

UNIVERSITÉ DU QUÉBEC EN OUTAOUAIS

DOCTORAL THESIS

**Measuring Performance Improvement In Software Engineering Methods
Of Artificial Intelligence And Analytics Projects After Cloud Apps Adoption**

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTORATE IN
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Measuring performance improvement in software engineering methods of artificial intelligence and Analytics projects after cloud apps adoption

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ABSTRACT

ERP adoption is well known to require engineering practices improvement. Cloud era platforms, with IaaS, SaaS, and PaaS, along with a mix of proprietary and open-source code, are changing the efficiency, speed, scale, and innovativeness of how enterprise systems are developed and implemented. Instead of lengthy implementation with high risk, IT personnel find new opportunities for creating valuable apps that enable faster end user change.

One key issue that remains elusive is to accurately measure IT team performance impact after moving to cloud apps. A model is proposed to explain performance improvement and help uncover configurations contingent on industry and organizational contexts.

Using an Empirical Software Engineering (ESE) perspective, with focus on primary data collection, we carry out interviews with, and survey, cloud app vendors, platform consultants, and adopters of leading cloud ERPs, e.g., Microsoft Dynamics 365. We analyze the factors enabling or hindering successful innovation in development teams. Cloud offerings are compared to traditional ones to measure improvement in innovative outcomes.

Software engineering practices are identified along a spectrum of structured and agile methods. Team and deliverable performance are measured and correlated to various potential factors impacting innovation. Their configurations are categorized and serve to provide advice on cloud app development and adoption strategies.

Our analysis relies on correlations and machine learning algorithms to test hypotheses explaining performance. Findings are interpreted to deduce relevant lessons for software engineering of artificial intelligence and analytics projects.

Mesure de l'amélioration des performances des méthodes d'ingénierie logicielle dans les projets d'intelligence artificielle et d'analyse de données après l'adoption d'applications cloud

SHANKAR IYER

RÉSUMÉ

L'adoption d'un ERP est reconnue pour nécessiter une amélioration des pratiques d'ingénierie. Les plateformes cloud, avec IaaS, SaaS et PaaS, ainsi qu'un mélange de code propriétaire et open source, transforment l'efficacité, la rapidité, l'échelle et l'innovation du développement et de la mise en œuvre des systèmes d'entreprise. Au lieu d'une mise en œuvre longue et risquée, les équipes informatiques découvrent de nouvelles opportunités pour créer des applications à forte valeur ajoutée qui accélèrent l'adaptation des utilisateurs finaux.

L'une des principales difficultés réside dans la mesure précise de l'impact sur les performances des équipes informatiques après la migration vers les applications cloud. Un modèle est proposé pour expliquer l'amélioration des performances et identifier les configurations adaptées aux contextes sectoriels et organisationnels. Dans une perspective d'ingénierie logicielle empirique (ISE), axée sur la collecte de données primaires, nous menons des entretiens et des enquêtes auprès de fournisseurs d'applications cloud, de consultants en plateformes et d'utilisateurs de progiciels de gestion intégrée (PGI) cloud de pointe, tels que Microsoft Dynamics 365. Nous analysons les facteurs qui favorisent ou entravent l'innovation au sein des équipes de développement. Les offres cloud sont comparées aux offres traditionnelles afin de mesurer l'amélioration des résultats en matière d'innovation.

Les pratiques d'ingénierie logicielle sont identifiées selon un spectre de méthodes structurées et agiles. La performance des équipes et des livrables est mesurée et corrélée à divers facteurs susceptibles d'influencer l'innovation. Leurs configurations sont catégorisées et servent à formuler des recommandations sur les stratégies de développement et d'adoption d'applications cloud.

Notre analyse s'appuie sur des corrélations et des algorithmes d'apprentissage automatique pour tester des hypothèses expliquant la performance. Les résultats sont interprétés afin d'en tirer des enseignements pertinents pour l'ingénierie logicielle des projets d'intelligence artificielle et d'analyse de données.

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1. INTRODUCTION

1.1 Problem Statement

Among the numerous digital technologies available today, **Artificial Intelligence and Analytics (AIA)** are among the most impactful opportunities for cloud application adoption, whether cloud-native or hybrid. These technologies often build upon prior **Enterprise Resource Planning (ERP)** adoption, which is widely recognized to enhance engineering practices, workflow standardization, and overall project efficiency (Schütte & Kari, 2025).

In modern enterprises, ERP systems such as **Microsoft Dynamics 365 (Finance & Operations)**, **IBM Maximo**, and **Salesforce CRM** serve as foundational platforms that support cloud-based AIA initiatives. Integration of these platforms allows organizations to leverage both operational and strategic data to drive informed decision-making and innovation. While this study primarily focuses on **Microsoft Dynamics 365 in Small- and Medium-sized Enterprises (SMEs)**, the findings and proposed framework are designed to offer insights adaptable to other enterprise contexts and platforms, recognizing context-specific limitations.

Cloud-era platforms—including **Infrastructure as a Service (IaaS)**, **Platform as a Service (PaaS)**, and **Software as a Service (SaaS)**—offer significant advantages in scalability, deployment speed, and system flexibility. However, they also introduce challenges in system integration, process alignment, and governance.

IT teams must navigate these complexities while balancing speed, reliability, and innovation when developing AIA applications. **Development and Operations (DevOps)** practices, along with **DataOps**, have further reshaped AIA project implementation and maintenance. These approaches enable iterative deployment, continuous testing, and faster adaptation to user feedback, but require coordination across multiple roles and organizational alignment (Hammerschmidt, Stolz & Posegga, 2025).

For clarity, throughout this study:

- **Cloud Apps:** Enterprise applications deployed in cloud environments, including SaaS solutions.
- **AIA Projects:** Initiatives integrating Artificial Intelligence and Analytics capabilities to improve organizational decision-making and innovation.
- **DevOps and DataOps:** Structured software engineering and data management methodologies supporting iterative development, continuous integration, and collaboration.

Understanding how these practices affect team performance, collaboration, and innovation outcomes in real-world enterprise contexts is essential. At the same time, the focus on SMEs and a single ERP platform imposes **some limits on the generalizability** of the results.

1.2 Research Objectives

The primary objective of this study is to measure and analyze the **impact of cloud adoption on IT team performance in AIA projects**, while producing actionable insights for enterprise practitioners. Specifically, the study focuses on the following objectives:

1. **Measure IT team performance outcomes:** Assess innovation, collaboration, delivery efficiency, and goal achievement after adopting cloud-based AIA solutions, including comparisons to pre-cloud ERP environments.
2. **Identify critical project success factors (X1–X4):** Examine how project experience, complexity, technology adoption, management strategies, and lessons learned influence AIA project outcomes. The study also investigates multi-factor interactions to identify combinations producing the most effective performance improvements.
3. **Develop a reusable framework:** Create a structured model linking team practices, cloud adoption, and project outcomes, applicable across enterprise contexts and project sizes.
4. **Evaluate cloud and DevOps practices:** Understand how DevOps, DataOps, and CI/CD practices affect project efficiency, innovation, and team collaboration, identifying enablers and barriers to effective cloud adoption.

5. **Bridge academic research and enterprise practice:** Provide empirically grounded recommendations for IT leaders and project managers, moving beyond vendor marketing claims and algorithm-centric studies.
6. **Support measurement and benchmarking:** Establish methods to quantify team performance and correlate practices with influencing factors, enabling future benchmarking and validation in cloud-based AIA projects.

Note: The study acknowledges **limitations in scope due to platform focus and SME context.**

1.3 Research Methodology

A **qualitative case study approach** was employed to capture real-world practices and complexities in enterprise AIA projects. Data was collected through **structured interviews with 120 informants** from multiple SMEs, including software engineers, data analysts, solution architects, CTOs, CIOs, and PMO personnel.

Expert Participant Validation and Scope:

To ensure the **integrity and trustability** of the data, a rigorous validation process was conducted. All informants were verified through professional **LinkedIn profiles** and recognized ERP/AIA expert communities to confirm their years of experience and professional standing. Furthermore, while Microsoft Dynamics 365 served as a primary focal case for the SME context, the study was **technology-agnostic**; informants were not restricted by the specific platforms used, ensuring the findings represent a broad spectrum of cloud-native and hybrid enterprise solutions.

Data Collection:

- **Interviews:** Each interview lasted 1–2 hours and was recorded, transcribed, and systematically coded to extract thematic insights.
- **Scoring:** Multi-dimensional scoring converted qualitative responses into quantitative measures to capture the interplay of project factors (X1-X4) and outcomes (Y1, Y2).
- **Bias Mitigation:** Neutral question phrasing, anonymized coding, and cross-validation by multiple coders were applied. Additionally, the study acknowledges the potential for

social desirability bias among experts and mitigated this through the triangulation of qualitative claims against objective project outcomes.

Machine Learning Analysis:

Conducted using **Orange Data Mining** to identify non-linear patterns and correlations among project variables.

By combining qualitative coding, multi-factor scoring, and computational analysis, the study provides a comprehensive understanding of the complex factors influencing cloud-based AIA project success, beyond what can be captured in traditional algorithm-focused research.

1.4 Research Outcome

The research produces three primary contributions that bridge the gap between academic theory and enterprise practice in the field of Empirical Software Engineering:

1. **Empirical Contribution – Large-Scale Field Evidence:** This study provides extensive empirical data derived from 120 structured interviews with AIA experts. By capturing real-world practices from projects with budgets ranging from \$1M to \$50M+, it uncovers field evidence and practical challenges such as the "human factor" and operational bottlenecks that are frequently absent from current algorithm-centric literature.
2. **Theoretical Contribution – Reusable Success Framework:** The research establishes a structured framework for AIA project success by identifying and measuring four critical independent variables (X1–X4: Project Experience, Technology Adoption, Management Strategy, and Lessons Learned) and their impact on team performance (Y1) and deliverable outcomes (Y2). This provides a reusable conceptual model for future researchers to test and validate across different enterprise contexts.
3. **Practical & Managerial Contribution – Actionable Benchmarking:** The study offers evidence-based recommendations for IT leaders to optimize cloud adoption and DevOps

practices. By demonstrating how iterative development and automation enhance collaboration, the research provides a toolkit for enterprises to quantify team performance and improve innovation outcomes in cloud-native environments.

Beyond these core pillars, the research contributes to the broader discourse on Empirical Software Engineering by illustrating how hybrid and agile methods are effectively applied in cloud-based AIA projects. The resulting performance measurement models—categorized by role, process step, and technology adoption provide a foundational roadmap for future AIA development initiatives. This structured approach ensures that the insights gained are directly grounded in empirical analysis, laying the foundation for the conclusions and strategic recommendations presented in Chapter 6.

1.5 Thesis Outline

This thesis is structured into six key chapters to systematically address the research objectives and questions.

Chapter 1: Introduction sets the context of the study by presenting the problem statement, research objectives, and the overarching research questions (RQ1 and RQ2). It highlights the research contributions and limitations, providing the foundational scope for the empirical analysis. This chapter also introduces the **Figure 1 Operationalization of AIA Predictive Model Variables** as the primary lens for the study.

Chapter 2: Literature Review provides a comprehensive review of academic and industry literature regarding AIA, cloud ERP adoption, and project capabilities. It identifies gaps in how technical factors influence organizational goals. This chapter culminates in the **Hypothesis Development (H1–H10)**, featuring the **Figure 2 Conceptual Model for Combined AIA Project Impact**, which synthesizes AI, Cloud, and Software Engineering pillars into a unified predictive system.

Chapter 3: Research Methodology describes the qualitative case study approach and the multi-stage data collection process. It details the **Expert Participant Validation** process—disclosing

how the 120 AIA informants were verified via LinkedIn and ERP expert communities to ensure data trustability. The chapter further explains the analytical methods, including coding and the development of scoring models using **Orange Data Mining**.

Chapter 4: Results Analysis presents a detailed analysis of both qualitative and quantitative findings. It systematically tests **Hypotheses H1 to H8** (individual variable impacts) and **Hypotheses H9 and H10** (combined systemic impact). This chapter uses visual data representations to demonstrate the correlation between project parameters and final application outcomes.

Chapter 5: Discussion interprets the results within the context of existing literature and the original research objectives. It discusses how the findings contribute to **Empirical Software Engineering Theory**, compares results with prior studies, and highlights the managerial and technical implications for organizations adopting cloud-based AIA solutions.

Chapter 6: Conclusion summarizes the main findings and provides a final assessment of the research questions. It outlines the practical contributions to the field, acknowledges study limitations, and suggests specific opportunities for future research in automated project performance forecasting.

2. LITERATURE REVIEW

2.1. Conceptual Framework

Digital transformation is creating a new context requiring an evolving role for corporate leaders, including Chief Executive Officer (CEO), Chief Information Officer (CIO), Chief Digital Officer (CDO), Chief Technology Officer (CTO), and Chief Financial Officers (CFO). They must refocus the financial and performance mindset of project governance toward digital innovation value, linked to human capital, Analytics and Artificial Intelligence (AIA) and knowledge intensity.

The proposed conceptual structure is presented not merely as a static case study, but as a reusable framework for evaluating AIA project maturity and performance. By categorizing independent variables into four distinct pillars (X1 to X4) and mapping them to specific performance outcomes (Y1, Y2), this framework provides a structural template for future researchers.

It is designed to be platform-independent, allowing for the benchmarking of IT team performance across different ERP ecosystems—such as SAP, Oracle, or Microsoft—and various organizational scales. This reusability ensures that the methodology can be adapted to evolving cloud-native environments and diverse industrial contexts.

To understand the success of these initiatives, this study identifies a three-pillar framework based on contemporary digital practices:

- Cloud Platforms (IaaS, PaaS, SaaS): Enable scalable infrastructure and on-demand computing resources for enterprise systems (Buyya et al., 2017).
- Artificial Intelligence & Analytics (AIA): Supports data-driven software development and intelligent decision-making in modern organizations (Mohammad et al., 2025).
- AI-Driven DevOps / AIOps: AI improves Cloud Computing's Impact on the Digital Transformation of the Enterprise (Merlo et al., 2025).

This study maps these pillars to the independent variables: **Cloud** relates to **Project Complexity**; **AI** relates to **Technologies Used**; and **Software Engineering** relates to **Project M Strategy and Lessons Learned**.

2.1.1. Analytics and AI (AIA)

In (Khosrojerdi et al., 2022), the authors examined 108 studies on the integration of artificial intelligence and data analytics (AIA) within smart grid projects, exploring how AI-based and analytics-driven technologies are powering dynamic energy management, fault and disturbance detection, real-time voltage stability assessments, home and building energy optimization, and automated SCADA data processing. It categorizes applications into AI-centric, analytics-centric, and hybrid designs, inspecting architectural frameworks and design methodologies across diverse use cases. The synthesis highlights both technical and managerial insights such as lessons for effective AIA architecture in smart grid project planning, governance, and implementation and underscores the need for capability-focused integration of AI/analytics with project management approaches to support renewable integration and overall grid automation

In (Zhu et al., 2024), the authors did a study that introduces an AI-assisted analytical (AIA) model designed to estimate seismic displacements in friction-isolated bridge portfolios subjected to pulse-like near-fault ground motions. The authors examined the Traditional machine learning (TML) methods that are commonly used in seismic performance analysis but often fall short in capturing displacement behavior within the sensitive pulse-effect intervals. To address this, the study proposes a novel AI-assisted analytical (AIA) method that combines the physical clarity of analytical modeling with the parameter optimization power of artificial intelligence.

In (Gou et al., 2021), In the context of Analytics and Artificial Intelligence (AIA), the authors presented VATLD is a novel visual analytics system that integrates AI-driven techniques to enhance the accuracy and robustness of traffic light detection models in autonomous driving. Leveraging deep learning, VATLD incorporates disentangled representation learning to semantically structure data for better human interpretability, while semantic adversarial learning applies AI to expose model vulnerabilities and generate robustness insights with minimal manual intervention. Through visual summarization and automated risk identification, VATLD bridges analytics and AI by translating complex model behavior into actionable improvements. This AIA-driven framework not only supports detailed performance evaluation but also informs strategic enhancements to ensure safer, more reliable deployment of traffic light detectors in real-world autonomous systems.

2.1.1.1. AIA Projects in Practice

In (Wijayasekera et al., 2022), the authors explore how Data Analytics and Artificial Intelligence (AI) can enhance the execution and performance of megaprojects through digital project delivery.. The authors highlight how these technologies can improve decision-making, coordination, and efficiency across project lifecycles. They also identify emerging challenges, such as integration, scalability, and governance, that need to be addressed to realize the full potential of digitalization. The paper ultimately offers both practical implications for project practitioners and theoretical direction for scholars interested in the intersection of AI, analytics, and project organizing.

In (Liu & Li, 2022), focus on the integration of Artificial Intelligence (AI) with business systems to enhance enterprise performance. It highlights how man-machine collaboration enables better decision-making, knowledge sharing, and performance optimization through augmented analytics and intelligent automation. It offers a broader organizational view, grounded in theoretical frameworks like the resource-based and knowledge-based views of the firm.

In (Quintero-Gómez et al., 2024), the authors did a study that uses a combination of data analytics and artificial neural networks (ANNs) to explore how socio-demographic factors and personality traits influence academic success among university students. Key findings include that high school GPA is a strong predictor of university performance, first-generation college students tend to achieve higher GPAs, and gender differences in academic outcomes vary by context. The research highlights the value of predictive analytics in identifying success indicators and offers insights for designing more inclusive and effective educational strategies.

2.1.1.2. AIA Project Frameworks

In (Górriz et al., 2020), the authors in the paper offer a comprehensive review of recent advances in data science and artificial intelligence (AI), focusing on the dynamic interplay between natural and artificial computation. The study synthesizes key developments in both theoretical models and applied domains, providing a baseline framework for the global AI research community. It covers emerging applications in robotics, neuroscience, brain-computer interfaces, and medicine, while also offering insight into future trends and the expanding role of AI in addressing complex, interdisciplinary challenges.

In (Teo Susnjak, 2024), the author did a study that addresses key gaps in Learning Analytics by proposing an integrated framework that combines transparent predictive modeling with prescriptive analytics to support at-risk learners more effectively. While much existing research has focused primarily on prediction—using machine learning to identify students likely to drop out—this work goes further by incorporating eXplainable AI (XAI) techniques to interpret predictions and generate individualized, actionable feedback.

In (V. O. K. Li et al., 2021), in this paper the authors propose a comprehensive AI- and big data-driven framework for personalized air pollution monitoring and health management, aiming to improve individual well-being by providing real-time, tailored alerts and advice. It identifies various key challenges such as sparse urban air quality data, missing or erroneous human-input data, complexity and heterogeneity of data and uncertain impact of smart alerts on behavior change.

2.1.1.3. AIA Project Performance

In (Jammeli et al., 2023), the authors did a study that focuses on enhancing urban solid waste (USW) management by predicting the required number of waste bins using AI-based forecasting models. Given that solid waste data forms a real-valued time series, the researchers emphasize the use of sequential models—specifically Long Short-Term Memory (LSTM) and Bidirectional LSTM (BLSTM).. Their superior performance highlights the strength of deep learning in capturing temporal patterns, making them highly effective tools for optimizing bin allocation and improving operational efficiency in USW systems.

In (Yoshikuni et al., 2024), the authors in this study highlights the performance impact of big data analytics (BDA)-driven dynamic capabilities on environmental sustainability across enterprises in India and the USA. Using data from 319 firms and applying partial least square structural equation modeling and qualitative comparative analysis, the research identifies seven high-performing configurations where BDA-enabled capabilities in sensing, seizing, and transforming significantly enhance environmental outcomes. The findings show that these capabilities are especially effective in dynamic and hostile environments, with U.S. service sector and small enterprises showing strong green performance through radical process innovation, while Indian large product firms achieve performance gains via incremental innovation.

In (Charles et al., 2025), the authors examine how AI-driven prescriptive and cognitive analytics are revolutionizing business decision-making and performance optimization across sectors. Central to the discussion is the Analytics Onion framework, which integrates Perspective Analytics, Responsible Analytics, and the traditional analytics progression (descriptive to cognitive)—emphasizing the critical balance between AI capabilities, human judgment, and ethical considerations. The papers demonstrated performance-enhancing applications in areas such as service automation, business location strategy, ESG evaluation, energy efficiency, and customer churn reduction.

2.1.1.4. AIA Projects after Cloud ERP Adoption

In (Tavakoli et al., 2023), the authors studied how the Technology Acceptance Model (TAM) is influenced by Artificial Intelligence (AI) and cloud computing within the media environment. Using data from 368 professionals at the National Iranian Oil Company and structural equation modeling via PLS 2.0, the research finds that AI significantly and positively impacts technology acceptance when integrated with cloud computing.

In (Kouatli, 2022), the author proposes a fuzzy logic-based augmentation to traditional quantitative survey analysis to address participant uncertainty in long questionnaires, such as those assessing cloud computing acceptance. The approach is demonstrated through a cloud acceptance survey, offering a step-by-step guide, and is particularly useful for long, complex surveys where response inconsistency may distort findings.

In (Zhou et al., 2021) paper, the authors presents a semantic discovery mechanism for improving medical transportation logistics under cloud-based healthcare systems, leveraging IoT and AI technologies for enhanced knowledge management and operational innovation. The approach tackles the challenge of matching heterogeneous transportation resources with medical delivery tasks by using ontology modeling to represent both resource and task information.

2.1.2. AIA and Software Engineering Project Structure

2.1.2.1. AIA Project Capabilities

In (Müller et al., 2024), the authors address the high rate of Desk rejections of artificial intelligence (AI)–related submissions to the Project Management Journal® (PMJ) are high. This article provides an overview and state-of-the-art snapshot on academic and practitioner work to derive at potential future research topics and guidelines on the execution and reporting of AI-related studies in project management.

In (Felicetti et al., 2024), the authors investigate how project managers are integrating generative AI tools—particularly ChatGPT—into their workflows, using Adaptive Structuration Theory to analyze adoption behaviors. Based on a survey of Italian project managers and analyzed through Partial Least Squares Structural Equation Modeling, the research finds that Innovation Attitude, Peer Influence, and Task-Technology Fit significantly shape how AI tools are appropriated.

In (Jing et al., 2025), the authors did a study that examines the relationship between Cultural Intelligence (CQ) and Project Management Performance, with Artificial Intelligence (AI) abilities as a mediating factor. Using a quantitative, positivist approach and data from 374 project managers in the construction industry, the researchers applied SMART PLS 4.0 for analysis. The findings highlight that higher cultural intelligence positively influences project performance, especially when integrated with AI capabilities.

2.1.2.1.1. Project Experience and Complexity

In (Bouzguenda et al., 2022), authors emphasize the project-based experience of designing and implementing a solar-powered smart irrigation system using off-the-shelf components. Developed as part of a senior design project, it offered students hands-on experience in integrating renewable energy technologies, wireless communication, and embedded systems to solve real-world agricultural challenges.

In (Nakitare et al., 2023), the authors highlight the project experience of the African Library Project (ALP), which has successfully collaborated with over 1,500 partners to establish 3,762 school and community libraries across 13 African countries, distributing nearly 3.9 million books. Drawing on both implementation experience and secondary data, the paper shares practical lessons learned

from managing a large-scale, long-term literacy initiative. The paper contributes toward establishing a practical framework for guiding future literacy initiatives.

In (Katerji & Karami-Akkary, 2025), the authors present the project experience of a school-based improvement initiative in a Lebanese private school, aiming to empirically illustrate the process of building school capacity in a non-Western context. The project was conducted through a school-university partnership, a relatively uncommon approach in the region.

2.1.2.1.2. Technologies and Architecture

In (Setaki & van Timmeren, 2022), the authors explore how disruptive digital technologies can enable a circular economy (CE) in the building industry, focusing on the construction and demolition phases, which are the most waste-intensive. This paper aims at The aim is to clarify how and where digital innovations (e.g., AI, IoT, BIM) can be strategically implemented to support resource efficiency and waste reduction in a circular building lifecycle.

In (Xu et al., 2023), the authors introduce a technology-driven approach to Neural Architecture Search (NAS) by proposing a proxy validation loss landscape to efficiently identify optimal neural network architectures. Instead of relying solely on actual validation loss during training, the method learns a predictive mapping from neural architectures to their expected validation losses.

In (Brozovsky et al., 2024), the authors provides a comprehensive technological mapping of digital tools in the AEC sector, emphasizing the urgency of bridging the gap between innovation and practice and also analyzes the technological landscape in the Architecture, Engineering, and Construction (AEC) sector, highlighting the slow pace of digital adoption despite growing interest.

2.1.2.1.3. Project Management and Strategy

In (Pretorius et al., 2023), the authors investigate the evolution of project management maturity in organizations within a developing country, comparing 2020 data to a similar 2010 study. Based on 600 survey responses covering 9,389 projects, the findings show a decline in average project management maturity from 2.88 (2010) to 2.64 (2020). Despite this decline, most projects were still perceived as successful.

In (Phung et al., 2023), the authors develop and empirically tests a model for Sustainable Project Management (SPM) aimed at achieving Sustainable Project Success (SPS) in construction-building projects. The study finds that stakeholder management and sustainability goal definition have a significant direct impact on sustainable success. The research highlights the need to address all five components to effectively support sustainability in projects.

In (Dalto et al., 2024), the authors examine how project management can facilitate the adoption of the circular economy (CE) in agribusiness through a systematic literature review of 70 articles. The study highlights efforts to reduce agro-waste by transforming it into by-products. The research contributes by clarifying how project management can enable CE adoption in agribusiness and offers practical insights to support its viability.

2.1.2.1.4. Lessons Learned and Competencies

In (Williams et al., 2023), the authors found that combining hands-on, unplugged activities with ethical discussions effectively engaged middle school students in learning AI concepts and exploring their societal impacts. Partnering with trained teachers enriched the learning experience, while reducing technical and knowledge barriers ensured accessibility for students from diverse backgrounds. The success of the online workshops demonstrated that remote AI education can be both inclusive and impactful.

In (Ruwaida et al., 2023), the authors revealed that strong stakeholder engagement is essential for effective TSO-DSO-customer coordination, as collaboration builds trust and facilitates implementation. It also highlighted the importance of availability remuneration to incentivize flexibility providers. A key lesson learned was the need for clearly defined technical requirements and precise market timings to ensure reliable system operation.

In (Gyrard et al., 2025), the authors highlighted several key lessons learned in advancing interoperability for health data within the EHDS2 context. Effective collaboration among diverse stakeholders was essential to address fragmentation and standardization challenges, particularly in metadata, data access, and processing. Adopting common interoperability standards, aligned with the European Interoperability Framework (EIF) and ISO guidelines, proved crucial for integrating heterogeneous data sources.

2.1.2.2. AIA Product Performance

In (Nemitallah et al., 2023), the authors highlight several key lessons learned regarding AI applications for optimizing boiler performance and controlling emissions. It underscores that data-driven AI approaches—such as neural networks, genetic algorithms, fuzzy logic, and hybrid systems—show great promise in improving combustion efficiency and reducing NOx emissions while minimizing costs. The success of AI models largely depends on high-quality, representative data and appropriate model selection.

In (Zhang et al., 2024), the authors introduce a robust evaluation framework focused on assessing the performance of supply chain management (SCM) platforms under uncertain and complex conditions. The approach followed in developing the product effectively handles imprecise data and decision-maker limitations to provide accurate and reliable assessments of SCM platform performance.

In (Xin et al., 2024), the authors highlight the growing role of artificial intelligence (AI) and machine learning (ML) in optimizing formulas, selecting ingredients, predicting performance, and analyzing structure-properties in cosmetic product development. The review also covers ML applications in formula optimization and detecting hazardous ingredients such as allergens. By examining recent research from the past four years, it showcases current trends and advancements in ML-driven innovation within the cosmetics industry.

2.1.2.3. AIA Project Goals

In (Nasir et al., 2023), the authors mention that primary goal of this study is to evaluate how Artificial Intelligence (AI) aligns with and contributes to the United Nations' 17 Sustainable Development Goals (SDGs), with a focus on promoting social good across society, the economy, and the environment. The research highlights a disproportionate focus on SDG 9 (Industry, Innovation, and Infrastructure), while critical goals related to gender equality, clean water, life below water, and life on land (SDGs 5, 6, 14, and 15) receive minimal attention. The findings call for more inclusive and balanced AI development.

In (Nahar, 2024), the author describe the goal of this study is to forecast the long-term impact of AI-based innovation on the achievement of Sustainable Development Goals (SDGs) across different countries, addressing a critical gap in existing research. Using system dynamics modeling

and grounded in the Technology Enactment Framework from Institutional Theory, the study simulates AI's influence on SDGs from 2022 to 2030 in 22 countries across five continents. The research aims to provide nuanced insights into the complex, varied impact of AI-driven innovation on SDG progress.

In (Wei et al., 2025), the authors aim to explore the transformative role of Artificial Intelligence (AI) in advancing photochemical hydrogen generation to support renewable energy development and achieve sustainable environmental goals. The ultimate goal is to provide strategic insights and policy recommendations to guide the development, implementation, and scaling of AI-driven hydrogen technologies in alignment with sustainability targets.

2.2 Research Questions

To our knowledge, this systematic literature review mentioned in section 2.1 is the attempt to show the different ways to implement latest technologies such as Artificial Intelligence (AI), Big Data technologies in a conceptual model. This resulted in identifying the most trending topic with 38 relevant articles. Finally, we conducted a comprehensive analysis of the data contained within the subset of 120 AIA interview analysis and organized the data in a way to answer the research questions.

2.2.1 RQ 1: How AIA project capabilities parameters impact final business AIA application product performance?

When it comes to project performance, we must take into consideration many factors such as cost of the entire project, how much time will be spent on this project, what will be the scope of the project, what different kinds of requirements will be considered and how is the overall user experience in this project.

When it comes to product performance, we must take into account many factors such as how will be the Quality of Service (QOS), what level of innovation will be achieved in this project in terms of code optimization and advanced algorithms will be used in this project, how compatible the project is terms of working with other correlated systems, what level of productivity will be achieved and how would be the process integration in this project.

In (Kohli & Melville, 2019), the authors believe that as part of the IT strategy senior team, Business, Technology, and Accounting Executives must look beyond the traditional framework of business-technology alignment and help the organization to refocus on value-driven digital innovation with a deeper understanding of how organizations lead people to co-develop digital capabilities.

In (Ramesh & Delen, 2021), the authors mention that as such, they present new challenges as digital transformation intensifies, where evolving requirements imply new approaches to recruiting and managing a new generation of accounting and IT professionals and teams, while keeping organizational performance stable, and avoiding “digital failure”

Among numerous digital technologies, Artificial Intelligence and Analytics (AIA) are one of the most strategic to executive leadership. AIA-driven tools are prevalent in accounting and are transforming the way professionals work. At the same time, executives are increasingly involved in AIA implementation projects, most often in business value assessments, but also in managing risks and benefits realization.

We want to see how different project parameters involved in building the final business AIA application product used by the organisation impacts the performance of the final business AIA application product. For that we would like to see how different project parameters such as AIA Projects experience complexity level, Technologies used in the different AIA projects, Project Management strategy involved in each of the AIA project implementation and Lessons Learned from each AIA project implemented impact the performance of final business AIA application product.

2.2.2 RQ 2: How do AIA capabilities parameters impact final business AIA application goals achieved?

The objectives of this study are to accurately measure IT team performance impact after moving to cloud apps for AIA. We attempt to clarify without doubts, beyond the fuzzy marketing of vendors, how AIA project best practices can help companies reach their best performance. For this purpose, a model is proposed to explain performance improvement and help uncover

configurations contingent on industry and organizational contexts. The purpose of this study is therefore exploratory, attempting to pinpoint the actual digital innovation practices, and their impact on software project outcome.

This study has the potential to contribute to empirical software engineering theory. The AIA project practices identified shall fit within the spectrum of hybrid, structured, and agile methods. Team and deliverable performance measurement models can be used in the future by development teams, helping to measure and correlate their practices to various potential factors impacting innovation. Their configurations being categorized by project role and process steps, it will be possible to use them to provide advice on AIA and cloud app development and adoption strategies.

We want to see how different project parameters involved in building the final business AIA application product used by the organisation impacts the goals achieved of the final business AIA application product. For that we would like to see how different project parameters such as AIA Projects experience complexity level, Technologies used in the different AIA projects, Project Management strategy involved in each of the AIA project implementation and Lessons Learned from each AIA project implemented impact the goals achieved of final business AIA application product

2.3 Hypothesis

This section will outline in detail each hypothesis and their theoretical grounding. These hypotheses map the study's core pillars to specific capability parameters. The above-mentioned **AIA Predictive Model Framework** in **Figure 1** serves as a conceptual blueprint that illustrates the causal relationships between project-specific determinants and their eventual success metrics. By mapping independent variables such as project complexity (X1), technological stack (X2), management strategy (X3), and historical lessons learned (X4) against dependent outcomes like performance (Y1) and goal attainment (Y2), the framework provides a structured basis for testing specific research hypotheses. It essentially transforms qualitative project characteristics into a quantitative predictive flow, allowing the AIA engine to weigh the influence of each input to forecast whether a project will meet its defined KPIs or require preemptive intervention.

AIA Predictive Model Framework

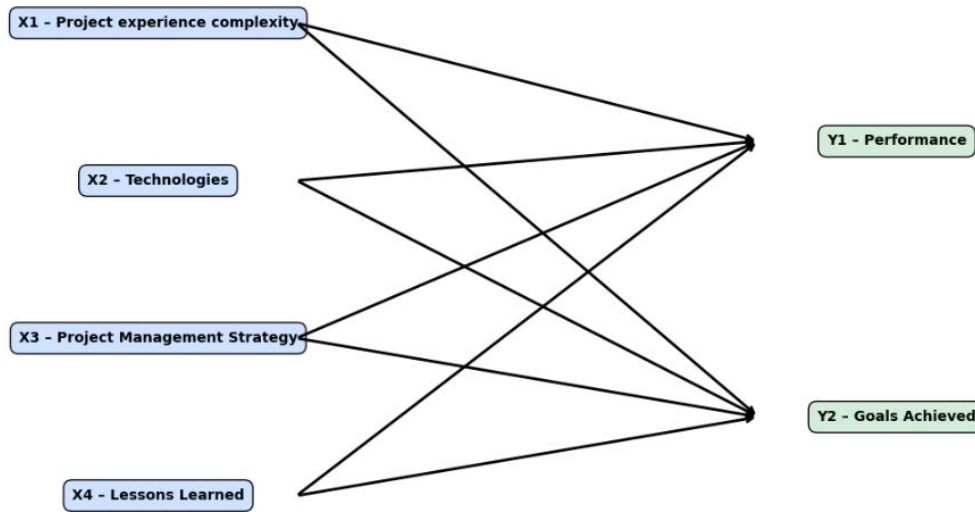


Figure 1 Operationalization of AIA Predictive Model Variables

2.3.1 H1: Positive Relationship between Overall performance of final business AIA application and AIA Projects experience complexity level

In this hypothesis, we believe that the overall performance of the final business AIA application used by the organisation positively aligns with the different AIA project complexity levels mentioned by AIA interview participants.

Suppose, if an AIA interview participant has worked on 2 or 3 AIA projects [simple AIA project complexity level] for building the final business AIA application. We will analyse how AIA project complexity level influences the overall performance of the AIA business application

2.3.2 H2: Positive Relationship between Overall performance of final business AIA application and different technologies used in AIA projects

In this hypothesis, we believe that the overall performance of the final business AIA application used by the organisation positively aligns with the different technologies used in building Final business AIA application.

For example if an AIA interview participant has used less than 5 technologies in their different AIA projects for building the final business AIA application. We will analyse how different technologies used in AIA projects influences the overall performance of the AIA business application.

2.3.3 H3: Positive Relationship between Overall Overall performance of final business AIA application and different project management strategy used in AIA projects

In this hypothesis, we believe that the overall performance of the final business AIA application used by the organisation positively aligns with the different project management strategy used in building Final business AIA application.

For example if an AIA interview participant has used multiple project management strategies in their different AIA projects for building the final business AIA application. We will analyse how multiple project management strategies used in AIA projects influences the overall performance of the AIA business application.

2.3.4 H4: Positive Relationship between Overall performance of final business AIA application and lessons learned from different AIA projects

In this hypothesis, we believe that the overall performance of the final business AIA application used by the organisation positively aligns with the lessons learned from different AIA projects.

For example if an AIA interview participant has gained lessons learned from different AIA projects. We will analyse how these lessons learned from different AIA projects influences the overall performance of the AIA business application.

2.3.5 H5: Positive Relationship between Overall goals achieved from final business AIA application and AIA Projects experience complexity level

In this hypothesis, we believe that the overall goals achieved from the final business AIA application used by the organisation positively aligns with the different AIA project complexity levels mentioned by AIA interview participants.

Suppose, if an AIA interview participant has worked on 2 or 3 AIA projects [simple AIA project complexity level] for building the final business AIA application. We will analyse how AIA project complexity level influences the Overall goals achieved from AIA business application.

2.3.6 H6: Positive Relationship between Overall goals achieved from final business AIA application and different technologies used in AIA projects

In this hypothesis, we believe that the overall goals achieved from the final business AIA application used by the organisation positively aligns with the different technologies used in building the Final business AIA application.

For example if an AIA interview participant has used less than 5 technologies in their different AIA projects for building the final business AIA application. We will analyse how different technologies used in AIA projects influences the overall goals achieved from AIA business application.

2.3.7 H7: Positive Relationship between Overall goals achieved from final business AIA application and different project management strategy used in AIA projects

In this hypothesis, we believe that the overall goals achieved from the final business AIA application used by the organisation positively aligns with the different project management strategy used in building the Final business AIA application.

For example if an AIA interview participant has used multiple project management strategies in their different AIA projects for building the final business AIA application. We will analyse how multiple project management strategies used in AIA projects influences the Overall goals achieved from AIA business application.

2.3.8 H8: Positive Relationship between Overall goals achieved from final business AIA application and lessons learned from different AIA projects

In this hypothesis, we believe that the overall goals achieved from the final business AIA application used by the organisation positively aligns with the lessons learned from different AIA projects.

For example if an AIA interview participant has gained lessons learned from different AIA projects. We will analyse how these lessons learned from different AIA projects influences the Overall goals achieved from AIA business application.

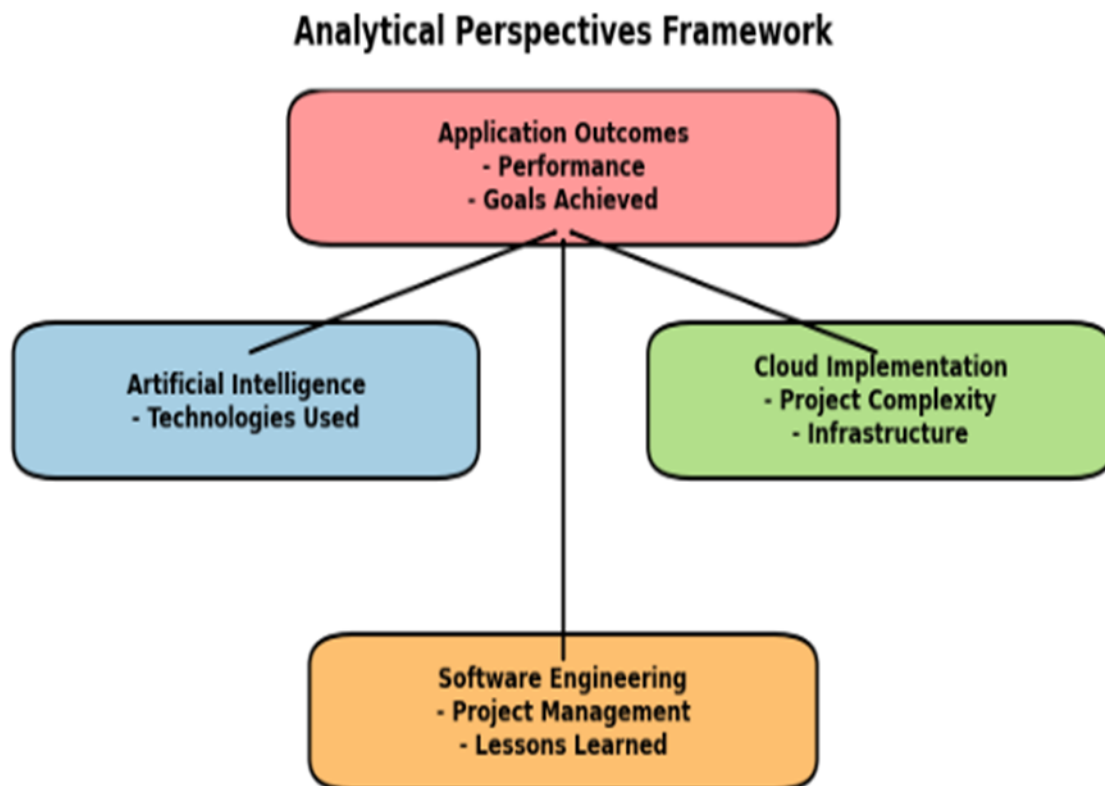


Figure 2 Conceptual Model for Combined AIA Project Impact

The **Figure 2 Conceptual Model for Combined AIA Project Impact** serves as the integrated theoretical framework that synthesizes individual project determinants into three primary technical pillars: Artificial Intelligence, Cloud Implementation, and Software Engineering. While the

preceding hypotheses (H1 through H8) isolate the independent effects of specific variables, this model illustrates the convergence point where these domains collectively influence final application outcomes. By establishing this structural hierarchy, the framework provides the necessary grounding for the "combined impact" analyzed in Hypotheses 9 and 10, which posit that superior product performance and strategic goal attainment are the systemic result of a synergistic interaction between technological sophistication, infrastructure scale, and matured engineering methodologies.

2.3.9 H9: Positive Relationship between Overall performance of final business AIA application and combined impact of AIA Projects experience complexity level , different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projects

In this hypothesis, we believe that the overall goals achieved from the final business AIA application used by the organisation positively aligns with the combined impact of AIA Projects' experience complexity level, different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projects.

For example if an AIA interview participant has worked on different complexity of AIA projects for building the final business AIA application, used different technologies in their different AIA projects for building the final business AIA application, used multiple project management strategies in their different AIA projects for building the final business AIA application and gained lessons learned from different AIA projects. We will analyse how these combined factors of project parameters influence the Overall performance of the final business AIA application.

2.3.10 H10: Positive Relationship between Overall goals achieved from final business AIA application and combined impact of AIA Projects experience complexity level , different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projects

In this hypothesis, we believe that the overall goals achieved from the final business AIA application used by the organisation positively aligns with the combined impact of AIA Projects' experience complexity level, different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projects.

For example if an AIA interview participant has worked on different complexity of AIA projects for building the final business AIA application, used different technologies in their different AIA projects for building the final business AIA application, used multiple project management strategies in their different AIA projects for building the final business AIA application and gained lessons learned from different AIA projects. We will analyse how these combined factors of project parameters influence the Overall goals achieved from final business AIA application.

3 RESEARCH METHODOLOGY

3.1 Data collection and Analysis

The data collection is based on interviews with 120 informants drawn from Small-Medium Enterprises (SMEs) having adopted a leading cloud ERP. To ensure a more comparable sample of cases, and properly develop a scoring model, all companies and informants will have built their AIA projects around Microsoft Dynamics 365 (D365).

To ensure also that AIA apps and cloud features are similarly compared, all AIA projects will have focused on the Finance and Operations module of D365, for which the predecessor was branded Dynamics AX until 2020. A broad view of all business, technology, and management factors will be required. Therefore, all informants will be at executive ranks, 5 per company (i.e., CEO, CFO, CIO, CTO, PMO). Each will get up to 2-hours interview performed by the student, each recorded-transcribed-annotated to ensure coherence.

The data analysis will also rely on ontology-driven automated text analytics to ensure coherence in inter-case comparison. Queries on the annotated texts will demonstrate the model is formally validated by a majority of the 120 informants from the interviews. As well, semantic queries will automatically identify any new concepts we need to add to expand the model, with annotations that ensure the validation, expansion, and integration with core AIA project components (i.e., roles, tasks, processes, competencies, artefacts, tools, rules, etc.).

This work is guided by the systematic literature review methodology which specifies the techniques for literature identification, selection, and quality evaluation. All papers include choices that imply the purposeful inclusion and exclusion of factors—in other words, the paper scope. These choices may be self-evident to the authors, but they are not to the readers.

3.2 Integration and Synthesis of Results

The following databases were searched for research articles: Google Scholar, Science direct and IEEE. To identify the relevant articles, we broadened our research to include all articles that refer to the terms “project”, “metamodel”, “empirical”, “software”, “situational”, “awareness”, “information”, “system”.

We analysed 120 AIA interview transcripts and categorized them based on the project parameters that takes to build the final business AIA application that the organisation will use on daily basis to run their business such as Projects experience complexity level (X1), different technologies used (X2), different project management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4), Overall performance of the final business AIA application (Y1) and Overall goals achieved from the final business AIA application (Y2).

We measured project experience complexity level used (X1) based on the number of project(s) worked by each AIA participant in order to build the final business AIA application used by their respective organisation.

Table 1: Measuring Project experience complexity levels (X1)

X1	Projects experience complexity level
Value 1	Simple Worked on 1-3 projects
Value 2	Low complexity Worked on 3-5 projects
Value 3	Medium complexity Worked on 5-7 projects
Value 4	Moderately Complex 7-9 projects
Value 5	Super Complex >10 projects

As per **Error! Reference source not found.**, we have used Likert scale ^[41] to score project experience complexity levels and assigned value 1 to value 5 to distinguish the degree of project experience complexity levels.

Value 1 was identified as Simple project complexity i.e. if the AIA participant has only worked on 1-3 projects, value 2 was identified as Low project complexity i.e. if the AIA participant has only worked on 3-5 projects, value 3 was identified as Medium complexity i.e. if the AIA participant has only worked on 5-7 projects, value 4 was identified as Moderately Complex project complexity i.e. if the AIA participant has only worked on 7-9 projects and value 5 was identified as super Complex project complexity i.e. if the AIA participant has only worked on more than 10 projects in order to build the final project.

For measuring different technologies used (X2), we identified the different technologies used by each AIA participant in building the final business AIA application used by their respective organisation.

Table 2: Measuring different technologies used (X2)

X2	Technologies used
Value 1	Less than 5 technologies
Value 2	between 5-10 Technologies
Value 3	between 10-15 Technologies
Value 4	between 15-20 Technologies
Value 5	more than 20 Technologies

As per **Table 2**, we have used Likert scale ^[41] to score different technologies used (X2) and assigned value 1 to value 5 to distinguish the number of different technologies used in different AIA projects to build the final business AIA application.

Value 1 was identified as if Less than 5 technologies were used in building the final business AIA application, value 2 was identified as if 5 to 10 technologies were used in building the final business AIA application, value 3 was identified as if 10 to 15 technologies were used in building the final business AIA application, value 4 was identified as if 15 to 20 technologies were used in building the final business AIA application and value 5 was identified as if more than 20 technologies used in an AIA project.

For measuring different Project Management strategies used (X3), we identified the different Project Management strategies used by each AIA participant in building the final business AIA application used by their respective organisation.

Table 3: Measuring different Project Management strategies used (X3)

X3	Project Management strategy
V1	No agile
V2	Hybrid
V3	Low Agile
V4	Mild Agile
V5	Strong Agile

As per **Table 3**, we have used Likert scale ^[41] to score different Project Management strategies used (X3) and assigned value 1 to value 5 to distinguish the number of Project Management strategies used in different AIA projects to build the final business AIA application.

Value 1 was identified as No Agile model were used in building the final business AIA application, value 2 was identified as hybrid model i.e. mix of waterfall and agile model were used in building

the final business AIA application, value 3 was identified as low agile methodologies were used in building the final business AIA application, value 4 was identified as mild agile methodologies were used in building the final business AIA application and value 5 was identified as strong agile methodologies were used in building the final business AIA application.

For measuring what different lessons learned were (X4), we identified the different lessons learned by each AIA participant in different projects used in building the final business AIA application.

Table 4: Measuring what different lessons learned were (X4)

X4	Lessons Learned
V1	Bad
V2	No Alignment
V3	Low Alignment
V4	Mild Alignment
V5	Strong Alignment

As per **Table 4**, we have used Likert scale ^[41] to score what different lessons learned were (X4) and assigned value 1 to value 5 to identify the different lessons learned in different AIA projects to build the final business AIA application .

Value 1 was identified as “Bad” i.e. if the lessons learned from different AIA projects used in building the final business AIA application had a bad impact on the overall performance of the final business AIA application and in achieving the overall goals of the final business AIA application.

Value 2 was identified as “No Alignment” i.e. if the lessons learned from different AIA projects used in building the final business AIA application had a No impact on the Overall performance of the final business AIA application and in achieving the Overall goals of the final business AIA application.

Value 3 was identified as “low Alignment” i.e. if the lessons learned from different AIA projects used in building the final business AIA application had a very minimal or low impact on the Overall performance of the final business AIA application and in achieving the overall goals of the final business AIA application.

Value 4 was identified as “Mild Alignment” i.e. if the lessons learned from different AIA projects used in building the final business AIA application had a mild impact on the overall performance of the final business AIA application and in achieving the overall goals of the final business AIA application.

Value 5 was identified as “Strong Alignment” i.e. if the lessons learned from different AIA projects used in building the final business AIA application helps to improve the overall performance of the final business AIA application and also help to achieve the Overall goals of the final business AIA application.

For Overall performance of the final business AIA application (Y1), we measured the overall performance of the final business AIA application used by their respective organisation.

Table 5: Measuring Overall performance of the final business AIA application (Y1)

Y1	Final Product Performance
V1	Bad
V2	Needs little improvements
V3	Needs lot of improvements
V4	Meets Expectations
V5	Exceeds Expectations

As per

Table 5, we have used Likert scale ^[41] to score Overall performance of the final business AIA application (Y1) and assigned value 1 to value 5 to distinguish the overall performance of the final business AIA application used by their respective organisation .

Value 1 was identified as “Bad” i.e. the overall performance of the final business AIA application used by their respective organisation is bad, Value 2 was identified as “Need little improvement” i.e. the overall performance of the final business AIA application used by their respective organisation need little improvement, Value 3 was identified as “Need lots of improvement” i.e. the overall performance of the final business AIA application used by their respective organisation need lots of improvement, Value 4 was identified as “Meets Expectation” i.e. the overall performance of the final business AIA application used by their respective organisation Meets expectation and Value 5 was identified as “Exceeds Expectation” i.e. the overall performance of the final business AIA application used by their respective organisation exceeds expectation
For Overall goals achieved from the final business AIA application (Y2), we measured the Overall goals achieved from the final business AIA application used by their respective organisation.

Table 6: Measuring Overall goals achieved from the final business AIA application (Y2)

Y2	Goals Achieved
V1	Bad
V2	No influence to support AIA projects
V3	Low influence to support AIA projects
V4	mild influence to support AIA projects
V5	Strong influence to support AIA projects

As per

Table 6, we have used Likert scale ^[41] to score Overall goals achieved from the final business AIA application (Y2) and assigned value 1 to value 5 to distinguish Overall goals achieved from the final business AIA application used by their respective organisation.

Value 1 was identified as “Bad” i.e. the overall goals achieved from the final business AIA application used by their respective organisation shows bad influence and dependencies on the underlying AIA projects used.

Value 2 was identified as “No influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application used by their respective organisation shows No influence and dependencies on the underlying AIA projects used.

Value 3 was identified as “Low influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application used by their respective organisation shows low influence and dependencies on the underlying AIA projects used.

Value 4 was identified as “Mild influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application used by their respective organisation shows mild influence and dependencies on the underlying AIA projects used.

Value 5 was identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application used by their respective organisation shows strong influence and dependencies on the underlying AIA projects used.

3.3 Research tools

This section will discuss the machine learning algorithms and data mining tools used in this thesis.

For each of 120 AIA interview participants, we analysed each of their interview transcripts and assigned them their respective project parameters score. Below Table 7 provides the scores for the first 20 AIA participants out of 120 AIA interview participants.

Table 7: The scores for the first 20 AIA participants out of 120 AIA interview participants

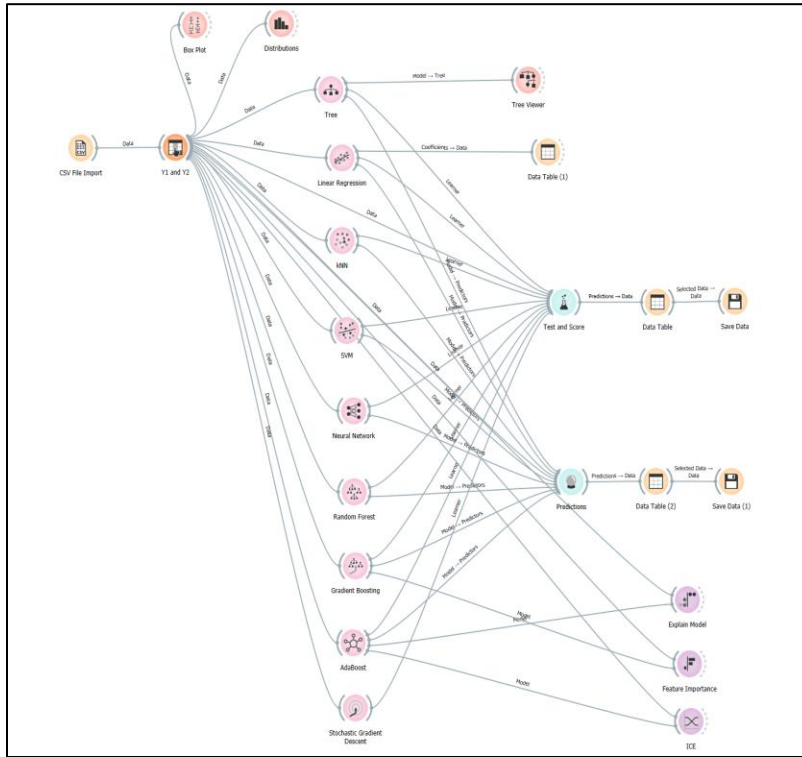
AIA Interview Participant number	Goals Achieved (Y2)	Final Product Performanc (Y1)	Projects experience complexity level (X1)	Technologies used (X2)	Project Managment strategy (X3)	Lessons Learned X4
1	4	4	3	2	5	2
2	5	5	4	3	2	3
3	4	5	5	2	2	5
4	4	4	2	1	2	2
5	5	5	5	3	5	5
6	5	5	2	2	5	5
7	4	4	5	2	1	2
8	5	5	4	3	5	2
9	3	3	2	2	1	2
10	4	3	2	1	1	2
11	3	3	5	1	1	3
12	3	3	4	2	1	2
13	4	3	5	3	2	3
14	3	4	2	1	1	4
15	5	5	5	1	5	4
16	4	3	2	3	5	4
17	5	5	4	1	5	2
18	4	5	3	5	1	4
19	4	3	4	2	2	3
20	3	4	5	1	5	5

In above **Table 7: The scores for the first 20 AIA participants out of 120 AIA interview participants**Table 7, we created a CSV dataset with all the scores of the project parameters that takes to build the final business AIA application that the organisation will use on daily basis to run their business such as Projects experience complexity level (X1), different technologies used (X2), different project management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4), Overall performance of the final business AIA application (Y1) and Overall goals achieved from the final business AIA application (Y2) of the 120 AIA interview participants.

3.3.1 Orange Data Mining Tool

Orange is a data mining tool used for analysis in many applications. Orange is an open-source data visualization software making it best suited for dataset analysis with added, machine learning capabilities. Orange is one stop place for developing workflows and understanding different basic machine learning algorithms with interactive visualizations. One of the most important features that Orange provides is live visual preview of the dataset manipulation making it very ideal for programming and performing qualitative data analysis.

Figure 3: Figure showing different Machine Learning models used on AIA Dataset



The CSV File Import feature of Orange data mining tool allows importing CSV dataset and there are a lot of options available in the import widget where the user sets the import parameters. Can be re-opened by pressing Import Options in the widget.

Once the imported dataset was arranged properly, then we applied the dataset to different Machine learning models such as Adaboost, Gradient boosting, Tree, Random Forest, k-nearest neighbors algorithm (k-NN), Support Vector Machines (SVM), Neural Network, Linear Regression and Stochastic Gradient. We will explain in-depth about these Machine learning models in 3.3.3. Machine learning Models

3.3.2 Statistics Concepts

3.3.2.1 Mean Squared Error (MSE)

Mean squared error (MSE) is a metric system used when there is a need to measure the average squared difference between the predicted values and the actual values in the dataset. The

MSE value provides a way to analyze the accuracy of the model. We will use the MSE system in order to analyse the AIA dataset

The formula for the Mean squared error (MSE) is

$$\text{MSE} = \frac{\sum(y_i - p_i)^2}{n}$$

where y_i is the i th observed value, p_i is the corresponding predicted value for y_i , and n is the number of observations. The Σ indicates that a summation is performed over all values of i .

3.3.2.2 Root Mean Squared Error (RMSE)

Root mean square error or root mean square deviation is commonly used measures for evaluating the quality of predictions.

Root mean square error can be expressed as

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N \|y(i) - \hat{y}(i)\|^2}{N}},$$

where N is the number of data points, $y(i)$ is the i -th measurement, and $\hat{y}(i)$ is its corresponding prediction.

3.3.2.3 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a measure of the average size of the mistakes in a collection of predictions, without taking their direction into account.

The MAE loss function formula:

- $MAE = (1/n) \sum_{i=1}^n |y_i - \hat{y}_i|$

where:

- n is the number of observations in the dataset.
- y_i is the true value.
- \hat{y}_i is the predicted value.

You can think about it as an estimate of predicting inaccuracy but not with direction i.e. over or under prediction as prime examples.

3.3.2.4 Mean Absolute Percent Error (MAPE)

Mostly for measuring forecasting accuracy, we tend to use MAPE (mean absolute percentage error)

$$MAPE = (1/n) * \sum (|actual - forecast| / |actual|) * 100$$

where:

- Σ – a fancy symbol that means “sum”
- n – sample size
- **actual** – the actual data value
- **forecast** – the forecasted data value

MAPE is used as it is easy to understand and explain. For example If the MAPE value of the forecasted model is 11.5% that means that the average difference between the forecasted value and the actual value is 11.5%. It is believed that lower the value of MAPE, the model is better to forecast values. For example, a model with a MAPE of 2% is more accurate than a model with a MAPE of 10%.

3.3.2.5 Coefficient of Determination, R-squared

The coefficient of determination, or R^2 , is a measure that provides information about the goodness of fit of a model. In terms of regression, it is a statistical measure of how well the

regression line approximates the actual data. Due to that nature R^2 is mostly used to predict future outcomes or in the testing of hypotheses.

$$R^2 = 1 - \frac{\text{sum squared regression (SSR)}}{\text{total sum of squares (SST)}},$$

$$= 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}.$$

The sum squared regression is the sum of the residuals squared, and the total sum of squares is the sum of the distance the data is away from the mean all squared. As it is a percentage it will take values between 0 and 1.

In (Sterba & Rights, 2022), the authors mentions that adding R^2 Strengthens hypothesis testing and also communicates model fit clearly and supports interpretation of results. Additionally, adding R^2 helps compare models. If you test multiple models, R^2 helps justify which one is better.

3.3.2.6 Standard Error

The standard error of the mean, or simply standard error, indicates how different the population mean is likely to be from a sample mean. ^[59]

When the population standard deviation is known, you can use it in the below formula to calculate standard error precisely.

Formula	Explanation
$SE = \frac{\sigma}{\sqrt{n}}$	<ul style="list-style-type: none"> SE is standard error σ is population standard deviation n is the number of elements in the sample

3.3.2.7 P Value

P values are used in hypothesis testing to help decide whether to reject the null hypothesis. The smaller the p value, the more likely you are to reject the null hypothesis. P-values help you show whether your findings are statistically meaningful.

As per (Debasish Das & Tutan Das, 2023), P-values are a core part of hypothesis testing in quantitative research. Reporting them shows that we are applying proper statistical methods and making evidence-based conclusions. P-values give readers a clear benchmark to judge which relationships are statistically reliable. In most cases, p value < 0.05 is considered as significant, p value < 0.01 is considered as highly significant and p value > 0.05 is considered as not significant. P-values help you make data-driven decisions about your hypotheses.

3.3.2.8 Linear regression

In (Montgomery et al., 2012), the authors mention that Regression analysis is a statistical technique for investigating and modeling the relationship between variables.

The **simple linear regression model**, that is, a model with a single regressor x that has a relationship with a response y that is a straight line. This simple linear regression model is

$$y = \beta_0 + \beta_1 x + \varepsilon$$

where the intercept β_0 and the slope β_1 are unknown constants and ε is a random error component. The errors are assumed to have mean zero and unknown variance σ^2 . Ideally we use using hypothesis testing on the coefficients, especially β_1

3.3.2.8.1 Common Hypothesis Testing

Linear regression models play an important role in hypothesis testing, especially in analyzing relationships between variables and making inferences about population parameters. Here's a clear explanation of how linear regression is used in hypothesis testing:

- Use of t-tests

T-tests are called t-tests because the test results are all based on t-values. T-values are an example of what statisticians call test statistics. A test statistic is a standardized value that is calculated from sample data during a hypothesis test

Test for Slope Coefficient β_1

Null Hypothesis (H_0): $\beta_1 = 0$

(No relationship between X and Y)

Alternative Hypothesis (H_1): $\beta_1 \neq 0$

(There is a relationship)

Test Statistic:

$$t = \frac{\hat{\beta}_1}{SE(\hat{\beta}_1)}$$

where $SE(\hat{\beta}_1)$ is the standard error of the estimated coefficient.

- Use of F Statistic / F Value

The F statistic is calculated by dividing the variance between groups by the variance within groups. The F critical value is a specific value that is used to determine whether the F statistic is statistically significant.

In general, if the F statistic is greater than the F critical value, then you can reject the null hypothesis; this means that there is a significant difference between the group variances.

Used when you have **multiple independent variables** (multiple regression).

Tests whether at least one of the coefficients is significantly different from zero.

Null Hypothesis (H_0): All $\beta_i = 0$ (no predictors matter)

Alternative Hypothesis (H_1): At least one $\beta_i \neq 0$

The **F-statistic** is computed using:

$$F = \frac{\text{Explained Variance}/p}{\text{Unexplained Variance}/(n - p - 1)}$$

As per (Z. Li et al., 2022), we also made use of T-test and Fvalue for hypothesis testing because both of these values add more to demonstrate Statistical Significance as t-test shows whether individual variables (coefficients) significantly affect your dependent variable and F-statistic helps to test whether your overall model is statistically significant. Also, Using and interpreting F and t-

tests correctly shows that including these tests supports your claims with empirical evidence in hypothesis testing and indicates that the authors understand the principles of hypothesis testing.

3.3.3. Machine learning Models

In this section, we will discuss the various machine learning models which we have used in this thesis.

3.3.3.1 Adaboost Model

In (Ahmad & Nikpoor, 2023), the authors mention that AdaBoost (Adaptive Boosting) is an ensemble machine learning algorithm that combines multiple weak learners (usually decision stumps—trees with one split) to form a strong classifier. It's widely used for classification and, to a lesser extent, regression.

Key Steps in AdaBoost Model:

Step 1 : Initialization

Given a training dataset $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, where x_i are the features and y_i are the labels ($y_i \in \{-1, +1\}$).

Initialize the weights for each data point w_1, w_2, \dots, w_N , such that:

$$w_i = \frac{1}{N} \quad \text{for all } i = 1, 2, \dots, N$$

This means every sample starts with an equal weight.

Step 2: Train Weak Classifiers

For each iteration $t = 1, 2, \dots, T$, a weak classifier $h_t(x)$ is trained using the weighted data. The classifier is trained to minimize the weighted classification error.

Step 3: Calculate error for each classifier:

The weighted classification error ϵ_t for the classifier $h_t(x)$ is calculated as:

$$\epsilon_t = \frac{\sum_{i:h_t(x_i) \neq y_i} w_i}{\sum_{i=1}^N w_i}$$

This gives the total weight of misclassified samples.

Step 4 : Calculate Classifier Weight (Alpha)

The weight of the weak classifier h_t is then computed as:

$$\alpha_t = \frac{1}{2} \ln \left(\frac{1 - \epsilon_t}{\epsilon_t} \right)$$

- If ϵ_t is small (good classifier), α_t is large, giving more importance to that classifier.
- If ϵ_t is large (bad classifier), α_t is small, giving less importance.

Step 5 : Calculate Update Weights for Next Iteration

After each weak classifier is added, the weights of the misclassified samples are increased to make them more important for the next classifier. The updated weights $w_i^{(t+1)}$ are calculated as:

$$w_i^{(t+1)} = w_i \cdot \exp(-\alpha_t y_i h_t(x_i))$$

Here:

- If $h_t(x_i)$ correctly classifies x_i (i.e., $y_i = h_t(x_i)$), the weight remains the same or decreases.
- If $h_t(x_i)$ misclassifies x_i (i.e., $y_i \neq h_t(x_i)$), the weight increases.

Step 6: Final strong classifier

The final strong classifier $H(x)$ is the weighted sum of all weak classifiers:

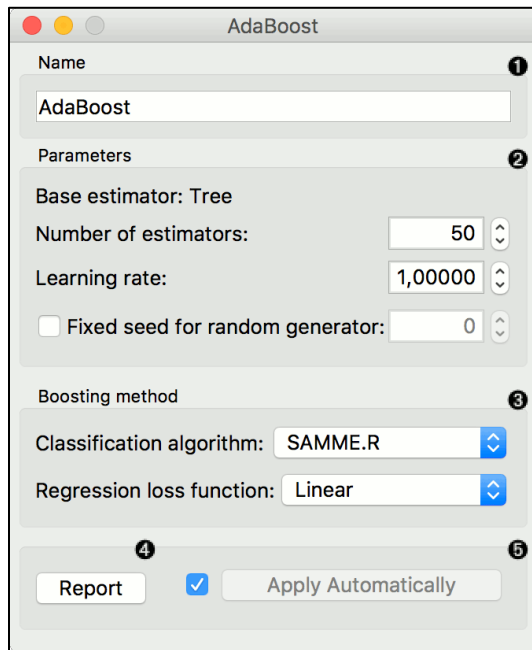
$$H(x) = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x) \right)$$

- Here, the sign function returns $+1$ if the sum is positive and -1 if it's negative.
- Each weak classifier's contribution is weighted by α_t , which depends on its performance.

3.3.3.1.1 Adaboost Model in Orange

The AdaBoost (short for "Adaptive boosting") widget is a machine-learning algorithm, formulated by Yoav Freund and Robert Schapire. We can use the Adaboost algorithm with other learning algorithms to boost their performance. It does so by tweaking the weak learners. AdaBoost works for both classification and regression.

Figure 4: Figure showing AdaBoost model input widget



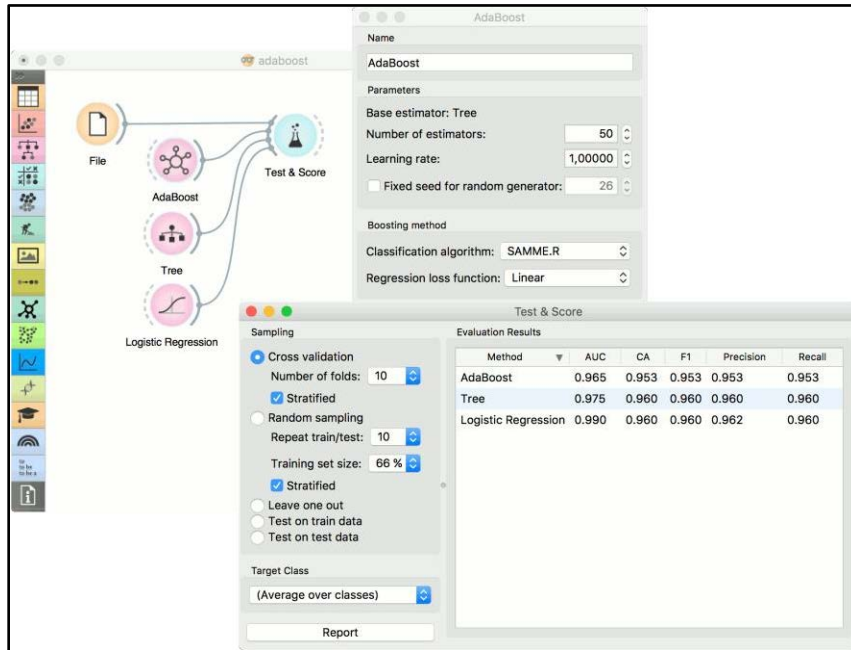
As you can observe in

Figure 4, that we need to set the input parameters such as base estimator, number of estimators, learning rate i.e. it determines to what extent the newly acquired information will override the old information, and we need to mention the Fixed seed for random generator i.e. set a fixed seed to enable reproducing the results.

We also must mention the Boosting method required i.e. Classification algorithm is SAMME (updates base estimator's weights with classification results) or SAMME.R (updates base estimator's weight with probability estimates) and Regression loss function (if regression on input is either Linear method or Square method or Exponential method).

Once these inputs are provided, then the AdaBoost model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. In below Figure 3, we have shown an example of the AdaBoost model, in terms of classification, we loaded the iris dataset. We used AdaBoost, Tree and Logistic Regression and evaluated the models' performance in Test & Score.

Figure 5: Figure showing example of AdaBoost model using orange data mining tool



3.3.3.1.2 Why did we use the Adaboost Model?

In (Huang et al., 2022), authors mentions that AdaBoost can achieve fair classification while preserving the advantages (i.e., interpretability, scalability, and accuracy) of the basic AdaBoost. The AdaBoost has several advantages for practical applications, such as, interpretability, scalability, and accuracy, but few work has employed it to deal with the fair classification.

We used AdaBoost method in our thesis to achieve good performance in fair classification. Adaboost Model also It turns weak models into strong models by focusing on misclassified points and correcting them iteratively. It offers high accuracy, low bias, and works well with small base models (e.g., decision trees). It is fast and computationally efficient for a wide range of tasks.

3.3.3.2 Gradient Boosting Model

In (Ahmad & Nikpoor, 2023), the authors mentions that Gradient Boosting model is another popular ensemble learning method, similar to AdaBoost model, but with a different mechanism for improving the predictive power of weak learners. Instead of adjusting weights based on misclassifications like in AdaBoost, Gradient Boosting builds an ensemble of weak learners by fitting each new model to the residual errors of the previous model.

Gradient Boosting model builds a strong model by sequentially adding weak learners (often decision trees). At each step, the model tries to correct the errors (residuals) made by the previous model, instead of directly adjusting sample weights as in AdaBoost model.

Key Steps in Gradient Boosting Model:

Step 1 : Initialization

The algorithm starts with a simple initial model. This could be just the mean of the target values (for regression) or a simple classifier (for classification).

Step 2: Calculate Residuals

At each iteration, the residual errors are computed, which represent the difference between the actual values and the predicted values of the current model.

$$r_i^{(t)} = y_i - f(x_i)^{(t)}$$

where:

- $r_i^{(t)}$ is the residual (error) for data point i at iteration t ,
- y_i is the true label of data point i ,
- $f(x_i)^{(t)}$ is the prediction of the model at iteration t for data point i .

Step 3: Update the Model

The new model is added to the ensemble, and the model is updated by combining the previous model's predictions and the new model's predictions

$$f(x)^{(t+1)} = f(x)^{(t)} + \alpha \cdot h_t(x)$$

where:

- $f(x)^{(t+1)}$ is the updated model at iteration $t + 1$,
- $f(x)^{(t)}$ is the model at iteration t ,
- $h_t(x)$ is the weak learner (tree) added in iteration t ,
- α is a **learning rate** that controls how much to adjust the model in each step.

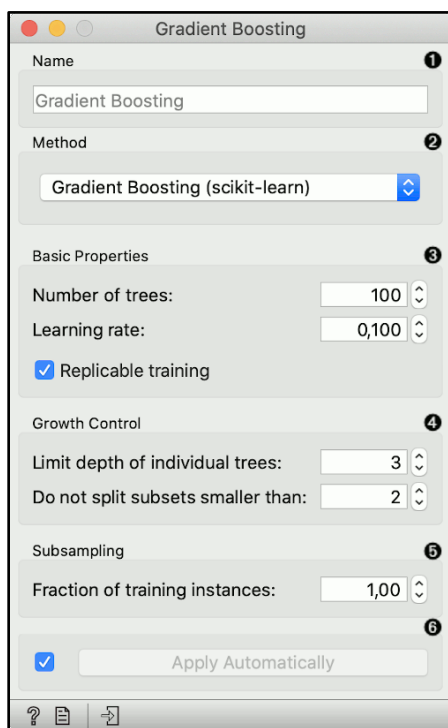
Step 4: Repeat

This process is repeated for a fixed number of iterations or until the residuals are minimized to a satisfactory level. At each step, the algorithm tries to improve the model by reducing the residual errors.

3.3.3.2.1 Gradient Boosting Model in Orange data mining tool

Gradient Boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

Figure 6: Figure showing Gradient Boosting model input widget

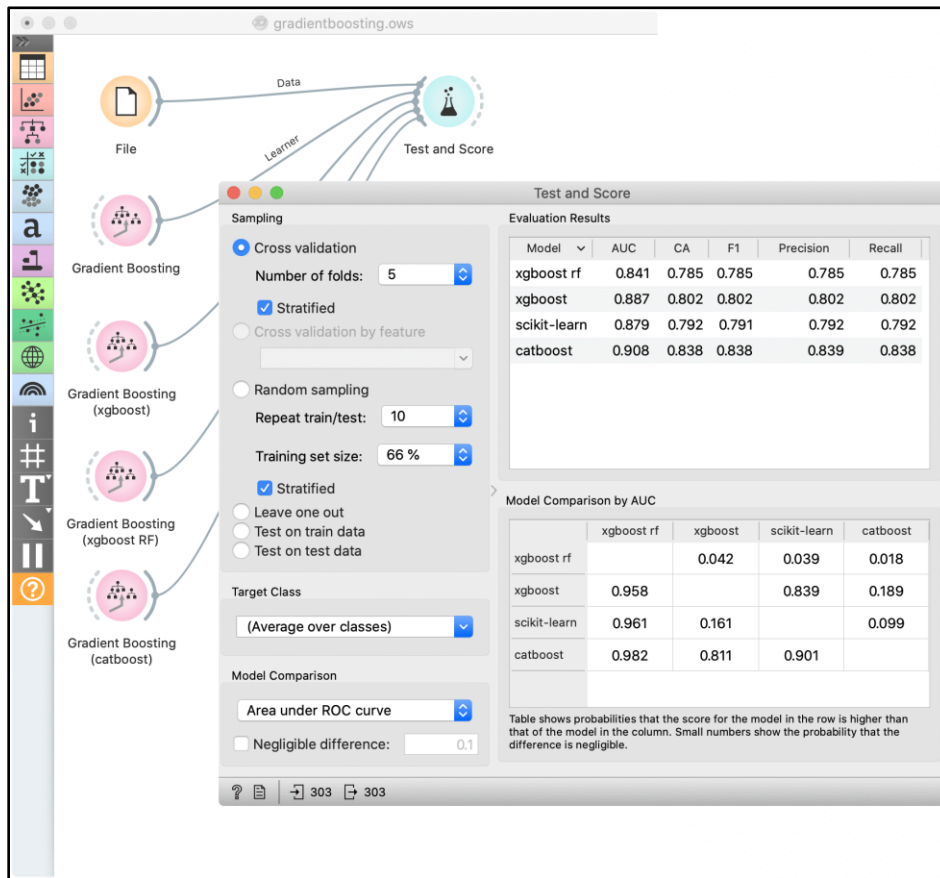


As you can observe in **Figure 6**, that we need to select the a gradient boosting method i.e. either Gradient Boosting (scikit-learn) or Extreme Gradient Boosting (xgboost) or Extreme Gradient Boosting Random Forest or Gradient Boosting (catboost). Also, we need to select basic properties such as number of trees, learning rate, and fixed seed for random generator i.e. set a fixed seed to enable reproducing the results also called as replicable training.

We also must mention the growth control parameters such as Limit depth of individual trees i.e. we need to specify the maximum depth of the individual tree and Do not split subsets smaller than i.e. to specify the smallest subset that can be split. This option is only available only for scikit-learn methods along with that we also need to specify the subsampling parameters

Once these inputs are provided, then the Gradient Boosting model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. In below Figure 5, we have shown an example of the Gradient Boosting model, in terms of classification, we loaded the heart disease dataset and evaluated the models' performance in Test & Score.

Figure 7: Figure showing example of Gradient Boosting model using orange data mining



3.3.3.2 Why did we use the Gradient Boosting Model?

In (Susik & Grabowski, 2025), the authors describe that Gradient boosting, typically applied to decision trees, is an ensemble of weak classifiers. As in other boosting methods, each newly added component of the ensemble tries to correct the errors of its predecessors. A novel idea of gradient boosting is that the loss function is quite arbitrary, as long as it is differentiable.

Gradient Boosting can create highly accurate models, especially for structured/tabular data. It works for both classification (binary or multi-class) and regression tasks. It can handle heterogeneous features, i.e., both numerical and categorical data. Gradient Boosting models can provide insights into which features are the most important for prediction. With careful tuning (e.g., using cross-validation, limiting tree depth, and adjusting the learning rate), Gradient Boosting can achieve high accuracy without overfitting.

3.3.3.3 Tree Model

In (Ahmad & Nikpoor, 2023), the authors mentions that in the context of algorithms, a tree is one of the most useful data structures due to its hierarchical data storage capabilities. While designing algorithms, we use trees wherever we need to represent hierarchical relationships among the data elements that we need to store or process. A Tree Model, commonly referred to as a Decision Tree, is a type of supervised learning algorithm that is widely used for both classification and regression tasks. It builds a model in the form of a tree-like structure, where:

- Each internal node represents a decision (based on a feature),
- Each branch represents an outcome of that decision, and
- Each leaf node represents a final prediction (class label or continuous value).

Key Steps in Tree Model:

Step1: Start at the Root Node

The algorithm begins at the root of the tree, where it looks at all features in the dataset and makes a decision based on the feature that best splits the data

Step 2: Split the Data

The algorithm chooses the feature and threshold (split value) that best separates the data into homogeneous groups. This decision is made based on a criterion, such as:

- Gini Impurity (used in classification)
- Entropy (information gain, also used in classification)
- Variance reduction (used in regression)

Step 3: Repeat the Process (Recursive Splitting)

This process is recursively applied to the subgroups of the data. At each step, a feature is selected, and the data is split again based on that feature until the stopping condition is met (e.g., reaching a maximum tree depth, having too few samples, or pure leaves).

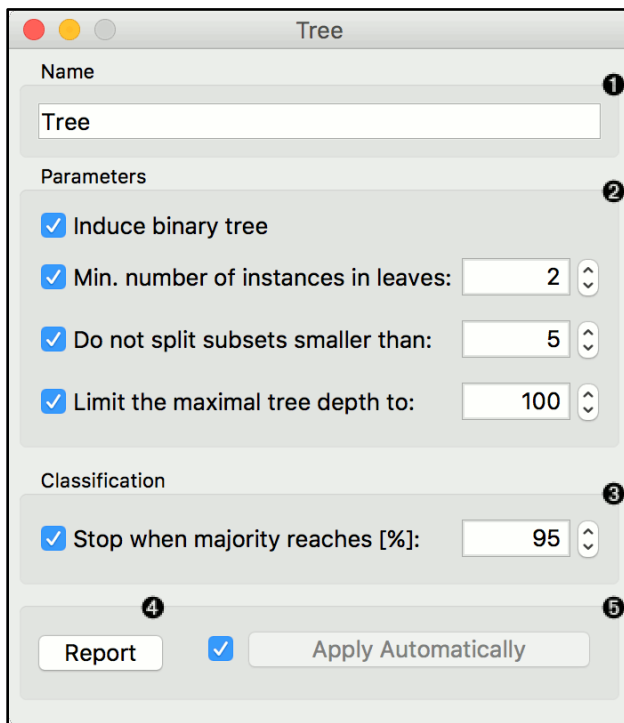
Step 4: Leaf Nodes

The leaf nodes of the tree represent the final decision. For classification, this is the majority class of the data points in that node. For regression, this is the mean of the target values in that node.

3.3.3.1 Tree Model in Orange data mining tool

Tree is a simple algorithm that splits the data into nodes by class purity. It is a precursor to Random Forest. Tree defined in Orange is designed in-house and can handle both categorical and numeric datasets. It can also be used for both classification and regression tasks.

Figure 8: Figure showing Tree model input widget

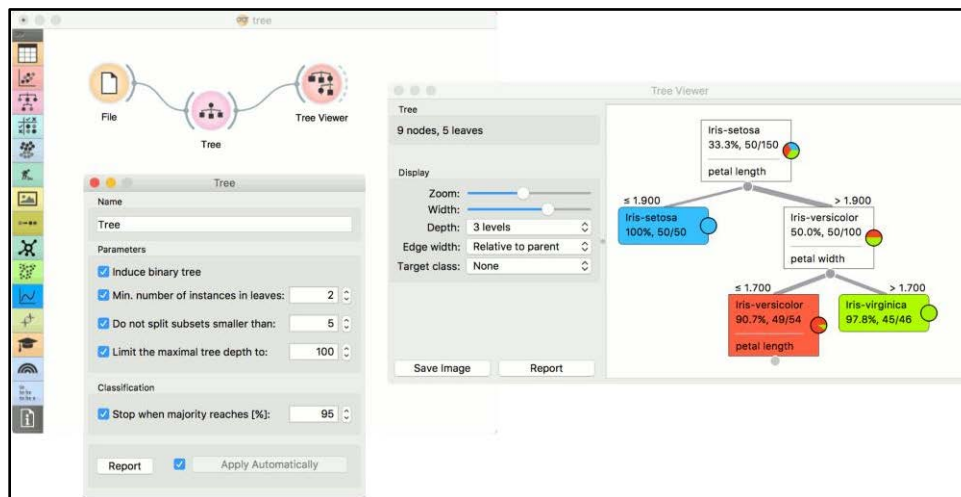


As you can observe in

Figure 8, we need to set the input tree parameters such as Induce binary tree which will build a binary tree and split it into two child nodes, Min. number of instances in leaves i.e. if we check this option then the algorithm will never construct a split, Do not split subsets smaller than i.e. this option if checked then it will forbid the algorithm to split the nodes with less than the given number of instances and we need to mention the Limit the maximal tree depth i.e. set a fixed seed to enable reproducing the results. Another option is to mention Stop when majority reaches i.e. this option will tell the model to stop splitting the nodes after a specified majority threshold is reached.

Once these inputs are provided, then the Tree model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. In below Figure 7, we have shown an example of the Tree model, in tree viewer.

Figure 9: Figure showing example of Tree model using orange data mining



3.3.3.2 Why did we use the Tree Model?

In (Agrawal & Adane, 2023), the authors mention that the accuracy of the decision tree forest algorithm depends upon the base learner and its diversification. The tree structure is easy to visualize, making it easy to understand how decisions are being made. Decision trees can capture non-linear relationships between features and the target variable. Decision trees can handle both types of features without needing any preprocessing like normalization or encoding. Unlike other algorithms (e.g., SVM, logistic regression), decision trees do not require normalization or standardization of features. Since decision trees are transparent, you can interpret the model easily and understand how a particular prediction was made.

3.3.3.4 Random Forest Model

In (Ahmad & Nikpoor, 2023), the authors mention that the Random Forest algorithm is an ensemble learning method that achieves its effectiveness by combining the outputs of numerous decision trees, thereby reducing both bias and variance. It is an ensemble method built on the idea of combining multiple Decision Trees to improve prediction accuracy and reduce overfitting.

In terms of predictions, the Random Forest model employs a democratic voting system. When a new instance of data is fed into the model for prediction, each decision tree in the forest generates

its own label. The final prediction is determined by majority voting, meaning the label that received the most votes from all the trees becomes the overall prediction.

Step 1: Create Bootstrapped Datasets (Bagging)

From the original training data of size N , randomly sample N rows with replacement to create a new dataset. Repeat this process M times to create M different training datasets.

These are your "bootstrap" samples.

Step 2: Grow Decision Trees

For each of the M bootstrapped datasets:

- Build a Decision Tree, but do not use all features.
- At each node (split), randomly select a subset of k features from the total features.
- Use only those k features to determine the best split.
- Repeat until the tree reaches the maximum depth or another stopping condition.

Step 3: Make Predictions

For Classification:

Each tree votes for a class. The final prediction is the majority vote.

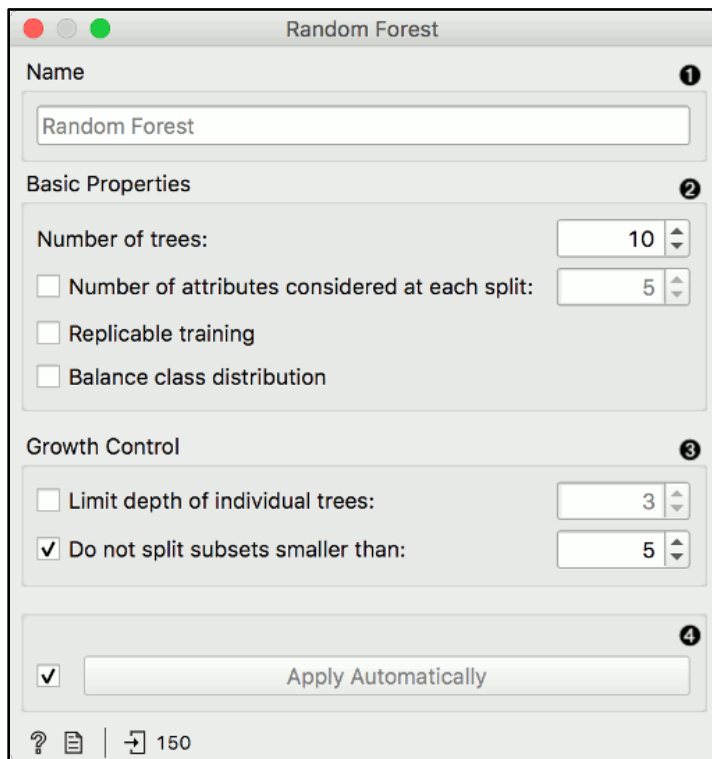
For Regression:

Each tree predicts a numeric value. The final prediction is the average of all tree outputs.

3.3.3.4.1 Random Forest Model in orange data mining tool

Random forest is an ensemble learning method used for classification, regression and other tasks. It was first proposed by Tin Kam Ho and further developed by Leo Breiman (Breiman, 2001) and Adele Cutler. The model builds a set of decision trees. Each tree is developed from a bootstrap sample from the training data.

Figure 10: Figure showing Random Forest model input widget



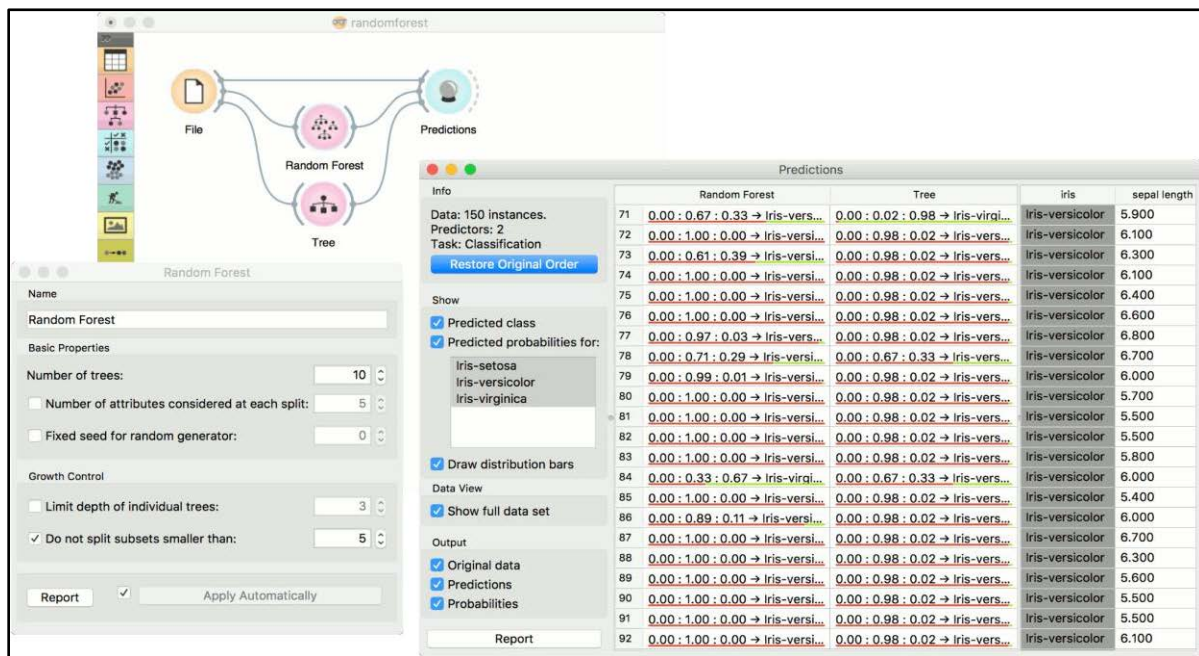
As you can observe in

Figure 10, we need to input certain basic parameters such as Number of trees which will Specify how many decision trees will be included in the forest, Number of trees considered at each split i.e. we need to specify how many attributes will be arbitrarily drawn for consideration at each node, Replicable training i.e. we need to fix the seed for tree generation, which enables replicability of the results and specify Balance class distribution which will weigh classes inversely proportional to their frequencies.

Also, for growth control, we can set the Limit depth of individual trees property to help the user set the depth to which the trees will be grown and the user can also set Do not split subsets smaller than property that will allow to select the smallest subset that can be split.

Once these inputs are provided, then the Random Forest model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. In below Figure 9, we have shown an example of the Random Forest model, in terms of classification, we loaded the iris dataset and evaluated the models' performance in Test & Score.

Figure 11: Figure showing example of Random Forest model using orange data mining



3.3.3.4.2 why did we use the Random Forest Model?

In (Wen et al., 2022), Random Forest is an ensemble learning method that involves the bootstrapped aggregation of several regression trees to predict an outcome, good at handling massive datasets, data heterogeneity, high-dimensional feature spaces and complex data structures. Random forest reduces overfitting as trees are built on different samples and features, so they don't all make the same errors. Random forest handles Noise and Outliers in a High-Dimensional Data.

3.3.3.5 kNN Model

In (Guo et al., 2006), the authors mention that kNN is a similarity-based learning algorithm and is known to be very effective for a variety of problem domains including text categorization. K-Nearest Neighbors (KNN) is one of the simplest and most intuitive machine learning algorithms, used for both classification and regression tasks. KNN predicts the output for a new data point by looking at the 'K' closest data points (neighbors) from the training set.

- Classification: Majority vote among neighbors (which class appears most often).
- Regression: Average the values of the neighbors.

Step 1: Choose K

Pick the number of neighbors to consider (e.g., $K = 1$ or $K = 4$).

Step 2: Calculate Distance

Use a distance metric (usually Euclidean distance) to measure how close each training point is to the new test point.

$$\text{Distance} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + \dots}$$

Step 3: Find K Nearest Neighbors

Select the K points with the smallest distance to the test point.

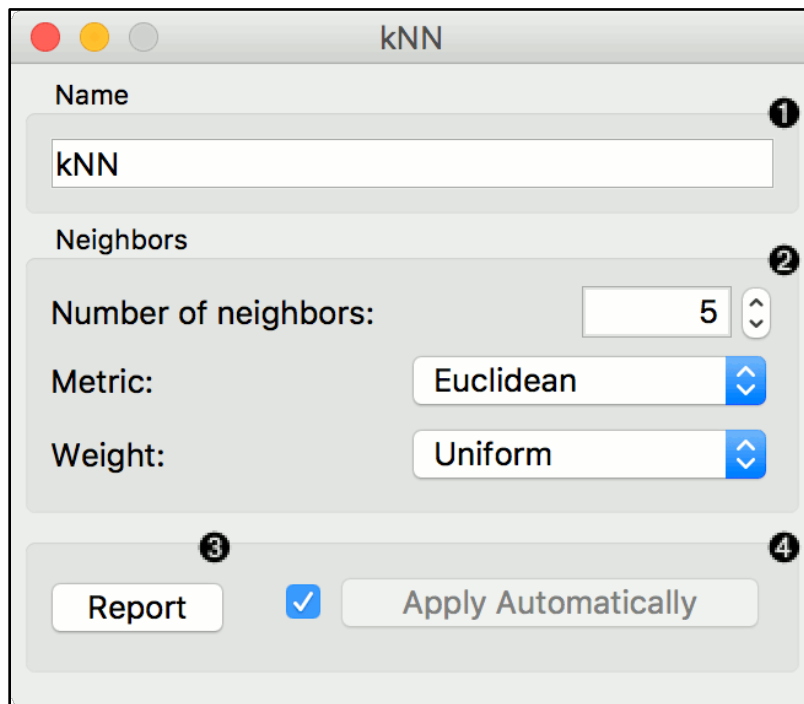
Step 4: Make Prediction

- Classification: Take a majority vote among the neighbors' labels.
- Regression: Take the average of the neighbors' target values.

3.3.3.5.1 kNN Model in orange data mining tool

The kNN widget helps us to Predict according to the nearest training instances and it uses the kNN algorithm that searches for k closest training examples in feature space and uses their average as prediction.

Figure 12: Figure showing kNN model input widget



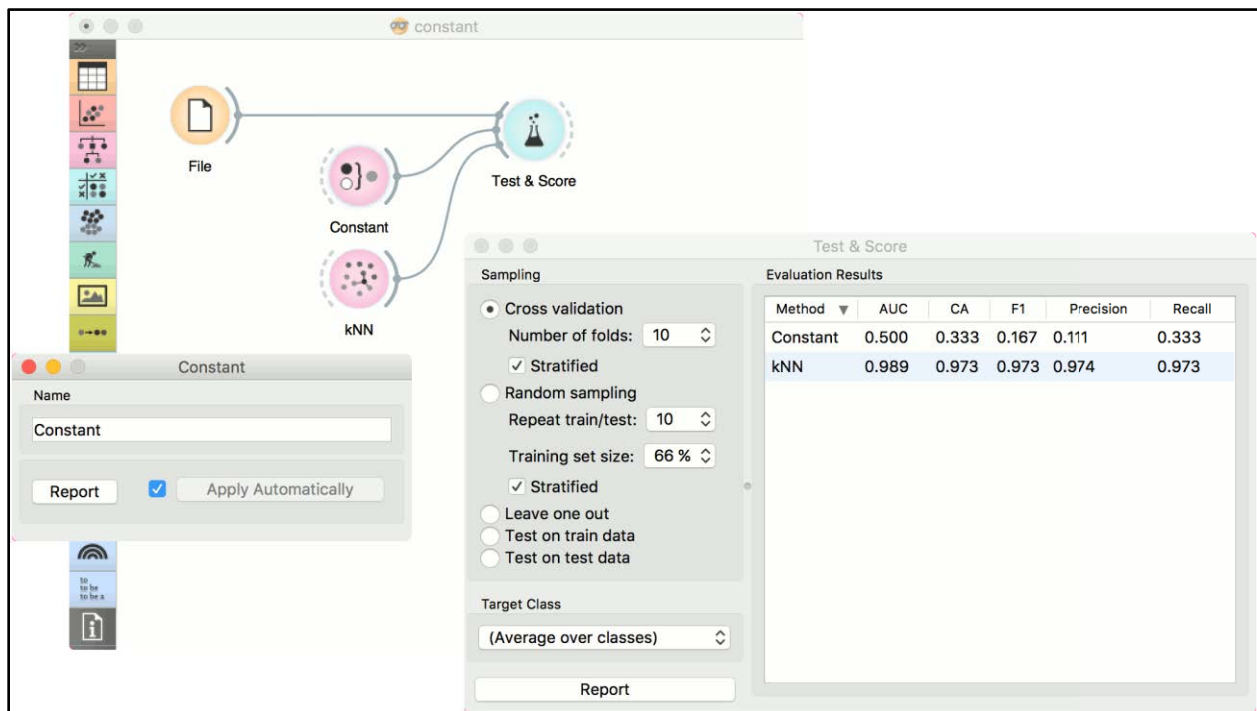
As you can observe in

Figure 12, we need to input certain parameters such as the number of nearest neighbors, the distance parameter (metric) and weights as model criteria. For distance parameter (metric) values, we can use either Euclidean i.e. straight line distance between two points, or Manhattan i.e. sum of absolute differences of all attributes or Maximal i.e. greatest of absolute differences between attributes or Mahalanobis i.e. distance between point and distribution. [55]

Also, for weights parameters we can use either uniform in which all points in each neighborhood are weighted equally or distance in which closer neighbors of a query point have a greater influence than the neighbors further away.

Once these inputs are provided, then the kNN model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. Below Figure 11, we have shown an example of the kNN model, in terms of classification, we loaded the iris dataset and evaluated the models' performance in Test & Score.

Figure 13: Figure showing example of kNN model using orange data mining



3.3.3.5.2 why did we use the kNN Model?

In (Guo et al., 2006), the authors mention that kNN model is very simple to understand and implement. No training required (it's a lazy learner) and very flexible as it works for both classification and regression.

3.3.3.6 SVM Model

In (Ahmad & Nikpoor, 2023), the authors mention that the SVM classifier is a robust tool in the machine learning arsenal, which functions by identifying an optimal decision boundary, or hyperplane, that distinctly segregates two classes. The key characteristic that sets SVMs apart is their optimization goal – it aims to maximize the margin, which is the distance between the decision boundary and the closest data points from either class, known as the ‘support vectors.’

Step 1: Input

Training dataset:

$$D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$$

where:

- $x_i \in \mathbb{R}^n$ (feature vectors)
- $y_i \in \{-1, +1\}$ (class labels)

Step 2: Define the Hyperplane

The hyperplane can be written as:

$$w \cdot x + b = 0$$

Where:

- w : weights (normal vector)
- b : bias or intercept

We want this hyperplane to separate the two classes.

Step 3: Maximize the Margin

Margin = Distance between hyperplane and support vectors

We want to:

- Minimize: $\frac{1}{2}\|w\|^2$
- Subject to:

$$y_i(w \cdot x_i + b) \geq 1 \quad \text{for all } i$$

This is a **convex optimization problem**.

Step 4: Solve Using Lagrange Multipliers

Use the **Lagrangian** and **Karush-Kuhn-Tucker (KKT)** conditions to solve the constrained optimization.

We compute:

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^n \alpha_i [y_i(w \cdot x_i + b) - 1]$$

- α_i are Lagrange multipliers
- Only non-zero α_i 's correspond to **support vectors**

Step 5: Prediction Function

Once the optimal w and b are found, predictions for a new point x are made using:

$$f(x) = \text{sign}(w \cdot x + b)$$

3.3.3.6.1 SVM Model in orange data mining tool

Support vector machine (SVM) is a machine learning technique that separates the attribute space with a hyperplane, thus maximizing the margin between the instances of different classes or class values. The technique often yields supreme predictive performance results. Orange embeds a popular implementation of SVM from the LIBSVM package. This widget is its graphical user interface

Figure 14: Figure showing SVM model input widget

The image shows a software interface for configuring an SVM model. The window title is "SVM". It contains several sections with numbered callouts:

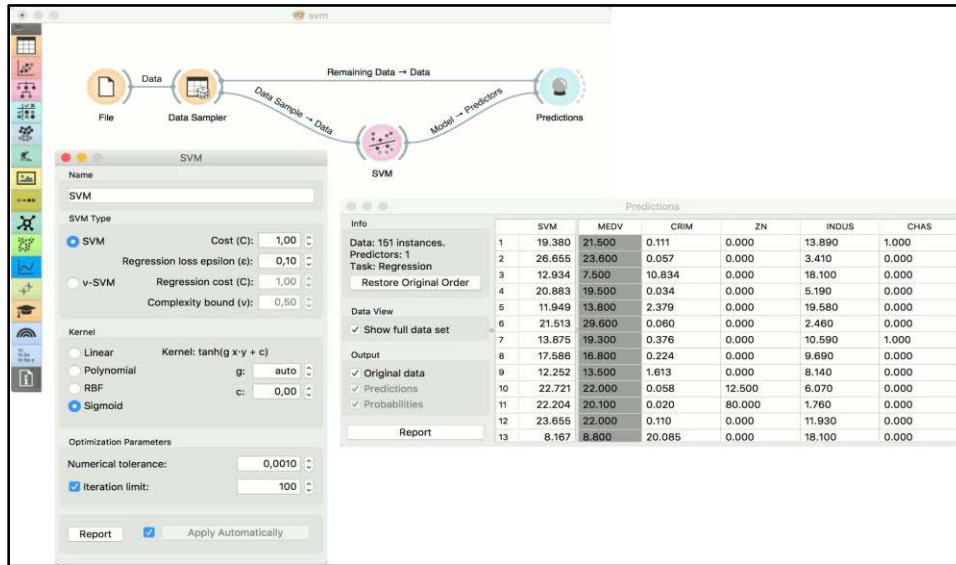
- 1**: Name field containing "SVM".
- 2**: SVM Type section with radio buttons for "SVM" (selected) and "ν-SVM". Parameters include Cost (C): 1,00, Regression loss epsilon (ε): 0,10, Regression cost (C): 1,00, and Complexity bound (ν): 0,50.
- 3**: Kernel section with radio buttons for "Linear", "Polynomial", "RBF" (selected), and "Sigmoid". The kernel function is $\text{Kernel: exp}(-g|x-y|^2)$ and the parameter g is set to "auto".
- 4**: Optimization Parameters section with "Numerical tolerance: 0,0010" and a checked "Iteration limit: 100".
- 5**: A "Report" button.
- 6**: A checked "Apply Automatically" checkbox.

As you can observe in

Figure 14, we need to input certain parameters such as the SVM type with test error settings. SVM and ν -SVM are based on different minimization of the error function. We also need to specify the Kernel value. Kernel is basically a function that transforms attribute space to a new feature space to fit the maximum-margin hyperplane, thus allowing the algorithm to create the model with Linear, Polynomial, RBF and Sigmoid kernels. Also, we need to set the permitted deviation from the expected value in the Numerical Tolerance section. We also need to tick the box next to Iteration Limit to set the maximum number of iterations permitted.

Once these inputs are provided, then the SVM model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. In below Figure 13, we have shown a regression example of the SVM model, we loaded the housing dataset and split the data into two data subsets (Data Sample and Remaining Data) with Data Sampler. The sample was sent to SVM which produced a Model, which was then used in Predictions to predict the values in Remaining Data.

Figure 15: Figure showing example of SVM model using orange data mining



3.3.3.6.2 Why did we use the SVM Model?

In (Ramu et al., 2025), the authors mentions that SVMs are popular binary and multi-class classifiers, their performance varies depending on the size of the training dataset and the difficulty of the classification task. SVMs are particularly difficult to scale up to large datasets or to handle non-linear interactions in large datasets; SVMs work well for small data, but their training time grows exponentially with the number of samples and features.

3.3.3.7 Neural Network Model

In (Ahmad & Nikpoor, 2023), the authors mentions that a neural network, at its most fundamental level, is composed of individual units known as neurons. These neurons serve as the cornerstone of the neural network, with each neuron performing its own specific task. The true power of a neural network unfolds when these individual neurons are organized into structured layers, facilitating complex processing.

Step 1: Initialize Weights and Biases

Randomly initialize the weights W and biases b for all layers.

Step 2: Forward Propagation

For each input x :

1. Compute output for the first hidden layer:

$$z^{[1]} = W^{[1]}x + b^{[1]}$$

$$a^{[1]} = \text{activation}(z^{[1]})$$

2. Repeat for each subsequent layer:

$$z^{[l]} = W^{[l]}a^{[l-1]} + b^{[l]}$$

$$a^{[l]} = \text{activation}(z^{[l]})$$

3. Final output $\hat{y} = a^{[L]}$, where L is the output layer.

Step 3: Compute Loss (Error)

Use a **loss function** to calculate the error between prediction \hat{y} and true label y :

- For classification (cross-entropy):

$$\text{Loss} = - \sum y \log(\hat{y})$$

- For regression (mean squared error):

$$\text{Loss} = \frac{1}{n} \sum (\hat{y} - y)^2$$

Step 4: Backpropagation (Compute Gradients)

Use the **chain rule** to compute the gradient of the loss with respect to each weight and bias:

1. Compute output layer gradient:

$$\delta^{[L]} = \hat{y} - y$$

2. For each layer going backward:

$$\delta^{[l]} = (W^{[l+1]})^T \delta^{[l+1]} \cdot f'(z^{[l]})$$

3. Compute gradients:

$$\frac{\partial \text{Loss}}{\partial W^{[l]}} = \delta^{[l]} (a^{[l-1]})^T$$

$$\frac{\partial \text{Loss}}{\partial b^{[l]}} = \delta^{[l]}$$

Step 5: Update Weights and Biases

Use **gradient descent** (or a variant like Adam) to update the parameters:

$$W^{[l]} = W^{[l]} - \eta \frac{\partial \text{Loss}}{\partial W^{[l]}}$$
$$b^{[l]} = b^{[l]} - \eta \frac{\partial \text{Loss}}{\partial b^{[l]}}$$

Where:

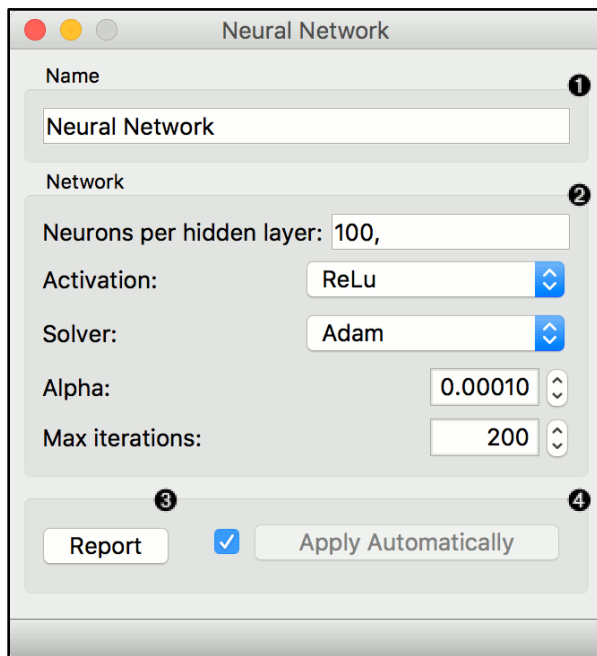
- η is the **learning rate**

Repeat Steps 2–5 for multiple epochs (passes through the entire dataset) until the loss is minimized.

3.3.3.7.1 Neural Network Model in orange data mining tool

The Neural Network widget uses sklearn's Multilayer Perceptron algorithm that can learn non-linear models as well as linear.

Figure 16: Figure showing Neural Network Model input widget



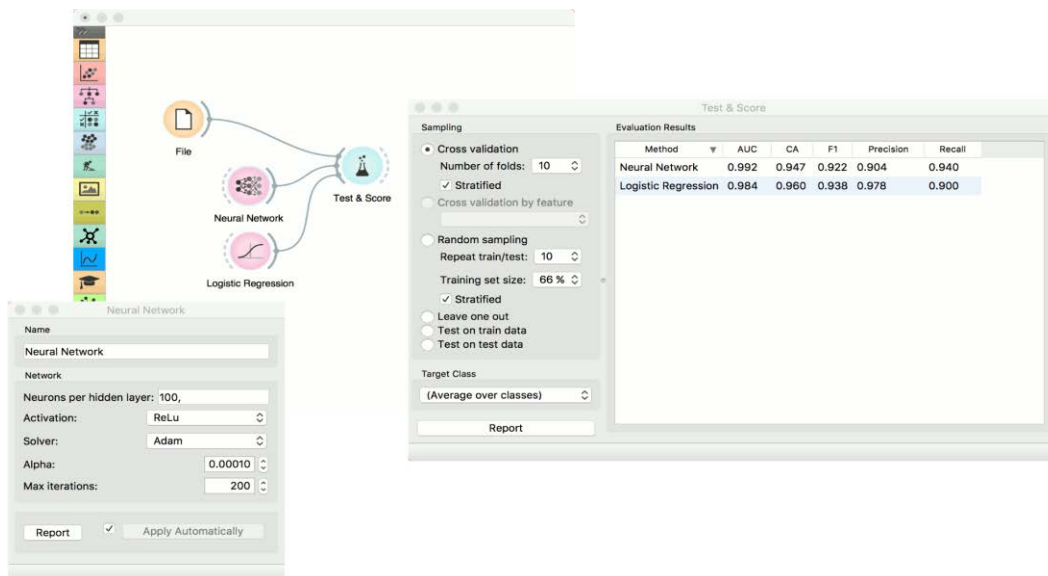
As you can observe in **Figure 16**, we need to input model parameters such as Neurons per hidden layer which, defined as the i th element, represents the number of neurons in the i th hidden layer.

We also need to specify the Activation function for the hidden layer, which can be either Identity that is useful to implement linear bottleneck or it can be Logistic which generally symbolises the logistic sigmoid function or it can be tanh which generally symbolises the hyperbolic tan function or it can be ReLu which generally symbolises rectified linear unit function .

Also, we need to set the Solver for weight optimization which can be either L-BFGS-B which is generally used as an optimizer in the family of quasi-Newton methods or stochastic gradient descent [SGD] or stochastic gradient-based optimizer. In addition to that we also need to specify the value of Alpha i.e. L2 penalty (regularization term) parameter and the value of the maximum number of iterations.

Once these inputs are provided, then the Neural Network model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. In below **Figure 17**, we have shown an example of the Neural Network model, in terms of classification, we loaded the iris dataset and evaluated the models' performance in Test & Score.

Figure 17: Example of the Neural Network model using orange data mining



3.3.3.7.2 Why did we use the Neural Network Model?

In (Lin et al., 2023), Neural Network Model can model non-linear relationships.

It automatically extracts features from raw data. Scalable to large datasets

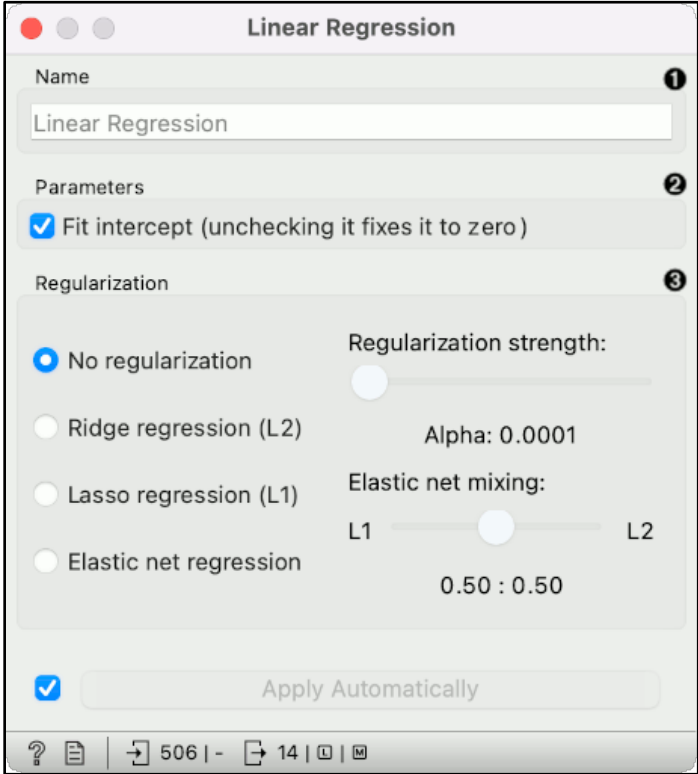
It can handle structured and unstructured data. It Work well with high-dimensional inputs (e.g., images, video, audio)

3.3.3.8 Linear Regression Model in Orange data mining tool

In section [3.3.2.8 Linear regression](#), we have explained Linear regression in details and can be referred to

The Linear Regression model constructs a learner/predictor that learns a linear function from its input data. The model can identify the relationship between a predictor x_i and the response variable y . We can apply the linear regression algorithm with optional L1 (LASSO), L2 (ridge) regularization.

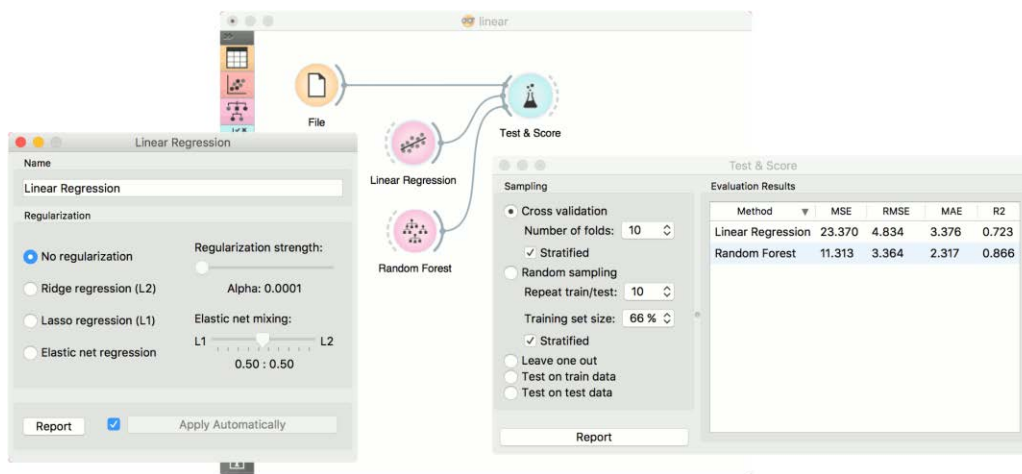
Figure 18: Figure showing Linear Regression model input widget



As you can observe in **Figure 18**, we need to input model parameters such as Fit intercept, and we also need to choose a model to train such as either we can choose no regularization or a Ridge regularization (L2-norm penalty) or a Lasso bound (L1-norm penalty) or an Elastic net regularization

Once these inputs are provided, then the Linear Regression model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly. In below **Figure 19**, we have shown an example of the Linear Regression model, in terms of classification, we loaded the housing dataset and evaluated the models' performance in Test & Score.

Figure 19: Example of the Linear Regression model using orange data mining



3.3.3.9 Stochastic Gradient Descent Model

In (Turali et al., 2024), the authors mention that Stochastic Gradient Descent (SGD) is a fundamental optimization technique in machine learning, due to its efficiency in handling large-scale data. The Stochastic Gradient Descent (SGD) algorithm, also known as the Least Mean Squares (LMS) algorithm, is widely used in telecommunications, signal processing, and machine learning.

Step 1: Repeat for a number of epochs

Each **epoch** means one complete pass through the training dataset.

a. Shuffle the Training Data

This ensures the model does not learn a pattern from the order of the data.

b. Loop over each example $(x^{(i)}, y^{(i)})$

For each data point:

Step 2: Compute the Model Prediction

$$\hat{y}^{(i)} = f(x^{(i)}; \theta)$$

This is the current output of the model using the current parameters.

Step 3: Compute the Loss

$$\mathcal{L}^{(i)} = \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

Examples of common loss functions:

- Regression: $\mathcal{L} = \frac{1}{2}(y - \hat{y})^2$
- Classification: $\mathcal{L} = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$

Step 4: Compute the Gradient of the Loss w.r.t Parameters

$$g^{(i)} = \nabla_{\theta} \mathcal{L}^{(i)}$$

This gives the direction and magnitude to change parameters in order to reduce the loss.

Step 5: Update the Parameters

$$\theta = \theta - \eta \cdot g^{(i)}$$

Where:

- η is the **learning rate**: a small scalar that controls the update size.

3.3.3.9.1 Stochastic Gradient Descent Model in orange data mining tool

The Stochastic Gradient Descent model uses stochastic gradient descent that minimizes a chosen loss function with a linear function. The algorithm approximates a true gradient by considering one sample at a time, and simultaneously updates the model based on the gradient of the loss function.

Figure 20: Figure showing Linear Regression model input widget

The image shows a software interface for configuring a Stochastic Gradient Descent (SGD) model. The window title is "Stochastic Gradient Descent". The interface is organized into several sections:

- Name:** A text input field containing "SGD".
- Algorithm:** A dropdown menu.
- Classification loss function:** A dropdown menu set to "Hinge". Below it is a spin box for the parameter ϵ set to "0,10".
- Regression loss function:** A dropdown menu set to "Squared Loss". Below it is a spin box for the parameter ϵ set to "0,10".
- Regularization:**
 - Regularization method: A dropdown menu set to "Ridge (L2)".
 - Regularization strength (α): A spin box set to "0,00001".
 - Mixing parameter: A spin box set to "0,15".
- Learning parameters:**
 - Learning rate: A dropdown menu set to "Constant".
 - Initial learning rate (η_0): A spin box set to "0,0100".
 - Inverse scaling exponent (t): A spin box set to "0,2500".
 - Number of iterations: A spin box set to "5".
 - Shuffle data after each iteration
 - Fixed seed for random shuffling: A spin box set to "0".
- Buttons:** A "Report" button and a checked checkbox for "Apply Automatically".

As you can observe in

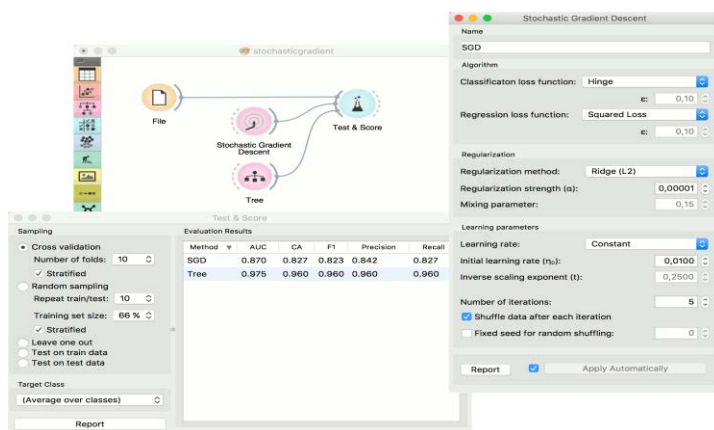
Figure 20, we need to input model parameters such as Classification loss function which can be Hinge (linear SVM) or Logistic Regression (logistic regression SGD) or Modified Huber (smooth loss that brings tolerance to outliers as well as probability estimates) or Squared Hinge (quadratically penalized hinge) or Perceptron (linear loss used by the perceptron algorithm) or Squared Loss (fitted to ordinary least-squares) or Huber (switches to linear loss beyond ϵ) or Epsilon insensitive (ignores errors within ϵ , linear beyond it) or Squared epsilon insensitive.

We also need to specify the value of the Regression loss function that can be either Squared Loss (fitted to ordinary least-squares) or Huber (switches to linear loss beyond ϵ) or Epsilon insensitive (ignores errors within ϵ , linear beyond it) or Squared epsilon insensitive (loss is squared beyond ϵ -region). Along With that we also need to specify Regularization norms to prevent overfitting which can be either none or Lasso (L1) or Ridge (L2) or Elastic net (mixing both penalty norms). We also need to specify the learning parameters.

Once these inputs are provided, then the Stochastic Gradient Descent model produces a report. Based on the report if you want to modify a few settings then you can tick Apply Automatically. This will help the learner remember the pre-applied changes and make changes accordingly.

In below **Figure 21**, we have shown an example of the Stochastic Gradient Descent model, in terms of classification task, we loaded the iris dataset and evaluated the models' performance in Test & Score.

Figure 21: Example of the Stochastic Gradient Descent model using orange data mining



3.3.3.9.2 why did we use the Stochastic Gradient Descent Model?

In (Turali et al., 2024), the authors mention that we should use Stochastic Gradient Descent Model as it is Fast and scalable for large datasets, can escape local minima better than batch gradient descent and works well with online learning.

3.4 Technical Validation and Analytical Configuration

3.4.1 Bias Mitigation: Social Desirability

To address the potential for **Social Desirability Bias**—the tendency of expert informants to provide overly positive self-assessments of their projects (Michael, C2)—the study employed a multi-layered validation strategy. This included neutral question phrasing, anonymized data coding, and the triangulation of qualitative claims against objective Likert-scale performance metrics. By cross-verifying professional "opinions" with "multidimensional scoring," the research minimizes the impact of participant subjectivity and ensures data integrity.

3.4.2 Neural Network Architecture (Orange Data Mining)

The computational analysis to identify non-linear correlations was performed using the **Multilayer Perceptron (MLP)** algorithm within the Orange Data Mining Suite. To ensure technical transparency and reproducibility, the configuration was specified as follows:

- **Architecture:** A feedforward neural network with **two hidden layers** (100 nodes each).
- **Activation Function:** **ReLU** (Rectified Linear Unit) to manage non-linear complexities in the project data.
- **Solver:** **Adam** (a stochastic gradient-based optimizer) for efficient weight adjustment.
- **Validation:** **10-fold cross-validation** was applied to confirm the robustness of the predictive paths between the X variables and Y outcomes, preventing model over-fitting.

4. RESULTS ANALYSIS

In this section, we will analyse the results gathered for each of the 10 hypothesis mentioned in section [2.3](#) in both quantitative and qualitative format and also, analyse the overall results of the CSV dataset of the 120 AIA interview participants with all the scores of the project parameters that takes to build the final business AIA application that the organisation will use on daily basis to run their business.

4.1 H1: Positive Relationship between Overall performance of final business AIA application and AIA Projects experience complexity level

4.1.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding Measuring Project experience complexity levels (X1) and Measuring Overall performance of the final business AIA application (Y1). Following are some of our findings:

For Measuring Project experience complexity levels (X1), following AIA interview participant mentioned these:

1. “I have been with the IT industry technology industry for the past 16 plus years now. Started off as a programmer, predominantly leading data engineering. Most successful project was credit programs done for customers across Canada involving data analysis and AI models to provide reward and recognition outcomes”.
[AIA interview participant#5]
2. “software architect in asset management software. We do Implementations changes, predictive maintenance support for Software one integrate a lot with different products such as mapping tools and mapping software.”. [AIA interview participant#1]
3. “In the IT industry for over 10 years. being in a developer role, now in management mix and match both my computer science engineering and also management expertise”.
[AIA interview participant#8]

For Measuring Overall performance of the final business AIA application (Y1), following AIA interview participant mentioned these:

4. “we had close to 105 million transactions that occurred over a period of 30 years, solution that was implemented was was well designed” [AIA interview participant#5]
5. “.Post implementation businesses were able to complete their operations on a daily basis.” [AIA interview participant#1]
6. “performance was a key area, so we were able to identify the right set of people who know how to actually execute the product.” [AIA interview participant#8]

4.1.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for Measuring Project experience complexity levels (X1) and Measuring Overall performance of the final business AIA application (Y1) for each of 120 AIA interview participants and can be found in Appendix section [7.a](#)

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for Measuring Project experience complexity levels (X1) and Measuring Overall performance of the final business AIA application (Y1) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 8:Regression Results for H1

	X1	Constant
Y1	-0.006414101795	4.126666974
StdErr	0.06626916451	0.2061279965
R2	0.0000793838615	0.8905541838
F-stat	0.009368039339	118
	0.007429667913	93.584237
T-stat	-0.09678863228	20.01992473
P-value	0.4615313645	0

From **Table 8**, for measuring Project parameter X1 and Y1 of AIA interview participants, the reported value of standard error mentioned is 0.066, the value of R2 mentioned is 0.000, the value of F-stat mentioned is 0.009, and the value of P-value mentioned is 0.461.

4.1.3 Hypothesis Analysis

In this section, we will discuss the findings in the qualitative analysis section ([4.1.1](#)) and Table 8 mentioned in the quantitative analysis section ([4.1.2](#)).

2 of the 3 AIA participants' likert score values of Overall performance of the final business AIA application (Y1) mentioned in the quantitative analysis section ([4.1.2](#)) i.e. AIA participant#5 and AIA participant#8 with Likert score value of 5 indicates that the overall performance is either exceeding expectation or meeting expectation of the final build AIA application and hence converging with the transcripts mentioned by the AIA interview participants #5 and AIA interview participants #8 respectively.

From **Table 8**, for measuring Project parameter X1 and Y1 of AIA interview participants, the value of P-value mentioned is 0.461 which indicates that the hypothesis is valid as the smaller the p value, the more likely you are to reject the null hypothesis. The value of R² mentioned is 0.000 which represents that the model partially predicts the outcome.

The reported value of standard error is 0.066 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean, the value of F-stat mentioned is 0.009 which implies that the restricted model doesn't fit the data as well as the

unrestricted model., the correlation coefficient is -0.007 which is relatively very weak for this hypothesis

Based on the overall analysis provided in the above paragraph of **Table 8**, it is pretty evident that there is negative alignment between Measuring Project experience complexity levels (X1) and Measuring Overall performance of the final business AIA application (Y1) supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient .

4.2 H2: Positive Relationship between Overall performance of final business AIA application and different technologies used in AIA projects

4.2.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding measuring different technologies used (X2), and Measuring Overall performance of the final business AIA application (Y1). Following are some of our findings:

For measuring different technologies used (X2), following AIA interview participant mentioned these:

7. “ Used technologies such as Firewalls, Switches, network based tools”
[AIA interview participant#15]
8. “ Used technologies such as CRM Salesforce, Sharepoint, Oracle service Cloud based tools” [AIA interview participant#17]
9. “ Used technologies such as Java based tools” [AIA interview participant#21]

and Measuring Overall performance of the final business AIA application (Y1), following AIA interview participant mentioned these:

10. “ Performance wise like we just closely monitor the system performance, CPU, network traffic events So we don't see any issues.” [AIA interview participant#15]
11. “ Performance wise, for me it was amazing and we always strive to improve the system application performance all the time.” [AIA interview participant#17]
12. “ Performance wise was good and we strive to identify other factors that can help to improvise it at all different levels.” [AIA interview participant#21]

4.2.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for measuring different technologies used (X2) and measuring Overall performance of the final business AIA application (Y1) for each of 120 AIA interview participants and can be found in Appendix section [7.b](#).

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for measuring different technologies used (X2) and Measuring Overall performance of the final business AIA application (Y1) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 9: Regression Results for H2

	X2	Constant
Y1	-0.007868522036	4.12872592
StdErr	0.0607345598	0.1771569261
R2	0.0001422233081	0.8905262001
F-stat	0.01678473754	118
	0.01331091644	93.57835575
T-stat	-0.1295559244	23.30547278
P-value	0.4485720529	0

From **Table 9**, for measuring Project parameter X2 and Y1 of AIA interview participants, the reported value of standard error mentioned is 0.060, the value of R2 mentioned is 0.0001, the value of F-stat mentioned is 0.016, the value of T-test mentioned is -0.129 and the value of P-value mentioned is 0.448.

4.2.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section ([4.2.1](#)) and the same AIA participants' with relevant likert scores in the quantitative analysis section ([4.2.2](#)).

3 of the 3 AIA participants' likert score values of Overall performance of the final business AIA application (Y1) mentioned in the quantitative analysis section ([4.2.2](#)) i.e. AIA participant#15, AIA participant#17 and AIA participant#21 with Likert score value of 5 indicates that the overall performance is either exceeding expectation or meeting expectation of the final build AIA application and hence converging with the transcripts mentioned by the AIA participant#15, AIA participant#17 and AIA participant#21 respectively.

From **Table 9**, for measuring Project parameter X2 and Y1 of AIA interview participants, the value of P-value mentioned is 0.4485720529 which indicates that the hypothesis is valid as the smaller the p value, the more likely you are to reject the null hypothesis. The value of R^2 mentioned is 0.0001422233081 which represents that the model partially predicts the outcome

The reported value of standard error is 0.0607345598 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean, The value of F-stat mentioned is 0.01678473754 which implies that the restricted model doesn't fit the data as well as the unrestricted model., the correlation coefficient is -0.007868522036 which is relatively very weak for this hypothesis.

Overall based on the analysis provided in the above paragraph of **Table 9**, it is pretty evident that there is negative alignment between for measuring different technologies used (X2) and Measuring Overall performance of the final business AIA application (Y1) supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient.

4.3 H3: Positive Relationship between Overall Overall performance of final business AIA application and different project management strategy used in AIA projects

4.3.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding measuring different Project Management strategies used (X3), and Measuring Overall performance of the final business AIA application (Y1). Following are some of our findings:

For measuring different Project Management strategies used (X3), following AIA interview participant mentioned these:

13. “ Used agile project methodology”

[AIA interview participant#22, AIA interview participant#25]

14. “ Used scrum and agile project methodology” [AIA interview participant#29]

and For Measuring Overall performance of the final business AIA application (Y1), following AIA interview participant mentioned these:

15. “ Project performance is the most important factor for success of any project. We are held accountable if the project doesn't perform well.” [AIA interview participant#22]

16. “ Performance was good because everything was completed on time .”

[AIA interview participant#25]

17. “ Software Performance was good .” [AIA interview participant#29]

4.3.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for different Project Management strategies used (X3) and for measuring Overall performance of the final business AIA application (Y1) for each of 120 AIA interview participants and can be found in Appendix section [7.c](#).

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their

business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for different Project Management strategies used (X3) and Measuring Overall performance of the final business AIA application (Y1) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 10: Regression Results for H3

	X3	Constant
Y1	0.1864503094	3.365639601
StdErr	0.05205887626	0.2212757417
R2	0.09804786103	0.8458032184
F-stat	12.82734094	118
	9.176462727	84.41520394
T-stat	3.581527739	15.21016075
P-value	0.0002509268627	0

From **Table 10**, for measuring Project parameter X3 and Y1 of AIA interview participants, the reported value of standard error mentioned is 0.052, the value of R2 mentioned is 0.098, the value of F-stat mentioned is 12.827, the value of T-test mentioned is 3.581 and the value of P-value mentioned is 0.0002.

4.3.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section ([4.3.1](#)) and the same AIA participants' with relevant likert scores in the quantitative analysis section ([4.3.2](#)).

3 of the 3 AIA participants' likert score values of Overall performance of the final business AIA application (Y1) mentioned in the quantitative analysis section ([4.3.2](#)) i.e. AIA participant#22, AIA participant#25 and AIA participant#29 with Likert score value of 5 indicates that the overall performance is either exceeding expectation or meeting expectation of the final build AIA application and hence converging with the transcripts mentioned by the AIA participant#22, AIA participant#25 and AIA participant#29 respectively.

From **Table 10**, for measuring Project parameter X3 and Y1 of AIA interview participants, the value of P-value mentioned is 0.0002 which indicates that the hypothesis is valid as the higher the p value, the more likely you are to accept the null hypothesis. The value of R^2 mentioned is 0.098 which is pretty significant and represents that the model partially predicts the outcome.

The reported value of standard error is 0.052 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean , The value of F-stat mentioned is 12.827 which implies that the restricted model fit the data as well as the unrestricted model., the correlation coefficient is 0.186 which is relatively above the accepted level for this hypothesis.

Overall based on the analysis provided in the above paragraph of **Table 10**, it is pretty evident that there is positive alignment between Measuring different Project Management strategies used (X3) and Measuring Overall performance of the final business AIA application (Y1) supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient.

4.4 H4: Positive Relationship between Overall performance of final business AIA application and lessons learned from different AIA projects

4.4.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding measuring what different lessons learned were (X4), and Measuring Overall performance of the final business AIA application (Y1). Following are some of our findings:

For measuring what different lessons learned were (X4), following AIA interview participant mentioned these:

18. “ Doing cost benefit analysis in any project helps in long run”

[AIA interview participant#30]

19. “ Always take ownership of the product you develop” [AIA interview participant#32]

20. “ project focus should be on people to people management and understand the domain well” [AIA interview participant#33]

and for Measuring Overall performance of the final business AIA application (Y1), following AIA interview participant mentioned these:

21. “ performance was good as VFD (Variable frequency drive) that controls the speed of a motor. improved well.” [AIA interview participant#30]
22. “ Upgrading the legacy system always has different challenges but with a strong team we were able to finish it in time .” [AIA interview participant#32]
23. “ Project performance turnaround Time reduced by 45%.” [AIA interview participant#33]

4.4.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for different lessons learned were (X4) and for measuring Overall performance of the final business AIA application (Y1) for each of 120 AIA interview participants and can be found in Appendix section [7.d](#) .

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for measuring what different lessons learned were (X4) and measuring overall performance of the final business AIA application (Y1) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 11: Regression Results for H4

	X4	Constant
Y1	0.2932034461	3.07967791
StdErr	0.06805054665	0.2504192312
R2	0.1359371689	0.8278473231
F-stat	18.56414297	118
	12.7225862	80.86908047
T-stat	4.30861265	12.29808867
P-value	0.0000173983495	0

From **Table 11**, for measuring Project parameter X4 and Y1 of AIA interview participants, the reported value of standard error mentioned is 0.068, the value of R² mentioned is 0.135, the value of F-stat mentioned is 18.564, the value of T-test mentioned is 4.308 and the value of P-value mentioned is 0.000.

4.4.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section (4.4.1) and the same AIA participants' with relevant likert scores in the quantitative analysis section (4.4.2).

2 of the 3 AIA participants' likert score values of Overall performance of the final business AIA application (Y1) mentioned in the quantitative analysis section (4.4.2) i.e. AIA participant#30, AIA participant#32, with Likert score value of 4 indicates that the overall performance is meeting expectation of the final build AIA application and AIA participant#33, with Likert score value of 5 indicates that the overall performance is exceeding expectation of the final build AIA application and hence converging with the transcripts mentioned by the AIA interview participants #30, AIA interview participants #32 and AIA interview participants #33 respectively.

From **Table 11**, for measuring Project parameter X4 and Y1 of AIA interview participants, the value of P-value mentioned is 0.000 which indicates that the hypothesis is valid as the higher the p value, the more likely you are to accept the null hypothesis. The value of R² mentioned is 0.135 which is pretty significant and represents that the model partially predicts the outcome.

The reported value of standard error is 0.068 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean, The value of F-stat mentioned is 18.564 which implies that the restricted model fit the data as well as the unrestricted model, the correlation coefficient is 0.293 which is relatively above the accepted level for this hypothesis.

Overall based on the analysis provided in the above paragraph of **Table 11**, it is pretty evident that there is positive alignment between measuring what different lessons learned were (X4) and Measuring Overall performance of the final business AIA application (Y1) supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient.

4.5 H5: Positive Relationship between Overall goals achieved from final business AIA application and AIA Projects experience complexity level

4.5.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding Measuring Project experience complexity levels (X1) and measuring goals achieved from the final business AIA application (Y2). Following are some of our findings:

For Measuring Project experience complexity levels (X1), following AIA interview participant mentioned these:

24. “I worked for an engineering design fabrication and construction consulting company. They basically do design, engineering, procurement, fabrication and construction, mainly for oil and gas and the mining industry more focused on oil sands.”
[AIA interview participant#34]
25. “Project manager for the government sector more into dynamics and power platform automating expense reports for the entire organisation was one of the successful projects.”
[AIA interview participant#35]
26. “worked as a Network engineer on several projects related to data centers. Successful project was to implement a next generation solution in our data center.”
[AIA interview participant#36]

and measuring goals achieved from the final business AIA application (Y2), following AIA interview participant mentioned these:

27. “The goal was execution planning, project management and then handing over the work to the client.” [AIA interview participant#34]
28. “our goal was to automate it in such a way that we didn't have to input them manually.”
[AIA interview participant#35]

29. “The goal of the project was to update the hardware of the data center so it aligns with the next generation architecture.” [AIA interview participant#36]

4.5.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for Measuring Project experience complexity levels (X1) and measuring goals achieved from the final business AIA application (Y2) for each of 120 AIA interview participants and can be found in Appendix section [7.e](#).

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for Measuring Project experience complexity levels (X1) and Measuring goals achieved from the final business AIA application (Y2) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 12: Regression Results for H5

	X1	Constant
Y2	-0.01591989294	4.170504361
StdErr	0.06392451389	0.19883504
R2	0.000525333626	0.859045737
F-stat	0.06202195015	118
	0.04576969222	87.07923031
T-stat	-0.249042065	20.97469521
P-value	0.4018862433	0

From **Table 12**, for measuring Project parameter X1 and Y2 of AIA interview participants, the reported value of standard error mentioned is 0.063, the value of R2 mentioned is 0.000, the value

of F-stat mentioned is 0.062, the value of T-test mentioned is -0.249 and the value of P-value mentioned is 0.401.

4.5.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section ([4.5.1](#)) and the same AIA participants' with relevant likert scores in the quantitative analysis section ([4.5.2](#)).

2 of the 3 AIA participants' likert score values of overall goals achieved from the final business AIA application (Y2) mentioned in the quantitative analysis section ([4.5.2](#)) i.e. AIA participant#35 with Likert score value of 3 and AIA participant#36 with Likert score value of 4 indicates that the overall goals achieved is either having Low influence to support AIA projects or Neutral influence to support AIA projects and hence diverging with the transcripts mentioned by the AIA interview participants #35 and AIA interview participants #36 respectively.

From **Table 12**, for measuring Project parameter X1 and Y2 of AIA interview participants, the value of P-value mentioned is 0.401 which indicates that the hypothesis is valid as the smaller the p value, the more likely you are to reject the null hypothesis. The value of R^2 mentioned is 0.0005 which represents that the model partially predicts the outcome.

The reported value of standard error is 0.063 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean, The value of F-stat mentioned is 0.062 which implies that the restricted model doesn't fit the data as well as the unrestricted model, the correlation coefficient is -0.015 which is relatively very weak for this hypothesis.

Overall based on the analysis provided in the above paragraph of **Table 12**, it is pretty evident that there is negative alignment between measuring Project experience complexity levels (X1) and measuring goals achieved from the final business AIA application (Y2) is not supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient.

4.6 H6: Positive Relationship between Overall goals achieved from final business AIA application and different technologies used in AIA projects

4.6.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding measuring different technologies used (X2), and measuring goals achieved from the final business AIA application (Y2). Following are some of our findings:

For measuring different technologies used (X2), following AIA interview participant mentioned these:

30. “Used AI based technologies” [AIA interview participant#37]
31. “Used a lot of Software testing tools.” [AIA interview participant#41]
32. “Used different tools such as SSRS Reports, Microsoft dynamics AX 2012, Microsoft Dynamics 365 Finance & Operations, Power BI, Power Apps, C#.”
[AIA interview participant#43]

and measuring goals achieved from the final business AIA application (Y2), following AIA interview participant mentioned these:

33. “One of the main goals from a project management point of view was to achieve the project deliverables in an agile manner.” [AIA interview participant#37]
34. “The goal was to improve the performance of the application and every transaction or every business scenario should be performed within 3 to 5 seconds of range.”
[AIA interview participant#41]
35. “goals and objective objectives were really 2 cores. One was to ensure that the project would be delivered on time in scope and on budget. Second was to ensure that stakeholders were kept in tune.” [AIA interview participant#43]

4.6.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for measuring different technologies used (X2) and measuring goals achieved from the final business AIA application (Y2) for each of 120 AIA interview participants and can be found in Appendix section [7.f](#).

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for measuring different technologies used (X2) and measuring goals achieved from the final business AIA application (Y2) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 13: Regression Results for H6.

	X2	Constant
Y2	0.08430559324	3.906508004
StdErr	0.05808678723	0.169433625
R2	0.01753846631	0.851702985
F-stat	2.106483515	118
	1.528038877	85.59696112
T-stat	1.451372976	23.05627344
P-value	0.07469927116	0

From **Table 13**, for measuring Project parameter X2 and Y2 of AIA interview participants, the reported value of standard error mentioned is 0.058, the value of R2 mentioned is 0.017, the value of F-stat mentioned is 2.106, the value of T-test mentioned is 1.451 and the value of P-value mentioned is 0.074.

4.6.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section ([4.6.1](#)) and the same AIA participants' with relevant likert scores in the quantitative analysis section ([4.6.2](#)).

2 of the 3 AIA participants' likert score values of overall goals achieved from the final business AIA application (Y2) mentioned in the quantitative analysis section ([4.6.2](#)) i.e. AIA participant#37 and AIA participant#43 with Likert score value of 1 indicates that the overall goals achieved is

either having Strong influence to support AIA projects and hence converging with the transcripts mentioned by the AIA interview participants #37 and AIA interview participants #43 respectively.

From **Table 13**, for measuring Project parameter X2 and Y2 of AIA interview participants, the value of P-value mentioned is 0.074 which indicates that the hypothesis is valid as the higher the p value, the more likely you are to accept the null hypothesis. The value of R^2 mentioned is 0.017 which is pretty significant and represents that the model partially predicts the outcome.

The reported value of standard error is 0.058 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean, The value of F-stat mentioned is 2.106 which implies that the restricted model fit the data as well as the unrestricted model, the correlation coefficient is 0.084 which is relatively above the accepted level for this hypothesis.

Overall based on the analysis provided in the above paragraph of **Table 13**, it is pretty evident that there is positive alignment between measuring different technologies used (X2) and measuring goals achieved from the final business AIA application (Y2) supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient.

4.7 H7: Positive Relationship between Overall goals achieved from final business AIA application and different project management strategy used in AIA projects

4.7.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding measuring different Project Management strategies used (X3), and measuring goals achieved from the final business AIA application (Y2). Following are some of our findings:

For measuring different Project Management strategies used (X3), following AIA interview participant mentioned these:

36. “Used agile methodology for project management” [AIA interview participant#55]
37. “Used agile” [AIA interview participant#56]
38. “Used agile and JIRA” [AIA interview participant#57]

and measuring goals achieved from the final business AIA application (Y2), following AIA interview participant mentioned these:

- 39. “The goal was to build products based on different advanced analytics consumers' needs.” [AIA interview participant#55]
- 40. “The goal was to build the application successfully.” [AIA interview participant#56]
- 41. “The goal of the project was to decrease the processing times for the reports that are generated .” [AIA interview participant#57]

4.7.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for measuring different Project Management strategies used (X3) and measuring goals achieved from the final business AIA application (Y2) for each of 120 AIA interview participants and can be found in Appendix section [7.g](#).

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for measuring different Project Management strategies used (X3) and Measuring goals achieved from the final business AIA application (Y2) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 14: Regression Results for H7

	X3	Constant
Y2	0.1600580881	3.487435282
StdErr	0.05079386909	0.215898841
R2	0.07761783901	0.825250582
F-stat	9.929620705	118
	6.762454224	80.36254578
T-stat	3.151130068	16.15309866
P-value	0.001036874917	0

From **Table 14**, for measuring Project parameter X3 and Y2 of AIA interview participants, the reported value of standard error mentioned is 0.050, the value of R2 mentioned is 0.077, the value of F-stat mentioned is 9.929, the value of T-test mentioned is 3.151 and the value of P-value mentioned is 0.001.

4.7.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section ([4.7.1](#)) and the same AIA participants' with relevant likert scores in the quantitative analysis section ([4.7.2](#)).

2 of the 3 AIA participants' likert score values of overall goals achieved from the final business AIA application (Y2) mentioned in the quantitative analysis section ([4.7.2](#)) i.e. AIA participant#56 with Likert score value of 5 and AIA participant#57 with Likert score value of 4 indicates that the overall goals achieved is either having No influence to support AIA projects or Neutral influence to support AIA projects and hence diverging with the transcripts mentioned by the AIA interview participants #56 and AIA interview participants #57 respectively.

From **Table 14**, for measuring Project parameter X3 and Y2 of AIA interview participants, the value of P-value mentioned is 0.001 which indicates that the hypothesis is valid as the higher the p value, the more likely you are to accept the null hypothesis. The value of R² mentioned is 0.0776 which is pretty significant and represents that the model partially predicts the outcome

The reported value of standard error is 0.0507 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean, The value of F-stat mentioned is 9.929 which implies that the restricted model fit the data as well as the unrestricted model, the correlation coefficient is 0.160 which is relatively above the accepted level for this hypothesis.

Overall based on the analysis provided in the above paragraph of **Table 14**, it is pretty evident that there is positive alignment between measuring different Project Management strategies used (X3)

and measuring goals achieved from the final business AIA application (Y2) supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient.

4.8 H8: Positive Relationship between Overall goals achieved from final business AIA application and lessons learned from different AIA projects

4.8.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding measuring what different lessons learned were (X4), and measuring goals achieved from the final business AIA application (Y2). Following are some of our findings:

For measuring what different lessons learned were (X4), following AIA interview participant mentioned these:

42. “ everyone who wants to be in this domain is to stay updated with the new technologies and frameworks” [AIA interview participant#63]
43. “ It is crucial to engage stakeholders early and continuously throughout the project to ensure alignment with the organization, goals and objectives.”
[AIA interview participant#74]
44. “ new project managers should consider the use of artificial intelligence. ”
[AIA interview participant#81]

and measuring goals achieved from the final business AIA application (Y2), following AIA interview participant mentioned these:

45. “the goal was to achieve an ecommerce platform for the startup.”
[AIA interview participant#63]
46. “the primary goal was to reduce hospitals operational cost while improving the patient's outcome.” [AIA interview participant#74]
47. “the goal was mostly to make sure that these systems, when properly configured by me, would be functional if wanted to be used in any setup.”
[AIA interview participant#81]

4.8.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis we did on AIA interview participants. We analyzed the Likert score values to the answers for the questions for measuring what different lessons learned were (X4) and measuring goals achieved from the final business AIA application (Y2) for each of 120 AIA interview participants and can be found in Appendix section [7.h](#).

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for measuring what different lessons learned were (X4) and measuring goals achieved from the final business AIA application (Y2) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 15: Regression Results for H8

	X4	Constant
Y2	0.2593051411	3.21527113
StdErr	0.06647775368	0.244631509
R2	0.1142133118	0.808714009
F-stat	15.21491683	118
	9.950834788	77.17416521
T-stat	3.900630312	13.14332374
P-value	0.000080976581	0

From **Table 15**, for measuring Project parameter X4 and Y2 of AIA interview participants, the reported value of standard error mentioned is 0.066, the value of R2 mentioned is 0.114, the value of F-stat mentioned is 15.214, the value of T-test mentioned is 3.900 and the value of P-value mentioned is 0.000.

4.8.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section (4.8.1) and the same AIA participants' with relevant likert scores in the quantitative analysis section (4.8.2).

2 of the 3 AIA participants' likert score values of overall goals achieved from the final business AIA application (Y2) mentioned in the quantitative analysis section (4.8.2) i.e. AIA participant#63 with Likert score value of 3 and AIA participant#74 with Likert score value of 4 indicates that the overall goals achieved is either having low influence to support AIA projects or Neutral influence to support AIA projects and hence diverging with the transcripts mentioned by the AIA interview participants #63 and AIA interview participants #74 respectively.

From **Table 15**, for measuring Project parameter X4 and Y2 of AIA interview participants, the value of P-value mentioned is 0.000 which indicates that the hypothesis is valid as the higher the p value, the more likely you are to accept the null hypothesis. The value of R^2 mentioned is 0.114 which is pretty significant and represents that the model partially predicts the outcome.

The reported value of standard error is 0.066 which is a relatively low value of standard error and indicates that sample means are closely distributed around the population mean, The value of F-stat mentioned is 15.214 which implies that the restricted model fit the data as well as the unrestricted model, the correlation coefficient is 0.259 which is relatively above the accepted level for this hypothesis.

Overall based on the analysis provided in the above paragraph of **Table 15**, it is pretty evident that there is positive alignment between measuring what different lessons learned were (X4) and measuring goals achieved from the final business AIA application (Y2) supported by the value of the p-value, standard error, f-stat and negative value of the correlation coefficient.

4.9 H9: Positive Relationship between Overall performance of final business AIA application and combined impact of AIA Projects experience complexity level , different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projects

4.9.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding combined impact of Projects experience complexity level (X1), different technologies used (X2), different project management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4) on Overall performance of the final business AIA application (Y1). Following are some of our findings:

For Measuring Project experience complexity levels (X1), following AIA interview participant mentioned these:

48. “Masters in commerce in accounting and finance. context specialist in quality testing review documents related to patent infringements, intellectual property rights involved lot of reading, research litigation cases” [AIA interview participant#90]

49. “ in the IT field has around 15 years of experience, starting from development, to project manager now. Working in portfolio management, ETL created data warehouses used for analytical DB, for reporting purposes to make a strategic decision.”
[AIA interview participant#94]

50. “ I worked as a software developer. The most successful project would be functions performed by the mouse related to your hand movements and gestures.”
[AIA interview participant#96]

and for measuring different technologies used (X2), following AIA interview participant mentioned these:

51. “used different accounting software such as ohm, reporting software such as Power BI and Microsoft Office Excel” [AIA interview participant#90]

52. “used many technology tools like Microsoft Projects, Reporting softwares”
[AIA interview participant#94]

53. “used C#net using Visual Studio IDE, SQL Server database, Python”
[AIA interview participant#96]

and for measuring different Project Management strategies used (X3), following AIA interview participant mentioned these:

54. “We use to track Milestones” [AIA interview participant#90]

55. “used agile, Microsoft Projects as our project management tool”

[AIA interview participant#94]

56. “used agile project methodology” [AIA interview participant#96]

and for measuring what were the different lessons learned from the AIA projects (X4), following AIA interview participant mentioned these:

57. “ Keep learning about news tax laws and changes made to it”

[AIA interview participant#90]

58. “ Can make decision where we have direct ownership but lot of difficult decisions at the portfolio level” [AIA interview participant#94]

59. “ Can make decision where we have direct ownership but lot of difficult decisions at the portfolio level” [AIA interview participant#96]

and for Measuring Overall performance of the final business AIA application (Y1), following AIA interview participant mentioned these:

60. “ Tax Litigation softwares is constantly changing as per the needs of the laws. So performance also depends on including these changes as and when the changes occur.”

[AIA interview participant#90]

61. “Post implementation level system level performance was good and we provided after care support for enhanced help.” [AIA interview participant#94]

62. “I would say that this image processing is good. we need to consider what the constraints are and we need to address identified constraints when we do our project.”

[AIA interview participant#96]

4.9.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis of combined impact of Projects experience complexity level (X1), different technologies used (X2), different project management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4) on Overall performance of the final business AIA application (Y1) .

We created a CSV dataset with all the scores of the project parameters that takes to build the final business AIA application that the organisation will use on daily basis to run their business such as Projects experience complexity level (X1), different technologies used (X2), different project

management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4) and Overall performance of the final business AIA application (Y1).

Using the Orange data mining tool we were able to analyse our CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Following tables show the different values of Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Coefficient of Determination, R-squared and linear regression co-efficients for CSV dataset of AIA application when processed via different Machine learning Models

Table 16: Regression Model Performance Comparison scores of AIA Project Parameter Y1 (Final Product Performance)

Model	MSE	RMSE	MAE	MAPE	R2
Neural Network	1.040	1.020	0.804	0.208	-0.334
SVM	0.559	0.748	0.557	0.153	0.283
Linear Regression	0.627	0.792	0.670	0.181	0.196
Tree	0.364	0.603	0.451	0.121	0.534
kNN	0.569	0.754	0.632	0.171	0.270
Random Forest	0.342	0.585	0.491	0.130	0.562
Gradient Boosting	0.300	0.548	0.434	0.114	0.615
AdaBoost	0.205	0.453	0.274	0.069	0.737
Stochastic Gradient Descent	0.628	0.793	0.674	0.181	0.194

Table 17: Linear Regression Coefficients

	name	coef
1	intercept	2.704
2	X1	-0.00808859
3	X2	-0.0215408
4	X3	0.148541
5	X4	0.254135

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for measuring project parameters such as Projects experience complexity level (X1), different technologies used (X2), different project management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4) on Overall performance of the final business AIA application (Y1) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 18: Regression Results for H9

	X1	X2	X3	X4	Constant
Y1	0.2541345808	0.1485413301	-0.02154082956	-0.008088585983	2.704001406
StdErr	0.06854330001	0.05160634888	0.05531906017	0.06127765876	0.3612630297
R2	0.1964260493	0.808690973	#N/A	#N/A	#N/A
F-stat	7.027665483	115	#N/A	#N/A	#N/A
	18.38384133	75.20782534	#N/A	#N/A	#N/A
T-stat	3.707650211	2.878353794	-0.3893925438	-0.1319989397	7.484855032
P-value	0.0001617333073	0.002383758277	0.3488529637	0.4476078994	0

4.9.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section ([4.9.1](#)) and the same AIA participants' with the values in the quantitative analysis section ([4.9.2](#)).

From **Table 16**, The performance comparison across various regression models shows that AdaBoost Model achieves the best overall results, with the lowest error metrics (MSE: 0.205, RMSE: 0.453, MAE: 0.274, MAPE: 0.069) and the highest R² value (0.737), indicating strong predictive accuracy and fit. Gradient Boosting model and Random Forest Model also perform well. With Gradient Boosting slightly outperforming Random Forest in both accuracy and error reduction. In contrast, simpler models like Linear Regression Model and Stochastic Gradient

Descent Model show higher error values and low R^2 scores (~ 0.19), indicating weaker predictive capabilities. The Neural Network Model performs the worst, with the highest errors and a negative R^2 value, suggesting poor model fit, likely due to suboptimal training or overfitting. Models like SVM Model, kNN Model, and Decision Tree Model offer moderate performance but fall short of the ensemble methods, emphasizing the effectiveness of boosting algorithms for this dataset.

From **Table 17**, the coefficients of a linear regression model are presented, illustrating the relationship between each independent variable (X1 to X4) and the dependent variable. The intercept value of 2.704 represents the predicted outcome when all predictor variables are held at zero. Notably, variables X1 and X2 have negative coefficients (-0.3088 and -0.0215, respectively), indicating an inverse relationship with the dependent variable: as the values of X1 or X2 increase, the predicted outcome tends to decrease, assuming other variables remain constant. Conversely, X3 and X4 possess positive coefficients (0.1458 and 0.2547), suggesting a direct relationship where increases in these variables correspond to increases in the predicted outcome. The relative sizes of the coefficients imply that X1 has the most substantial negative impact on the dependent variable among the predictors.

According to **Table 18**, the p-values for X1 (0.000) and X2 (0.002) indicate strong statistical significance, supporting the rejection of the null hypothesis and suggesting a meaningful relationship with the outcome variable. In contrast, the p-values for X3 and X4 are not significant, implying a weaker or negligible impact. The R^2 values for X1 (0.196) and especially X2 (0.808) show that the model explains a substantial portion of the variance in the outcome for these variables, while X3 and X4 have minimal predictive power. The standard errors for X1 (0.068), X2 (0.051), X3 (0.055), and X4 (0.061) are relatively low, indicating consistent and reliable estimates. The F-statistic for X1 (7.027) suggests a good model fit, whereas the F-value for X2 (115), though high, is noted as not significant, and values for X3 and X4 are unavailable. The correlation coefficients for X1 (0.254) and X2 (0.148) fall within acceptable ranges, reinforcing their relevance to the model, while X3 and X4 do not meet the threshold. Furthermore, when analyzing project parameters X1 through X4 in relation to Y1 (based on data from AIA interview participants), stronger p-values were observed for X1 and X2 compared to X3 and X4. Interestingly, while individual p-values for Y1 vs. X1 and Y1 vs. X2 were not particularly strong,

the combination of Y1 with X3 and X2 yielded more significant results. This suggests that variables that may appear weak in isolation can have a stronger, more meaningful impact when analyzed collectively.

4.10 H10: Positive Relationship between Overall goals achieved from final business AIA application and combined impact of AIA Projects experience complexity level , different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projects

4.10.1 Qualitative Analysis

In this section, we analysed the transcript excerpts for the questions regarding combined impact of Projects experience complexity level (X1), different technologies used (X2), different project management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4) on Overall goals achieved from the final business AIA application (Y2). Following are some of our findings:

For Measuring Project experience complexity levels (X1), following AIA interview participant mentioned these:

63. “Working in insurance industry, I went to different transformations and learning new system as well because I also moved to different insurance company”

[AIA interview participant#102]

64. “worked as lead analyst, worked on projects where I have used artificial intelligence as well as analytics for my clients.” [AIA interview participant#107]

65. “Worked as a software developer, building software applications for aerospace industry was my successful project” [AIA interview participant#120]

and for measuring different technologies used (X2), following AIA interview participant mentioned these:

66. “Used technical apps such as Microsoft office, CRM apps.”

[AIA interview participant#102]

67. “Used a lot of software Testing tools with google analytics.”

[AIA interview participant#107]

68. “Used Python, java for programming.” [AIA interview participant#120]

and for measuring different Project Management strategies used (X3), following AIA interview participant mentioned these:

- 69. “Used waterfall Project Model” [AIA interview participant#102]
- 70. “Used JIRA project management tool” [AIA interview participant#107]
- 71. “Used agile Project Model” [AIA interview participant#120]

and for measuring what were the different lessons learned from the AIA projects (X4), following AIA interview participant mentioned these:

- 72. “ Be open minded and with changes and regarding learning process, procedures have a lot of of positivity in you to to deal with changes” [AIA interview participant#102]
- 73. “ all people should utilize these air tools for their career improvement”
[AIA interview participant#107]
- 74. “ I would recommend them to learn new skills” [AIA interview participant#120]

and for Measuring Overall goals achieved from the final business AIA application (Y2), following AIA interview participant mentioned these:

- 75. “ Goal was to relearn, learn when going through the transformation of having a new system.” [AIA interview participant#102]
- 76. “ The goal is to provide 100% quality to the project that we are assigned and use automated scheduling.” [AIA interview participant#107]
- 77. “ The goal was to develop a software application where we do the pairing and drawstring the flight pilots, crew members and everyone will be having a different time schedule.”
[AIA interview participant#120]

4.10.2 Quantitative Analysis

In this section, we will provide the findings of the quantitative analysis of combined impact of Projects experience complexity level, different technologies used, different project management strategy used for different projects that was worked on and what were different lessons learned in each of the projects on Overall goals achieved from the final business AIA applications.

We created a CSV dataset with all the scores of the project parameters that takes to build the final business AIA application that the organisation will use on daily basis to run their business such as Projects experience complexity level (X1), different technologies used (X2), different project

management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4), and Overall goals achieved from the final business AIA application (Y2) of the 120 AIA interview participants.

Using the Orange data mining tool we were able to analyse our CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their business. Following tables show the different values of Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Coefficient of Determination, R-squared and linear regression co-efficients for CSV dataset of AIA application when processed via different Machine learning Models.

Table 19: The scores of AIA Project Parameter Y2 (Goals Achieved) when processed via different Machine learning Models

Model	MSE	RMSE	MAE	MAPE	R2
Neural Network	1.128	1.062	0.887	0.233	-0.553
SVM	0.550	0.741	0.512	0.152	0.243
Linear Regression	0.600	0.774	0.627	0.176	0.174
Tree	0.326	0.571	0.414	0.116	0.550
kNN	0.508	0.713	0.582	0.164	0.301
Random Forest	0.385	0.621	0.489	0.136	0.469
Gradient Boosting	0.333	0.577	0.433	0.119	0.542
AdaBoost	0.293	0.542	0.354	0.090	0.596
Stochastic Gradient Descent	0.602	0.776	0.631	0.176	0.171

Table 20: Linear Regression Coefficients

	name	coef
1	intercept	2.71573
2	X1	-0.0194203
3	X2	0.0732566
4	X3	0.118183
5	X4	0.229214

Also, we created a CSV dataset with all the scores of the project parameters that it takes to build the final business AIA application that the organisation will use on a daily basis to run their

business. Using excel and statistical concepts, we were able to analyse our CSV dataset for the scores of the project parameters such as for measuring project parameters such as Projects experience complexity level (X1), different technologies used (X2), different project management strategy used for different projects that was worked on (X3) and what were different lessons learned in each of the projects (X4) on Overall goals achieved from the final business AIA application (Y2) for each AIA interview participant. Following tables show the different values of Standard Error, Coefficient of Determination i.e. R-squared, F Statistic or F Value, T-test and P-value for the CSV dataset of the AIA application.

Table 21: Regression Results for H10.

	X1	X2	X3	X4	Constant
Y2	0.2292141649	0.1181827057	0.07325657985	-0.01942025243	2.715732112
StdErr	0.06704326647	0.05047697148	0.05410843206	0.0599366299	0.3533569811
R2	0.1741511808	0.7909932027	#N/A	#N/A	#N/A
F-stat	6.06266708	115	#N/A	#N/A	#N/A
	15.17292163	71.95207837	#N/A	#N/A	#N/A
T-stat	3.418899122	2.341319264	1.353884729	-0.3240130861	7.685519907
P-value	0.0004352993163	0.01046872572	0.08921394331	0.3732583405	0

4.10.3 Hypothesis Analysis

In this section, we will compare the transcripts of the different AIA participants' interviews mentioned in the qualitative analysis section (4.10.1) and the same AIA participants' with relevant likert scores in the quantitative analysis section (4.10.2).

Table 19 compares various machine learning models based on multiple performance metrics: MSE, RMSE, MAE, MAPE, and R². Gradient Boosting exhibits the best overall performance with the lowest MSE (0.333), RMSE (0.577), MAE (0.433), and a high R² value (0.542), indicating strong predictive accuracy. Random Forest and AdaBoost also show strong results, with low error metrics and R² values close to 0.47 and 0.60 respectively. Conversely, the Neural Network performs the worst, with the highest errors and a negative R² (-0.553), indicating poor fit. Linear Regression and Stochastic Gradient Descent have moderate performance but are outperformed by ensemble methods like Gradient Boosting and Random Forest. Overall, ensemble models provide more reliable and accurate predictions in this comparison.

Table 20 appears to present the coefficients of a regression model. The "intercept" value is 2.71573, which represents the baseline value of the dependent variable when all predictors are zero. The coefficients for the predictors X1, X2, X3, and X4 are 0.24103, 0.0732566, 0.118183, and 0.229214, respectively. These positive coefficients indicate that each of these variables has a positive association with the outcome variable, meaning that as each predictor increases by one unit, the dependent variable is expected to increase by the corresponding coefficient value, assuming all other variables remain constant. The relatively small size of these coefficients suggests moderate effects of each predictor on the dependent variable.

From **Table 21**, the p-values indicate that predictors X1 (0.0004) and X2 (0.010) are statistically significant, meaning there is strong evidence to reject the null hypothesis for these variables. X3 (0.089) shows marginal significance, while X4 (0.373) is not significant, suggesting weaker evidence of an effect..

From **Table 21**, the R² values reveal that X1 (0.174) and especially X2 (0.790) explain a substantial portion of the variation in the outcome variable, indicating good predictive ability, whereas X3 and X4 contribute less meaningfully.

From **Table 21**., the reported value of standard error mentioned for X1 is 0.067, X2 is 0.050, X3 is 0.054 and X4 is 0.059 which are relatively low value of standard error and indicates that sample means are closely distributed around the population mean,

From **Table 21**., the value of F-stat for X1 mentioned is 6.062 which implies that the restricted model fit the data as well as the unrestricted model but for Values of X2 is 115 which is not significant and for X3, X4 it is NA value. Also, the correlation coefficient for X1 mentioned is 0.229, for X2 mentioned is 0.118 which is relatively above the accepted level for this hypothesis but not valid for values of X2, X3, X4.

Additionally, when examining project parameters (X1 to X4) against outcome Y1 for AIA interview participants, X1 and X2 consistently showed stronger p-values. Interestingly, individual comparisons such as Y1 vs. X1 or Y1 vs. X2 appeared less significant, but combinations like Y1

vs. X3 and Y1 vs. X2 produced stronger p-values. This pattern suggests that while some variables may seem weak when tested alone, their combined influence enhances the model's explanatory power.

4.11 Synthesis of Multidimensional Validity

A critical observation across the hypothesis testing phase is the disparity between individual variable correlations and the high statistical significance of the combined models. While standalone testing in earlier chapters showed that factors such as Project Experience (X1) and Technology Adoption (X2) often lacked strong linear predictive power in isolation, their integration into the combined models for **H9 and H10** reveals a different statistical reality.

As demonstrated in **Table 18 and Table 21**, when analyzed collectively, X1 and X2 achieve strong statistical significance ($p < 0.05$), and the ensemble machine learning models—specifically **AdaBoost and Gradient Boosting**—achieve a high coefficient of determination ($R^2 = 0.737$). This result shows that the success of AIA projects in cloud settings relies on complex, interconnected factors rather than single elements.

In complex SME contexts, a single factor like "Technology Adoption" (X2) may seem weak when measured alone. However, its **synergistic combination** with Project Experience (X1) and Management Strategy (X3) creates a robust predictive indicator for project outcomes (Y1) and goal achievement (Y2). The framework's reliability stems from the **systematic interplay** among its elements, as each variable can trigger the statistical relevance and practical usefulness of the others.

5 DISCUSSION

5.1 Results implications

5.1.1 Comparison of initial hypothesis H1: Positive Relationship between Overall performance of final business AIA application and AIA Projects experience complexity level and relevant literature

In this thesis, the analysis of Hypothesis H1, which explores the relationship between Project Experience Complexity Levels (X1) and the Overall Performance of the Final Business AIA Application (Y1), reveals a negative alignment. While the qualitative analysis of interview transcripts indicated that experienced professionals with complex project histories contributed to effective implementations, the quantitative findings contradict this, showing a weak and statistically insignificant correlation (P-value = 0.461, $R^2 = 0.000$, correlation coefficient = -0.007). This suggests that, despite high complexity and experience, these factors alone do not predict superior performance outcomes in AIA projects.

When comparing these findings with the broader academic literature, we see both similarities and contrasts. For instance, in Müller et al. (2024), the high desk rejection rates of AI-related submissions are attributed to methodological weaknesses and lack of clarity in execution, not necessarily the technical complexity or experience of the project team. This aligns with our finding that complexity or experience may not be sufficient indicators of performance unless rigorously aligned with robust methodology and reporting standards.

In Felicetti et al. (2024), project managers' adoption of generative AI tools is significantly influenced by Innovation Attitude and Task-Technology Fit, rather than experience alone. Their findings support the notion that contextual factors—such as how well the AI solutions align with organizational tasks—play a more critical role than simply having a complex or experienced background. This supports our result, where the complexity of experience didn't translate into higher application performance.

Jing et al. (2025) presents another dimension—highlighting that Cultural Intelligence (CQ) and AI capabilities, when mediated together, influence project success. This indicates that soft skills and integration capacity can outweigh raw technical experience in predicting outcomes, further validating our conclusion that experience complexity alone is insufficient.

On the technical front, Nemitallah et al. (2023) found that AI model performance in industrial applications (like boiler optimization) depends heavily on data quality and model selection, not merely on the experience of the implementers. Similarly, in our study, despite experienced participants, subpar or inconsistent project strategies may have undermined overall performance, as reflected in the regression outcomes.

From a performance evaluation standpoint, Zhang et al. (2024) emphasizes the need for robust frameworks under uncertain and complex conditions to truly assess success—again reinforcing that raw complexity (X1) is not predictive unless managed within a structured evaluation system.

Finally, Xin et al. (2024) in the cosmetics industry showcases how AI and ML success is closely tied to targeted innovation, predictive accuracy, and risk mitigation—suggesting that operational alignment, not just experience, is crucial. This echoes our insight that high complexity doesn't guarantee impact without alignment with business goals and performance metrics.

In conclusion, overall, the divergence between qualitative perceptions of project complexity and the quantitative underperformance of that variable highlights a broader theme in AI project research: Experience and complexity must be strategically aligned with context, model selection, and business needs. This mirrors conclusions drawn in recent literature, where successful AI application is rarely about experience alone, but rather about how intelligently and adaptively that experience is applied. Hence, our study contributes to the growing evidence that measurable success in AIA projects depends more on integration, contextual fit, and strategic alignment than on complexity of experience alone.

5.1.2. Comparison of initial hypothesis H2: Positive Relationship between Overall performance of final business AIA application and different technologies used in AIA projects and relevant literature

This thesis explored the relationship between the different technologies used (X2) in developing the final business AIA application and its overall performance (Y1). Qualitative analysis of participant interviews highlighted the use of diverse technologies such as firewalls, network tools, CRM platforms like Salesforce, SharePoint, Oracle Cloud services, and Java-based tools. Interviewees generally reported favorable system performance, emphasizing continuous monitoring and striving for ongoing improvements.

However, the quantitative analysis presents a contrasting perspective. Regression results (**Table 9**) show a very weak and statistically insignificant relationship between the variety of technologies used and the overall AIA application performance. The p-value of 0.448, which is well above the typical 0.05 threshold, suggests that we cannot reject the null hypothesis; there is no significant predictive relationship between the independent variable (X2) and the dependent variable (Y1). The coefficient of determination ($R^2 = 0.0001$) indicates that the model explains virtually none of the variance in overall performance. The very low F-statistic (0.016) and near-zero negative correlation coefficient further corroborate the absence of a meaningful association.

When comparing these findings with the broader academic literature, the findings resonate with broader observations in the literature regarding digital technology adoption. Brozovsky et al. (2024) emphasize a significant gap between technological innovation and practical application, particularly in the Architecture, Engineering, and Construction (AEC) sector, which can extend to similar business technology contexts. This indicates that having access to advanced tools does not automatically translate to improved outcomes without effective integration and strategy.

Similarly, Setaki & van Timmeren (2022) highlight that digital technologies like AI, IoT, and BIM can enable circular economy goals but require strategic and contextual implementation to yield resource efficiency benefits. This underlines the need for not just technology adoption but purposeful deployment aligned with organizational objectives.

Moreover, Nemitallah et al. (2023) and Zhang et al. (2024) show that successful AI and supply chain platform performance depends on high-quality data, appropriate model selection, and robust evaluation frameworks—factors that go beyond the mere use of diverse technologies.

In conclusion, this research reveals that while technologies used in developing the AIA application are diverse and sophisticated, their presence alone does not guarantee improved overall performance. Strategic alignment, integration, and management of technologies appear to be critical for translating technological investment into successful project outcomes.

Refined Synthesis of X2 (Technology) and Model Coherence

While the standalone statistical analysis ($p = 0.448$) suggests that Technology Adoption (X2) does not independently dictate Performance (Y1), this does not imply that technology is irrelevant. Rather, as demonstrated in the final Neural Network analysis, X2 is a contingent variable. Its predictive power is unlocked only when combined with Team Experience (X1) and Management Strategy (X3).

This addresses the jury's observation regarding the "determinant" nature of these factors; X2 is not a standalone determinant, but a synergistic component of the larger framework. This alignment between the rejected individual hypothesis and the successful combined model (H9, H10) confirms that in complex SME environments, the "mere presence" of technology is insufficient without the human and strategic factors to direct it.

5.1.3 Comparison to the initial hypothesis H3: Positive Relationship between Overall Overall performance of final business AIA application and different project management strategy used in AIA projects and relevant literature

This thesis investigated how different project management strategies (X3), such as agile and scrum methodologies, impact the overall performance (Y1) of the final business AIA application. Qualitative insights from participants emphasized the use of agile and scrum frameworks and highlighted the importance of timely project delivery and accountability as key contributors to project success. For example, participants noted that completing work on time and maintaining software performance were critical performance indicators.

Quantitatively, the regression analysis (**Table 10**) revealed a statistically significant positive relationship between project management strategies used and the overall performance of the AIA application. The p-value of 0.0002 strongly supports the hypothesis that the choice and application of effective project management methodologies positively influence project outcomes. The coefficient of determination ($R^2 = 0.098$) indicates a modest explanatory power of the model, while the F-statistic (12.827) and correlation coefficient ($r = 0.186$) further confirm a positive, albeit moderate, association.

When comparing these findings with the broader academic literature, the findings align closely with prior research on project management maturity and success. Pretorius et al. (2023) noted a decline in project management maturity but acknowledged ongoing perceptions of success, suggesting that methodologies like agile may help sustain performance despite broader challenges. Phung et al. (2023) emphasized stakeholder management and sustainability goals in project success, which agile frameworks inherently support through iterative feedback and collaboration. Dalto et al. (2024) further underline project management's role in facilitating innovative approaches such as circular economy adoption, illustrating the strategic value of adaptable methodologies like agile and scrum.

In the context of AI product performance, studies like Nemitallah et al. (2023) and Zhang et al. (2024) reinforce the importance of structured project execution in managing complexity and ensuring reliable system operation, consistent with the positive impact of project management strategies identified here.

In summary, this research provides evidence that project management strategies, particularly agile and scrum methodologies, positively impact the performance of AI applications in business settings. Emphasizing effective project management practices is essential for ensuring successful AI deployments.

5.1.4. Comparison to the initial hypothesis H4: Positive Relationship between Overall performance of final business AIA application and lessons learned from different AIA projects and relevant literature.

This study examined the influence of lessons learned and competencies (X4) on the overall performance (Y1) of the final business AIA application. Qualitative data revealed key themes such as the importance of cost-benefit analysis, ownership of developed products, and strong people-to-people management. Performance outcomes reported by participants highlighted tangible improvements including enhanced motor speed control, overcoming legacy system challenges, and significant reduction in project turnaround time.

Quantitatively, the regression results (**Table 11**) demonstrate a statistically significant positive relationship between lessons learned (X4) and overall application performance (Y1). The p-value of 0.000 strongly rejects the null hypothesis, supporting the idea that effective lessons learned contribute meaningfully to performance outcomes. The coefficient of determination ($R^2 = 0.135$) indicates a moderate explanatory power, while the F-statistic (18.564) and correlation coefficient ($r = 0.293$) further corroborate this positive association.

When comparing these findings with the broader academic literature, the findings are consistent with the literature emphasizing the critical role of lessons learned and competencies in project success. Williams et al. (2023) highlighted how combining hands-on activities with ethical and inclusive approaches enhances learning outcomes, which parallels the importance of ownership and stakeholder engagement reported here. Ruwaida et al. (2023) and Gyrard et al. (2025) similarly stress the role of clear requirements, stakeholder collaboration, and standards to improve system interoperability and reliability—elements closely tied to lessons learned during projects.

In terms of product performance, studies like Nemitallah et al. (2023), Zhang et al. (2024), and Xin et al. (2024) reinforce that leveraging data-driven approaches and rigorous evaluation frameworks—rooted in lessons learned—drive measurable improvements in AI and industrial applications.

In conclusion, this research highlights that lessons learned and competency development are key drivers of successful AIA project performance. Investing in knowledge capture, stakeholder collaboration, and ownership processes can meaningfully enhance AI application outcomes in organizational contexts.

5.1.5. Comparison to the initial hypothesis H5: Positive Relationship between Overall goals achieved from final business AIA application and AIA Projects experience complexity level and relevant literature.

The analysis explored the relationship between project experience complexity levels (X1) and the achievement of goals from the final business AIA application (Y2). Qualitative data from interview transcripts illustrated diverse project backgrounds ranging from engineering design in oil and gas, government automation projects, to next-generation data center upgrades. Goals emphasized planning, automation, and modernization.

Quantitatively, regression results (**Table 12**) reveal no statistically significant relationship between project experience complexity (X1) and goal achievement (Y2). The coefficient of determination ($R^2 = 0.000$) indicates that complexity does not explain variation in goal achievement. The p-value (0.401) is well above conventional significance thresholds, suggesting acceptance of the null hypothesis — that project complexity level does not predict project goal achievement in this dataset. The very low F-statistic (0.062) and correlation coefficient ($r = -0.015$) further support this finding.

When comparing these findings with the broader academic literature, the findings contrast with previous research emphasizing the critical role of project complexity and experience in shaping project outcomes. Bouzguenda et al. (2022) demonstrated how hands-on, complex engineering design projects provide practical learning that could enhance success. Nakitare et al. (2023) and Katerji & Karami-Akkary (2025) similarly underscore how complexity in literacy and educational improvement initiatives requires tailored management approaches.

The lack of significant correlation here might be due to the varied nature of AIA projects where technological, organizational, and contextual factors could overshadow pure complexity or

experience as predictors. This echoes Nasir et al. (2023) and Nahar (2024), who emphasize that achieving AI-related sustainable development goals requires more than technical or experiential inputs, involving systemic and institutional considerations.

In conclusion, while project experience complexity is intuitively important, this study finds no significant evidence that it directly influences goal achievement in AIA projects. This highlights the complex, multi-dimensional nature of AI-driven project success and calls for broader evaluative criteria.

5.1.6. Comparison to the initial hypothesis H6: Positive Relationship between Overall goals achieved from final business AIA application and different technologies used in AIA projects and relevant literature.

This thesis investigated how the use of different technologies (X2) relates to achieving project goals (Y2) in Artificial Intelligence Application (AIA) projects. The qualitative analysis revealed diverse technology usage, including AI-based tools, software testing suites, and enterprise platforms such as Microsoft Dynamics and Power BI. Interviewees emphasized goals aligned with agile delivery, application performance optimization, timely and on-budget completion, and stakeholder engagement.

Quantitative regression results (**Table 13**) showed a low but positive association between technology usage and goal achievement. Specifically, the coefficient of determination ($R^2 = 0.017$) indicates that technology explains around 1.7% of the variance in project goal achievement, reflecting a modest effect size. The p-value (0.074) is above the conventional threshold of 0.05 but still suggests a trend worth noting, indicating partial support for Hypothesis 6 (H6). The standard error (0.058) was low, suggesting reliable estimates, while the F-statistic (2.106) and correlation coefficient ($r = 0.084$) corroborate a weak positive relationship.

When comparing these findings with the broader academic literature, the findings resonate with Setaki and van Timmeren (2022), who highlighted the potential of disruptive digital technologies like AI, IoT, and BIM to promote resource efficiency and waste reduction in the building lifecycle, demonstrating strategic yet still emerging technological influence. Similarly, Brozovsky et al.

(2024) noted the slow adoption pace in the Architecture, Engineering, and Construction (AEC) sector, implying that despite available technologies, their impact on project outcomes remains limited by adoption barriers.

Xu et al. (2023) emphasized technological innovation through efficient neural architecture search, reflecting the cutting-edge AI tools mentioned by participants. Nonetheless, the limited variance explained in this study points to the complexity of translating advanced technology use into tangible goal achievement.

In conclusion, this study highlights a positive but limited relationship between the use of different technologies and goal achievement in AIA projects. While technology acts as a key enabler, broader strategic and organizational factors are essential for realizing project success.

5.1.7. Comparison to the initial hypothesis H7: Positive Relationship between Overall goals achieved from final business AIA application and different project management strategy used in AIA projects and relevant literature.

The objective of this analysis was to evaluate whether different project management strategies (X3)—particularly the use of Agile and related methodologies—have a measurable impact on the achievement of goals (Y2) in final AIA applications. Qualitative insights from participants highlighted the use of Agile methods, often paired with tools such as JIRA, to manage and deliver complex AI-driven projects. These participants also described clear and outcome-oriented goals—such as building analytics applications tailored to consumer needs, completing projects successfully, or reducing processing times.

When comparing these findings with the broader academic literature, the findings align with the broader academic consensus that while structured project management strategies like Agile can facilitate successful execution, they are not sufficient on their own to guarantee goal achievement. Pretorius et al. (2023) show that project success can persist even when project management maturity declines, pointing to the complexity of success metrics in practice.

Phung et al. (2023) emphasize the importance of stakeholder management and sustainability goals, suggesting that strategic alignment and goal clarity matter more than methodology alone.

Dalto et al. (2024) suggest that project management enables transitions like the circular economy in agribusiness only when combined with domain knowledge and broader systemic approaches.

This reinforces the idea that while project methodologies like Agile offer a framework for execution, they must be embedded within a well-defined goal structure and stakeholder engagement plan to truly drive success.

In summary, the data shows a statistically significant but modest relationship between project management strategies and AIA goal achievement. Insights can inform both research and practice by emphasizing the importance of strategic alignment and broader systems thinking in AIA project delivery.

5.1.8. Comparison to the initial hypothesis H8: Positive Relationship between Overall goals achieved from final business AIA application and lessons learned from different AIA projects and relevant literature.

When comparing these findings with the broader academic literature, the findings resonate with several studies:

(Williams et al., 2023): Emphasized the impact of ethics-focused, inclusive AI education—lessons that apply in both academic and professional project contexts.

(Ruwaida et al., 2023) stressed the importance of stakeholder collaboration and clear operational definitions, which directly align with participant #74's emphasis on stakeholder engagement as a learned competency. In (Gyrard et al., 2025) demonstrated how interoperability and standardization lessons enhanced long-term project success—mirroring the practical orientation of participant #81.

Also, the alignment of lessons learned with broader goals (Y2) ties back to the literature on AI and Sustainable Development Goals (Nasir et al., 2023; Nahar, 2024; Wei et al., 2025). These studies

highlight that strategic learning and goal alignment are essential for sustainable impact—a theme that surfaces in the interview excerpts and the moderate positive correlation in the data.

In conclusion, the findings demonstrate that lessons learned (X4) from AIA projects positively influence the extent to which project goals (Y2) are achieved. While not the only determinant, experiential learning plays a measurable and meaningful role in project success. The evidence supports the initial hypothesis (H8), aligns with contemporary literature, and offers practical guidance for enhancing goal alignment in future AI initiatives.

5.1.9. Comparison to the initial hypothesis H9: Positive Relationship between Overall performance of final business AIA application and combined impact of AIA Projects experience complexity level , different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projects relevant literature.

Our analysis offers a thorough integration of both qualitative and quantitative data to evaluate the combined impact of project factors (X1–X4) on the overall performance of the business AIA application (Y1). Although increased use of technology strongly correlates with Y1, the negative coefficient suggests over-reliance on tools or complexity of integration might hinder final performance. This aligns with (Brozovsky et al., 2024), where digital tools in AEC lacked effective implementation despite widespread availability. Technology alone is not a silver bullet—its strategic implementation matters more.

When comparing these findings with the broader academic literature, the findings align with Bouzguenda et al. (2022) and Setaki & van Timmeren (2022) in showing that real-world complexity and tech usage require careful planning and integration to drive positive outcomes.

Like Phung et al. (2023) and Dalto et al. (2024), project strategy alone is insufficient without stakeholder alignment and sustainability goals. Echoing Nemitallah et al. (2023) and Xin et al. (2024), high-quality data and contextual adaptation are essential in achieving AI-driven product performance.

The thesis illustrates that while individual factors such as experience (X1) and technology (X2) have statistically significant effects on project success (Y1), their direction of impact can be negative without strategic alignment. Furthermore, project management strategies (X3) and lessons learned (X4), though intuitively beneficial, lack consistent statistical significance on their own. However, in combination, these factors exhibit strong predictive power, especially when analyzed through ensemble ML models like AdaBoost. These insights underscore the importance of holistic integration of complexity, technology, strategy, and learning in shaping successful AIA applications—offering clear implications for future project planning, training, and policy decisions.

5.1.10. Comparison to the initial hypothesis H10: Positive Relationship between Overall goals achieved from final business AIA application and combined impact of AIA Projects experience complexity level , different technologies used in AIA projects, different project management strategy used in AIA projects and lessons learned from different AIA projectsand relevant literature.

The objective was to assess the combined effect of four key project parameters—project experience complexity (X1), technologies used (X2), project management strategies (X3), and lessons learned (X4) on the overall goals achieved in the final AIA business application (Y2). Both qualitative and quantitative analyses suggest that X1 and X2 are the most influential predictors, while X3 and X4 show weaker or marginal influence.

When comparing these findings with the broader academic literature, the findings from this thesis are consistent with existing literature. As reported by Bouzguenda et al. (2022), hands-on project experiences, particularly in technologically demanding domains such as smart agriculture systems, improve competency and positively impact project outcomes. This validates the high significance of project experience complexity (X1) observed in the current study.

The relevance of digital technologies (X2) as enablers of project success aligns with the observations by Setaki and van Timmeren (2022) and Xu et al. (2023), where technologies like Artificial Intelligence (AI), the Internet of Things (IoT), and Building Information Modeling (BIM) are shown to streamline processes and enhance resource efficiency and decision-making. However, the moderate impact found in the current study suggests that while such technologies

are foundational, they must be effectively integrated with experience and strategy to yield measurable success.

For project management strategies (X3), the current results reflect the findings of Pretorius et al. (2023), who highlighted variability in project management maturity and its influence on project success metrics in developing regions. Although the selected strategy (e.g., Agile, Waterfall, JIRA) matters, its impact may be secondary to execution fidelity and stakeholder engagement, as emphasized by Phung et al. (2023) in their work on sustainable project success.

Lessons learned (X4), though frequently emphasized in qualitative responses, did not exhibit a statistically significant relationship in the quantitative analysis. This outcome echoes the insights of Williams et al. (2023) and Gyrard et al. (2025), who argue that while reflective practices and learning processes are vital for long-term capability development, their effects may not be immediately observable within short-term project evaluation metrics.

In conclusion, the findings of this study affirm the multi-dimensional nature of achieving success in AI-based business applications. While project experience and technology adoption (X1 and X2) emerge as critical predictors of goal attainment (Y2), management strategies and lessons learned (X3 and X4) require contextual alignment and sustained application to yield tangible impacts. These outcomes not only support the initial hypotheses but also underscore the value of integrating technical competencies with strategic execution. The study further contributes to the literature by offering empirical insights that reinforce the importance of combined factors—rather than isolated interventions—in delivering successful AI-driven projects.

6 CONCLUSION

Building on the empirical analysis and framework introduced in [Chapter 1](#), this chapter summarizes the key findings, highlights contributions to both theory and practice, identifies limitations, and outlines directions for future research in cloud-based AIA project management.

This conclusion also reflects on the practical and strategic implications for IT teams, project managers, and enterprise decision-makers.

6.1. Expected Contributions

This research systematically examined the factors that influence performance and goal achievement in enterprise AIA projects. Based on 120 executive-level interviews, the study provides empirically validated insights into how project experience, technology adoption, project management strategies, and lessons learned collectively shape outcomes.

The contributions are fourfold:

1. **Large-Scale Empirical Evidence:** This study captures real-world experiences from projects ranging from \$1M to \$50M+, providing a unique view of enterprise AIA adoption that bridges gaps in current literature (Schütte & Kari, 2025). It highlights the practical challenges, trade-offs, and innovative practices that emerge in cloud-based project delivery.
2. **Framework for Project Success:** By identifying critical factors (X1–X4) affecting AIA project performance, this research develops a structured and reusable framework. This framework can guide future studies, benchmark performance, and provide actionable recommendations for enterprises adopting cloud-based AIA solutions (Kambala, 2025).
3. **Insights into Cloud and DevOps Practices:** The study demonstrates how modern methods such as DevOps, DataOps, and CI/CD influence innovation, collaboration, and delivery efficiency (Hammerschmidt, Stolz & Posegga, 2025). These findings offer practical guidance for IT teams seeking to optimize iterative processes and reduce deployment risks.
4. **Bridging Theory and Practice:** By moving beyond algorithm-centric research, the study addresses the broader enterprise software engineering perspective. It provides empirically grounded recommendations for IT leaders and project managers, emphasizing the interplay

between organizational factors, team practices, and technology adoption (Schütte & Kari, 2025).

Concrete examples of X1–X4 factors from real projects:

- **X1 – Project Experience:** Teams with prior cloud ERP implementation experience were able to reduce deployment time by 20–30% and avoid common integration pitfalls. Experienced solution architects facilitated cross-module integration between D365 Finance & Operations and CRM tools like Salesforce (Kambala, 2025).
- **X2 – Technology Adoption:** Projects incorporating modern cloud technologies, including automated CI/CD pipelines, DataOps workflows, and cloud monitoring tools (e.g., IBM QRadar), achieved higher stability and faster release cycles, improving end-user satisfaction (Schütte & Kari, 2025).
- **X3 – Project Management Strategies:** Agile and hybrid management methods, with iterative sprint planning and clear role definitions, correlated with higher team collaboration scores and reduced rework. Centralized dashboards and structured reporting enhanced executive visibility (Hammerschmidt, Stolz & Posegga, 2025).
- **X4 – Lessons Learned:** Teams that conducted formal post-project reviews and knowledge-sharing sessions improved subsequent project performance, particularly in cross-functional collaboration and early issue detection. Lessons from previous ERP and asset management integrations (e.g., IBM Maximo) directly influenced process improvements in later AIA projects (Kambala, 2025).

6.2 Implications for Practice

The findings have several practical implications:

- **For IT Teams and Developers:** Adoption of cloud platforms combined with structured AIA practices enhances collaboration, reduces cycle times, and supports continuous innovation. Teams can leverage the framework to identify which practices yield the greatest performance improvements (Schütte & Kari, 2025).
- **For Project Managers:** Understanding the critical factors influencing project success helps in resource allocation, risk management, and stakeholder engagement. Managers can

implement DevOps and DataOps strategies more effectively to align with enterprise goals (Hammerschmidt, Stolz & Posegga, 2025).

- **For Enterprises:** Organizations can adopt a data-driven approach to evaluate and benchmark AIA project practices, ensuring that technology adoption translates into measurable business value. Enterprises can also use insights from this study to inform cloud adoption strategies, governance models, and training programs (Kambala, 2025).
- **For Researchers:** The framework provides a baseline for studying cloud-based AIA projects across different ERP systems, industry sectors, and geographic regions. It can also guide the integration of qualitative and quantitative methods in future research (Schütte & Kari, 2025; Hammerschmidt, Stolz & Posegga, 2025).

6.3 Expected Limitations

Despite the contributions, this study has several limitations:

- **Data Source Limitations:** Reliance on self-reported interviews from executive-level participants may introduce social desirability bias. Operational or mid-level staff perspectives are not fully captured, which may overlook practical execution nuances (Hammerschmidt, Stolz & Posegga, 2025).
- **Scope and Generalizability:** The study focuses on SMEs and primarily on Microsoft Dynamics 365 (Finance & Operations). Results may not generalize to larger enterprises, other ERP platforms, or different organizational contexts (Schütte & Kari, 2025).
- **Measurement Constraints:** Some hypotheses, such as H5, lacked statistical significance, indicating that single-factor analysis may not capture the full complexity of multi-dimensional project interactions. Time constraints and NDA restrictions limited the collection of objective Enterprise Software Engineering (ESE) metrics (Kambala, 2025).
- **Analytical Limitations:** While ontology-driven text analytics and neural network modeling provided useful insights, the full potential of techniques like Partial Least Squares (PLS) analysis was not realized due to time and resource constraints (Hammerschmidt, Stolz & Posegga, 2025).
- **Empirical Data and NDA Constraints:** A significant limitation of this study was the inability to collect direct Empirical Software Engineering (ESE) metrics such as raw code

churn, commit frequency, or automated test logs due to strict **Non-Disclosure Agreements (NDAs)** with the participating SMEs. To overcome this, the study utilized high-level expert interviews and Likert-scale scoring as robust proxies. Future work should attempt to secure data-sharing agreements that allow for the integration of these quantitative logs to further validate the X1–X4 interactions.

6.4. Potential for Future Research

The findings of this study open several avenues for future research:

1. **Longitudinal Studies:** Observing AIA project outcomes over time would provide insights into how performance and goal achievement evolve post-deployment and help validate the framework in dynamic environments (Schütte & Kari, 2025).
2. **Expanded Enterprise Contexts:** Including larger organizations, multiple ERP platforms (e.g., SAP, Oracle), and multinational projects would improve generalizability and test the framework across diverse environments (Kambala, 2025).
3. **Inclusion of Operational and Mid-Level Staff:** Capturing perspectives from mid-level managers, developers, and analysts could provide a more complete understanding of team dynamics and execution challenges (Hammerschmidt, Stolz & Posegga, 2025).
4. **Advanced Analytics Techniques:** Applying ontology-driven text analytics, PLS modeling, and AI-enhanced simulations could refine predictions of project success factors, optimize project strategies, and enable scenario planning (Kambala, 2025).
5. **Integration with Objective Metrics:** Future studies should aim to bypass the current **NDA-related limitations** by securing data-sharing agreements that allow for the collection of direct **Empirical Software Engineering (ESE)** metrics. Specifically, future surveys should move beyond Likert scales to measure technical KPIs such as **Mean Time to Recovery (MTTR)**, **Change Failure Rate (CFR)**, **Deployment Frequency**, and **API Latency/Throughput** within AIA pipelines. Correlating these numerical system logs with the qualitative insights from this study would provide a more granular, bias-free validation of how the four factors (X1–X4) impact project outcomes.
6. **Research Dissemination and Collaboration:** Publishing findings in peer-reviewed journals and collaborating on industry-academia projects could test the framework in new

contexts, further validating and refining its practical applicability (Hammerschmidt, Stolz & Posegga, 2025).

7. **Exploration of Cross-Factor Interactions:** Future work can investigate how combinations of X1–X4 factors interact synergistically to affect project outcomes, providing deeper insights into high-performing team configurations and cloud adoption strategies (Kambala, 2025).

By addressing these areas, future research can build on the insights of this thesis to support evidence-based cloud adoption, improve team performance, and strengthen enterprise innovation in AIA projects.

7 APPENDIXES

7.a Comparison between Measuring Project experience complexity levels (X1) and Measuring Overall performance of the final business AIA application (Y1)

AIA interview participant#	Measuring Project experience complexity levels (X1)	Measuring Overall performance of the final business AIA application (Y1)
AIA interview participant#1	we gave a likert score value of 3 which is identified as medium project complexity i.e. if the AIA participant has only worked on 7-9 projects	We gave a likert score value of 4 which is identified as “Meets Expectations” i.e. the overall performance of the final business AIA application used by their respective organisation meets expectations.
AIA interview participant#5	we gave a likert score value of 5 which is identified as super Complex project complexity i.e. if the AIA participant has only worked on more than 10 projects in order to build the final project	We gave a likert score value of 5 which is identified as “Exceeds Expectations” i.e. the overall performance of the final business AIA application used by their respective organisation exceeds expectation
AIA interview participant#8	we gave a likert score value of 4 which is identified as Moderately Complex project complexity i.e. if the AIA participant has only worked on 7-9 projects	We gave a likert score value of 5 which is identified as “Exceeds Expectation” i.e. the overall performance of the final business AIA application used by their respective organisation exceeds expectation.

7.b Comparison between Measuring different technologies used (X2) and Measuring Overall performance of the final business AIA application (Y1)

AIA interview participant#	Measuring different technologies used (X2)	Measuring Overall performance of the final business AIA application (Y1)
AIA interview participant#15	we gave a likert score value of 2 i.e. between 5-10 technologies were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Exceeds Expectation” i.e. the overall performance of the final business AIA application used by their respective organisation Exceeds Expectation.
AIA interview participant#17	we gave a likert score value of 4 i.e. Less than 5 technologies were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Exceeds Expectations” i.e. the overall performance of the final business AIA application used by their respective organisation Exceeds Expectations.

AIA interview participant#21	we gave a likert score value of 2 i.e. between 5-10 technologies were used in building the final business AIA application	We gave a likert score value of 5 i.e. the overall performance of the final business AIA application used by their respective organisation Exceeds Expectations.
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7.c Comparison between Measuring different Project Management strategies used (X3) and Measuring Overall performance of the final business AIA application (Y1)

AIA interview participant#	Measuring different Project Management strategies used (X3)	Measuring Overall performance of the final business AIA application (Y1)
AIA interview participant#22	we gave a likert score value of 5 i.e. strong Agile model Project Management strategy were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Exceeds Expectations” i.e. the overall performance of the final business AIA application Exceeds Expectations..
AIA interview participant#25	we gave a likert score value of 5 i.e. strong Agile model Project Management strategy were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Exceeds Expectations” i.e. the overall performance of the final business AIA application Exceeds Expectations.

AIA interview participant#29	we gave a likert score value of 5 i.e. strong Agile model Project Management strategy were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Exceeds Expectations” i.e. the overall performance of the final business AIA application Exceeds Expectations..
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7.d Comparison between Measuring different lessons learned were (X4) and Measuring Overall performance of the final business AIA application (Y1)

AIA interview participant#	Measuring different lessons learned were (X4)	Measuring Overall performance of the final business AIA application (Y1)
AIA interview participant#30	We gave a likert score value of 5 i.e. identified as “Strong Alignment” i.e. if the lessons learned from different AIA projects had a strong impact on the Overall performance of the final business AIA application (Y1)	We gave a likert score value of 4 which is identified as “Meets Expectations” i.e. the overall performance of the final business AIA application used by their respective organisation Meets Expectations.
AIA interview participant#32	We gave a likert score value of 3 i.e. identified as “Low Alignment” i.e. if the lessons learned from different AIA projects had a low impact on the Overall performance of the AIA application (Y1)	We gave a likert score value of 4 which is identified as “Meets Expectations” i.e. the overall performance of the final business AIA application used by their respective organisation Meets Expectations.

<p>AIA interview participant#33</p>	<p>We gave a likert score value of 5 i.e. identified as “Strong Alignment” i.e. if the lessons learned from different AIA projects had a strong impact on the Overall performance (Y1)</p>	<p>We gave a likert score value of 5 which is identified as “Exceeds Expectations” i.e. the overall performance of the final business AIA application</p>
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7.e Comparison between Measuring Project experience complexity levels (X1) and Measuring goals achieved from the final business AIA application (Y2)

AIA interview participant#	Measuring Project experience complexity levels (X1)	Measuring goals achieved from the final business AIA application (Y2)
AIA interview participant#34	we gave a likert score value of 5 which is identified as super Complex project complexity i.e. if the AIA participant has only worked on more than 10 projects in order to build the final project	We gave a likert score value of 3 which is identified as “Low influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application has low influence to support AIA projects.
AIA interview participant#35	we gave a likert score value of 3 which is identified as Medium complexity i.e. if the AIA participant has only worked on between 5 to 7 projects in order to build the final project	We gave a likert score value of 4 which is identified as “Mild influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application has mild influence to support AIA projects.
AIA interview participant#36	We gave a likert score value of 4 which is identified as Moderately Complex i.e. if the AIA participant has only worked on between 7 to 9 projects in order to build the final project	We gave a likert score value of 2 which is identified as “No influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application.

7.f Comparison between Measuring different technologies used (X2) and Measuring goals achieved from the final business AIA application (Y2)

AIA interview participant#	Measuring different technologies used (X2)	Measuring goals achieved from the final business AIA application (Y2)
AIA interview participant#37	we gave a likert score value of 5 which is identified as if more than 20 technologies were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application has Strong influence to support AIA projects.
AIA interview participant#41	we gave a likert score value of 2 which is identified as if 5 to 10 technologies were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application has Strong influence to support AIA projects.
AIA interview participant#43	we gave a likert score value of 4 which is identified as if between 15 to 20 technologies were used in building the final business AIA application	We gave a likert score value of 4 which is identified as “Mild influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application.

7.g Comparison between Measuring different Project Management strategies used (X3) and Measuring goals achieved from the final business AIA application (Y2)

AIA interview participant#	Measuring different Project Management strategies used (X3)	Measuring goals achieved from the final business AIA application (Y2)
AIA interview participant#55	we gave a likert score value of 5 which is identified as Strong Agile model were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application has Strong influence to support AIA projects.
AIA interview participant#56	we gave a likert score value of 5 which is identified as Strong Agile model were used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application has Strong influence to support AIA projects.
AIA interview participant#57	we gave a likert score value of 5 which is identified as Strong Agile model were used in building the final business AIA application	we gave a likert score value of 4 which is identified as “mild influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application

7.h Comparison between Measuring different lessons learned were (X4) and Measuring goals achieved from the final business AIA application (Y2)

AIA interview participant#	Measuring different lessons learned were (X4)	Measuring goals achieved from the final business AIA application (Y2)
AIA interview participant#63	We gave a likert score value of 4 which is identified as “Mild Alignment” i.e. if the lessons learned from different AIA projects used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application.
AIA interview participant#74	We gave a likert score value of 5 which is identified as “Strong Alignment” i.e. if the lessons learned from different AIA projects used in building the final business AIA application	We gave a likert score value of 5 which is identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application has Strong influence to support AIA projects.
AIA interview participant#81	We gave a likert score value of 4 which is identified as “Mild Alignment” i.e. if the lessons learned from different AIA projects used in building the final business AIA application	we gave a likert score value of 1 which is identified as “Strong influence to support AIA projects” i.e. the overall goals achieved from the final business AIA application

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