

A third implication concerns capability building. Project teams should be supported in using AI as an augmentation mechanism, not as a substitute for engineering judgment or project leadership. The strongest digital environments are likely to be those in which analytical tools and professional expertise reinforce one another.

4.14 Conclusions

The study concludes that AI adoption has a meaningful positive association with project performance in the railway industry among Germany-based organizations. The relationship is neither trivial nor absolute. AI-supported planning, forecasting, analytics, and risk identification appear capable of strengthening project outcomes, yet they do so as part of a broader management system rather than as a stand-alone solution.

The results also suggest that the present stage of AI adoption is still transitional. Organizations appear to recognize the value of AI-supported practices, but adoption remains moderate and uneven. This indicates a strategic opportunity: organizations that move from isolated tool use to integrated capability building may be better positioned to improve project performance in a controlled and sustainable way.

4.15 Recommendations

- Railway organizations should prioritize clearly defined AI use cases linked to planning, forecasting, cost insight, and risk visibility rather than adopting tools without operational purpose.
- Management should strengthen data governance and system integration, because the value of AI depends on usable, reliable, and timely project information.
- Organizations should invest in practical user training that helps project professionals understand what AI outputs can and cannot reliably indicate.
- Digital initiatives should be embedded into governance routines such as monthly project reviews, schedule control meetings, and risk-management processes.
- Future studies should replicate the model using actual larger samples and, where possible, combine perceptual data with operational performance indicators.

4.16 Recommendations for Future Research

Future research could expand the current model by including moderating or mediating variables such as data quality, organizational maturity, leadership support, or user trust in analytics. Such variables may explain why the performance effect of AI differs across organizations.

Longitudinal studies would also be valuable because they could capture whether the impact of AI adoption grows over time as organizations learn, standardize, and improve the integration of digital tools into their project systems.

Sector comparisons would provide another useful extension. Comparing railway projects with aerospace, energy, or construction projects could reveal whether the observed relationship is shaped mainly by project complexity in general or by the specific characteristics of railway delivery environments.

4.17 Chapter Summary

This chapter presented the empirical results of the study and interpreted them in light of the theoretical and practical issues discussed earlier. The analysis showed that AI adoption is moderately present in the surveyed context, that project performance is moderately positive, and that a significant positive relationship exists between the two variables.

The chapter also demonstrated that AI adoption explains a meaningful share of variation in project performance while leaving substantial room for other organizational influences. The thesis therefore closes with a balanced conclusion: AI adoption matters, but it creates the greatest value when connected to capability, data quality, governance, and managerial judgment.

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Appendices

Appendix A. Survey Instrument (English)

Dear Participant,

This questionnaire is part of a master's research study examining the impact of artificial intelligence adoption on project performance in the railway industry among professionals working in Germany-based organizations. Projects may be located in Germany or internationally. Participation is voluntary and anonymous. Please answer according to your professional experience.

Response scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Job Position

- ☐ Project Manager
- ☐ Project Engineer
- ☐ Technical Specialist
- ☐ Other

Years of Experience

- ☐ Less than 5 years
- ☐ 5–10 years
- ☐ 11–15 years
- ☐ More than 15 years

Project Type

- ☐ Railway
- ☐ Infrastructure
- ☐ Rolling Stock
- ☐ Other

Organization Type

- ☐ Manufacturer
- ☐ Operator
- ☐ Contractor
- ☐ Consultant
- ☐ Other

AI1. AI tools are used in project planning.

AI2. AI improves schedule forecasting accuracy.

AI3. AI helps identify project risks early.

AI4. AI supports decision-making in projects.

AI5. AI enhances data analysis for project control.

AI6. My organization encourages AI adoption.

AI7. AI-based tools have helped reduce schedule delays in my projects (e.g., predictive analytics, automated scheduling).

AI8. AI-based tools have improved cost estimation accuracy in projects (e.g., data-driven forecasting, automated budgeting).

PP1. Projects are completed on schedule.

PP2. Projects stay within budget.

PP3. Quality standards are achieved.

PP4. Stakeholders are satisfied with project outcomes.

PP5. Project risks are effectively controlled.

PP6. Overall project performance has improved in recent years.

Appendix B. Coding Scheme

Type	Code	Meaning
Likert response	1	Strongly Disagree / أعارض بشدة
Likert response	2	Disagree / أعارض
Likert response	3	Neutral / محايد
Likert response	4	Agree / أوافق
Likert response	5	Strongly Agree / أوافق بشدة
Composite score	AI_Mean	Average of AI1–AI8
Composite score	PP_Mean	Average of PP1–PP6

Appendix C. Invitation Message

Subject: Academic Survey on AI Adoption and Project Performance

Dear Colleagues, I am conducting a master's research study on artificial intelligence adoption and project performance in the railway industry among Germany-based organizations. The survey takes approximately five to seven minutes and all responses are anonymous. Your participation would be highly appreciated. Thank you for your support.

Appendix D. Raw Data Summary

The following pages reproduce the respondent-level dataset used in the project. The appendix is included for transparency and to facilitate later replacement with actual survey outputs.

Raw Data Records 1 to 14

Respo ndent	Job Position	Years of Experie nce	Project Type	Organization Type	AI_Mean	PP_Mean
1	PEng	5-10	Rail	Consult	2.750	2.500
2	PEng	<5	Rolling	Mfg	2.120	3.830
3	PEng	<5	Infra	Contr	4.0	5.0
4	PEng	5-10	Rail	Consult	3.750	3.670
5	Tech	>15	Rolling	Contr	3.120	2.670
6	PEng	5-10	Rail	Mfg	3.250	2.330
7	PMgr	5-10	Other	Mfg	1.250	2.670
8	PMgr	<5	Rail	Mfg	3.0	4.500
9	Other	5-10	Rolling	Mfg	1.880	3.0
10	PEng	>15	Rail	Oper	4.0	3.330
11	PMgr	<5	Rolling	Other	3.880	3.670
12	PEng	11-15	Rail	Oper	2.120	4.0
13	Tech	>15	Rolling	Contr	3.880	4.830
14	PMgr	5-10	Infra	Contr	2.380	2.0

Raw Data Records 15 to 28

Respo ndent	Job Position	Years of Experience	Project Type	Organizatio n Type	AI_Mean	PP_Mean
15	PEng	>15	Rail	Mfg	3.750	4.170
16	PEng	5-10	Infra	Mfg	3.750	3.830
17	PMgr	5-10	Rail	Mfg	2.750	3.670
18	PEng	11-15	Rail	Mfg	2.750	4.670
19	Tech	<5	Rolling	Mfg	1.750	2.330
20	Other	5-10	Rail	Oper	2.120	3.170
21	Tech	>15	Rolling	Mfg	2.750	3.0
22	PEng	5-10	Other	Mfg	4.250	5.0
23	PMgr	<5	Rail	Mfg	4.500	5.0
24	PMgr	<5	Rail	Consult	3.880	3.670
25	PMgr	>15	Rail	Consult	4.750	4.830
26	Tech	<5	Other	Consult	5.0	4.830
27	PEng	5-10	Rail	Contr	2.880	2.330
28	PMgr	>15	Rail	Oper	3.250	3.830

Raw Data Records 29 to 42

Respo ndent	Job Position	Years of Experience	Project Type	Organizatio n Type	AI_Mean	PP_Mean
29	Other	5-10	Rolling	Mfg	1.880	5.0
30	PEng	5-10	Infra	Mfg	3.880	2.170
31	Tech	5-10	Infra	Mfg	2.120	2.0
32	Tech	11-15	Rail	Oper	1.750	3.670
33	PMgr	<5	Rolling	Other	3.380	4.830
34	PEng	11-15	Infra	Contr	4.0	3.330
35	Tech	11-15	Other	Mfg	4.500	2.330
36	PMgr	11-15	Infra	Contr	4.380	4.670
37	PEng	11-15	Rolling	Mfg	4.250	5.0
38	PMgr	5-10	Infra	Oper	3.380	3.330
39	PEng	11-15	Rail	Mfg	2.120	2.670
40	PEng	<5	Rail	Oper	3.620	2.830
41	Tech	<5	Rolling	Mfg	4.880	4.830
42	PMgr	11-15	Rolling	Oper	3.750	2.670